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Jekaterina DMITRIJEVA

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Unemployment and labour market policy in Central and Eastern Europe

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Directeur

Monsieur Thierry LAURENT, Professeur à l'Université d'Evry Val d'Essonne

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à Leonid et Nikolai

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"Il faut reconnaître que, parmi les intellectuels,
on rencontre parfois, à titre exceptionnel, des gens intelligents."

M. Boulgakov (Le Maître et Marguerite)

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"Evidence d'aujourd'hui, imagination d'hier."

(W.Blake, Le mariage du ciel et de l'enfer)

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Chapter 1

Introduction

Fifteen years of transition to market economy have been a chaotic and eventful period for the countries of Central and Eastern Europe and the Baltic States (CEEB)[1]. Brought by the breakdown of the Soviet Union in the very beginning of the 90's, the transition did not only mean the restructuring and reforming of the economy, but an overall transformation affecting all spheres of the society and establishing new market rules in relations between economic and social agents. The difficulty of building states and markets simultaneously, weak political structure and legal base coexisting with overall economic distortion (rapid inflation, falling output and increasing macroeconomic instability), have been realities of transition witnessed by all countries of CEEB region. In the labour market, transition was associated with intensive labour reallocation between sectors of the economy, high inflows into unemployment and inactivity, job shortage coexisting with an important mismatch (skill, geographical) between labor supply and labour demand.

Despite the severity of transitional recession, in a short period of 15 years the CEEB

[1] Hereinafter we alternate the expressions - transition countries, accession countries or new EU member states - when refereing to ten Central and Eastern European countries (including the Baltic states), which have undergone the process of economic transition in the 90's and have recently joint the European Union - the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia as well as Bulgaria and Romania.

countries have managed to stabilize the economy, displayed important economic growth and were able to meet the accession requirement of the European Union (EU). The success in managing transitional crisis in CEEB has often been attributed to the promotion and efficient implementation of economic policy. In line with OECD suggestions and further established European Employment Strategy (EES)[2], a great importance in mitigating the transition consequences in the labour market has been given to Active Labour Market Policy (ALMP) measures, *i.e.* employment stimulating programs that usually include direct job creation, wage subsidies to private sector, self-employment promotion and labour training. Those were implemented in the countries of Central, Eastern European and Baltic region starting from the early 90's.

The main objectives of this thesis are *(i)* to assess the development of aggregate and regional labour markets through the phases of late transition and EU accession on the example of several new EU member states (Latvia, Estonia and Slovenia) and *(ii)* to investigate the role of active labour market policy programmes in moderating the consequences of transitional shock and improving the performance of the labour market.

In this introductive chapter, we review the main transformations occurred in the labour market of CEEB countries due to systematic changes, discuss the current situation in the labour markets and point out the bottlenecks left as a transition heritage. We also present the empirical evidence on the implementation of ALMP programmes in new EU member states and discuss the potential role of these programmes in smoothing the impact of transition and in improving the performance of the labour market. Finally, we introduce the problematic of this thesis, review the core aspects and methodological approach of the analysis.

[2]Initiated by Delors White Paper in 1993, the EES was established by the Amsterdam Treaty (1997) and updated by the Lisbon European Council (2000). It makes employment promotion one of the key objectives of the EU economic policy.

1.1 Transition and labour markets in new EU member states

We review in what follows the developments through transition as well as the current situation in the labour market of new EU member states.

Despite the impressive contraction in the aggregate output in the initial phase of transition, by year 2000 all countries displayed positive rates of economic growth.

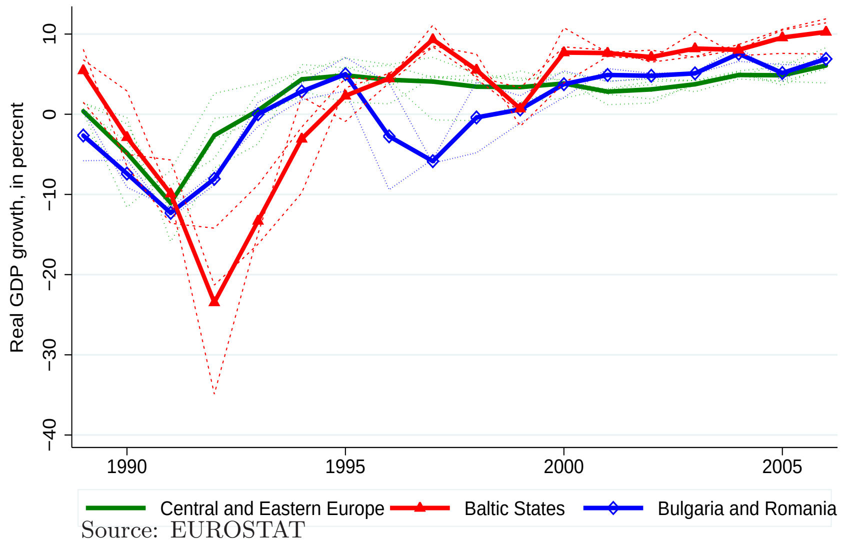
When speaking about the transition from a centrally planned to a free market economy in Central and Eastern Europe, a spectacular contraction in the aggregate output is most frequently evoked. The majority of Central European countries were quite successful in making a sustained progress in economic reform and displayed certain improvement of economic performance starting from the mid 90's (Czech Republic, Hungary, Poland, Slovenia and Slovakia), while others have experienced longer (Bulgaria and Romania) or sharper (Baltic states) transitional recession (see figure 1.1). The differences in the course and outcomes of the transition process are often attributed to strategies, scale and speed of economic change but also to the differences in political organization across countries and in pre-transition economic conditions.

Labour markets have adjusted to transitional shock through employment, but by 2005 the employment on population ratios in CEEB countries have approached the EU-15 average.

The characteristic feature of labour market development in CEEB countries is that the burden of the adjustment to transitional shock fell on employment, while for example in the Commonwealth of Independent States (CIS) wages served as adjustment variable. The differences in institutional settings are often held responsible for such divergence (Boeri and Terrell [2002]).

Despite the substantial fall in employment, that induced high inflows into open unem-

Figure 1.1: Growth in real GDP in new EU member states



Source: EUROSTAT

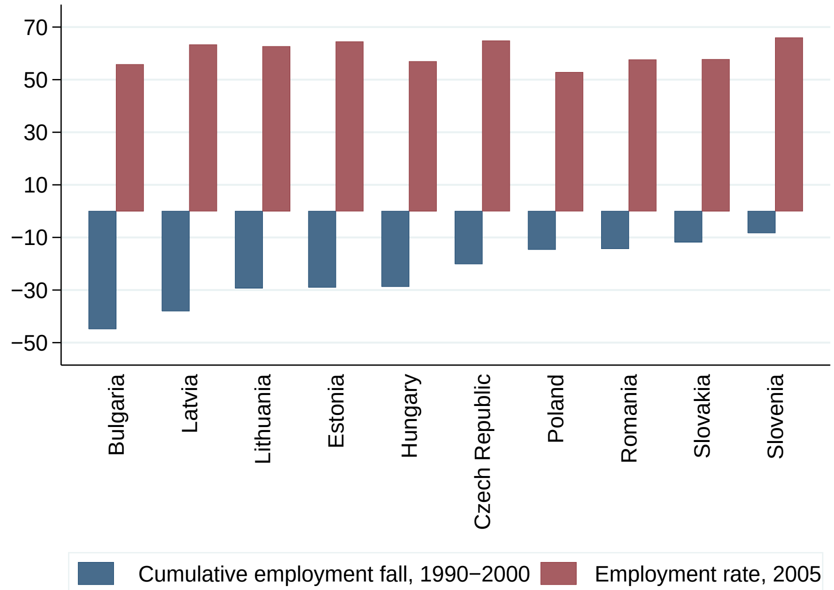
ployment[3] and inactivity and depressed national labour markets for at least a decade, by the year 2005 employment rates on population have approached the EU-15 average in the majority of countries (see figure 1.2).

The most desirable configuration of high participation and low unemployment, witnessing successful transition and restructuring, was achieved in the Czech Republic, the Baltic states and Slovenia[4]. The opposite case is presented by Poland and Bulgaria. High unemployment and low participation of the labour force implies lower employment level and witnesses the depressed state of the labour market. Here the phenomenon of high discouragement of workers coexisting with high unemployment may be related to a precarious situation of poor workers, who simply can not afford staying out of labour force (Rutkowski [2006]). In Hungary and Romania, low activity and low unemployment rates indicate high degree of discouragement among job seekers

[3] In this section we base our considerations on EUROSTAT data, mostly originating from national Labour Force Surveys. This involves ILO definition when referring to unemployment or unemployed. The comparisons with the EU are made using the average statistics for EU-15 (15 countries of the European Union, prior to Eastern Enlargement in 2004 and in 2007).

[4] By 2005, the unemployment rates ranged from 6 percent in Slovenia to 16-18 percent in Poland and Slovakia. The activity rates were around 60-62 percent in Hungary Romania, Bulgaria, and about 70 percent in all other countries, except Poland.

Figure 1.2: Employment in new EU member states



Source: EUROSTAT. Note: For Romania, cumulative employment fall from 1990 to 2002.

- due to limited job opportunities - and also suggests the over-development of the informal sector. In Slovakia the labour market is dynamic and while unemployment is hight, workers keep looking for jobs. Such markets may probably turn into dynamic and well performing ones (like in case the of Lithuania) but also face a risk of stagnation (like in the case of Poland).

Unemployment rates, high in transition, are now declining towards EU-15 level. The major problems remain regional disparity and the duration of unemployment.

In 2005, the share of long term unemployed[5] among job seekers was slightly above 40 percent in the EU. At the same time it was at least 10 percent higher in the Czech Republic, Estonia and Lithuania; it ranged close to 60 percent in Poland and Romania and it was extremely high in Slovakia (70 percent).

The process of adjustment to transitional shock has also created spatial inequalities in

[5] 12 months and more.

terms of unemployment and access to jobs between rural and urban areas.

The capitals, which benefit from the concentration of foreign investment and favorable climate for the creation of new firms and jobs, display high economic activity and low unemployment rates. Rural and especially old industrialized areas, in contrast, suffer from important job destruction due to the closure of outdated and inefficient enterprisers. Low employment opportunities and high unemployment is typical of such areas.

Substantial regional differences in unemployment rates still persist in CEEB countries despite significant amelioration in economic performance. The unemployment rates range from 5 to over 20 percent in Bulgaria in Slovakia, from 4-6 to around 15 percent in the Czech Republic, Estonia and Latvia. Overall, however, the dispersion of regional unemployment rates in CEEB and in other European countries is of a comparable level: from 20 to 40 percent for NUTS2 in 2005.

Insufficient through transition and enhanced by recent economic growth, labour demand stays low if compared to other European countries.

One of the main obstacles to employment growth in CEEB countries was related to significant contractions in labour demand during transition. Even in 2005, after 15 years of transition, the job vacancy rates[6] are at least two times lower in Lithuania, Slovakia, Slovenia, Bulgaria and Hungary than in EU-15. In Latvia and Czech Republic less than 1.5 percent of jobs are vacant on average, and only in Romania and Estonia job vacancy rates are comparable to those in the countries of EU-15 (2 percent)[7].

In terms of allocation of vacant jobs across sectors, public administration, education and health sectors display high vacancy rates (all countries except Czech Republic and Slovenia). Weak wages in these sectors may be responsible for low unemployed interest in offered vacancies. Other employing sectors are construction (Czech Republic, Slove-

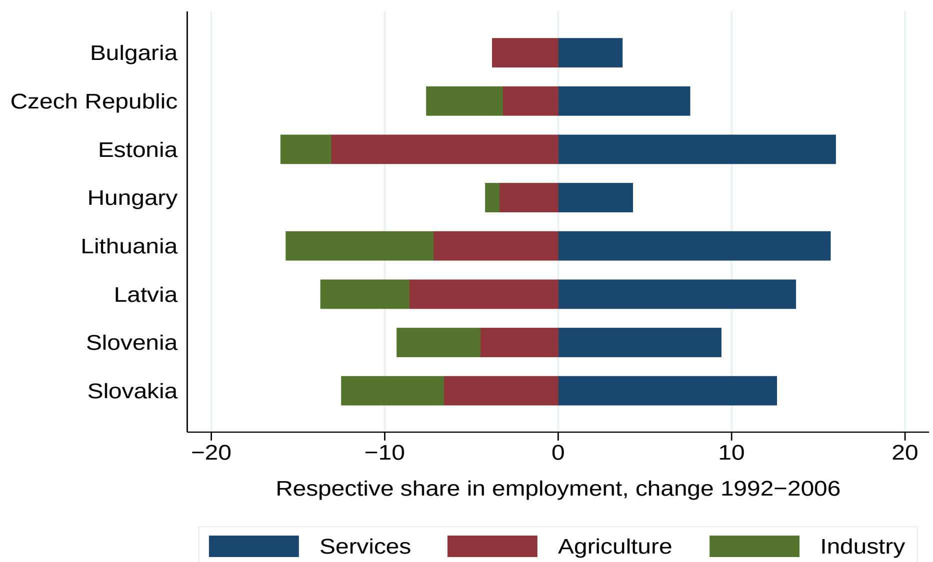
[6] The percentage of vacant posts in total pool of posts (vacant and taken).

[7] Vacancy data should however be interpreted with caution: varying collection methods across countries (through official sources for some countries or business and labour market surveys for others) may result in heterogenous coverage of labour market segments.

nia, Lithuania and Hungary), financial intermediation and real estate (Czech Republic and Slovenia), tourism (Slovenia) or hotel and restaurant sector (Bulgaria, Slovakia and Slovenia), transport, storage and communication (Latvia and Lithuania). Job opportunities in agriculture are high in Bulgaria, Czech Republic, Hungary and Romania, but limited in Slovakia and three Baltic states.

Intensive labour reallocation between the sectors of the economy has induced an important skill mismatch between labour supply and labour demand.

Figure 1.3: Employment development



Source: EUROSTAT. Note: For the Czech Republic and Slovakia, change 1994-2006; for Hungary and Slovenia, change 1995-2006; for Bulgaria, 2001-2004.

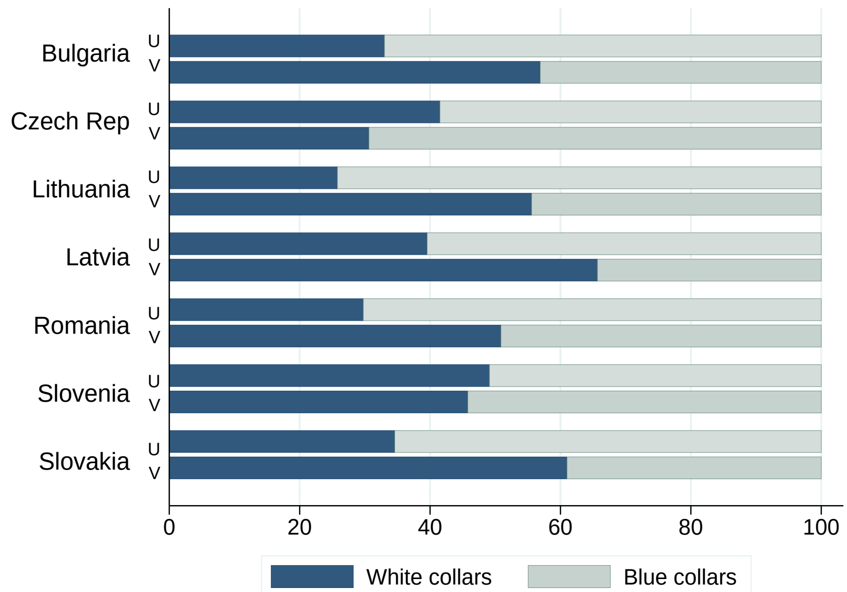
The reallocation of production and labour from agriculture and industry to services (see figure 1.3) has resulted in an important mismatch between the obsolete or inappropriate skills of workers and the requirements of the employers in new and developing sectors.

In Bulgaria, Latvia, Lithuania and Slovakia, most unemployed (over 40 percent of those with an occupation) are low skilled blue collars[8], while the job offers are mostly (over

[8]ISCO categories 8 and 9: plant and machine operators and assemblers, elementary occupations.

40 percent) addressed to high skilled white collars[9] (around 40 percent). In Czech Republic and Slovenia the matching pools are more balanced, but the workers seem to be overqualified with respect to the labour demand: the proportion of white collars among unemployed is higher than the one in proposed positions (see figure 1.4).

Figure 1.4: Occupational structure of unemployed and vacancy pools, 2005



Source: EUROSTAT. Note: White collars represent occupations under ISCO categories 1 to 5. Blue collars represent occupations under ISCO categories 6 to 9.

The restructuring has not only changed the structure of employment, but also its nature: from permanent full time employment contracts to part-time jobs and fixed term contracts.

By 2000, over 10 percent of employed in Lithuania, Latvia, Poland and Romania were working part-time (for comparison in EU-15 this share is 17 percent). Over 5 percent of workers had fixed term contracts in all countries except for Estonia and Romania (in EU-15 this share was 13 percent). While the flexibility of labour market is generally considered as favorable development, the surveys from transition countries (Hazans [2005]) evoke that workers accept part-time or fixed term contracts due to the lack of

[9]ISCO categories 1 to 3: Legislators, senior officials and managers, professionals, technicians and associate professionals.

full time permanent jobs.

Insufficient labour demand has also contributed to the fact that many people have turned to self employment. By 2000 every third Romanian worker, every fourth of Bulgarian or Polish worker, every fifth-sixth Czech, Lithuanian or Slovenian worker was self employed. The self employment rates are on average higher than the ones observed in the EU-15 (about 14 percent).

The employment level and quality also suffer from the development of informal markets.

By 2001, the size of shadow economy in CEEB economies was estimated to about 28 percent of GDP (going from 18 percent in Czech and Slovak Republics to almost 40 percent in Latvia and Estonia) and to about 23 percent of employment (up to 30 percent in Latvia, Estonia and Bulgaria). Moving to the informal sector in the CEEB is mainly related to tax evasion or overcoming labour market regulations. Moonlighting, when an employment in informal sector complements legal employment is also common. Apart from illegal employment (without an employment contract), underreporting of working hours or perceived wages is a very common practice. Naturally, job security, social payments, carrier opportunities and employer's participation in development of human capital of the employees are compromised and often left aside when the employment contract is not legally supported.

1.2 Labour market institutions and ALMP

The unprecedented and sharp increase in the unemployment in the beginning of the 90's revealed the inability of pre-existing labour market institutions to handle this type of situation. The initial response of policymakers consisted in relaxing labour market regulations to increase its flexibility; setting the unemployment benefit levels at generous levels in order to provide the adequate support to job seekers; introducing active labour market policy programmes to stimulate depressed labour market, as suggested by OECD and European experience.

The transitional recession being longer and sharper than initially expected, authorities have soon experienced a fiscal pressure and cut off benefit levels. Even nowadays, the generosity of passive system in the majority of CEEB countries remains low comparing to other EU members [10].

High unemployment and high social expenditure have likewise contributed to the fact that taxes on labour were high during transition. Despite the fact that tax rates have been decreased to allow higher employment, those still remain above the EU average (Anspal and Vork [2007]). In a transition context, the flexibility in the labour market often reflects the insufficient bargaining power of workers. Unions are in general weak: both average union density and collective bargaining coverage are much lower in CEEB than in EU (23 versus 43 percent for the former one and 72 versus 37 percent for the latter).

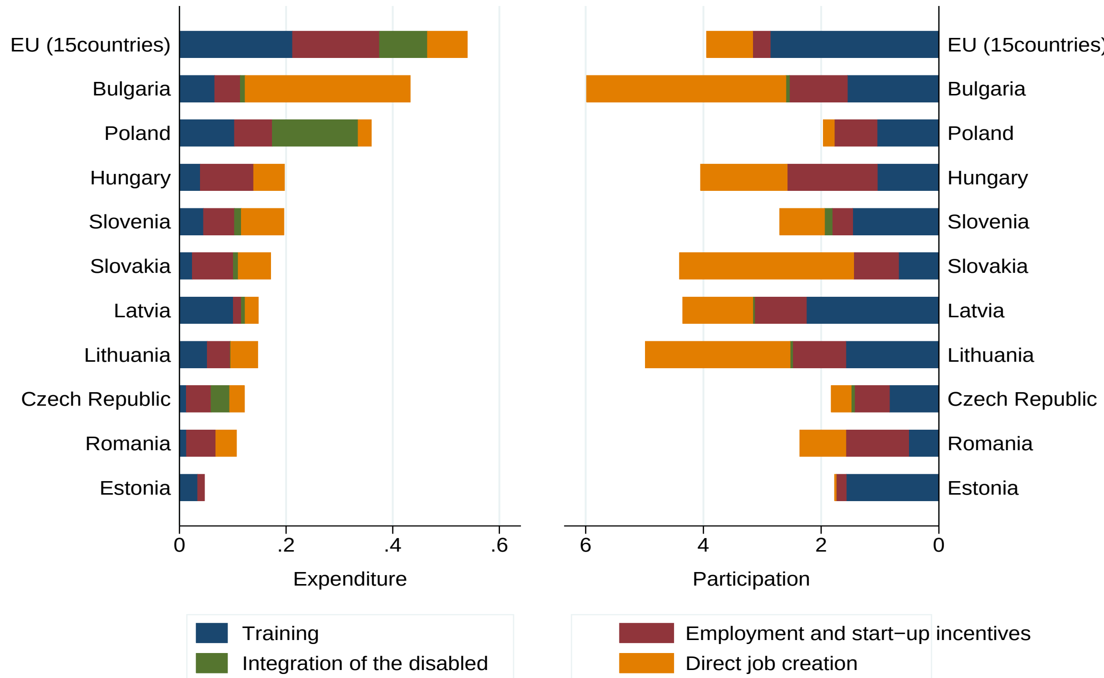
A development of a new institutional element - active labour market policy - has initially suffered from the lack of experience in the implementation, and high social expenditures left little place for ALMP in labour market policy budget. As transition progressed, substantial efforts were made in promoting this type of programmes.

Currently, the expenditure on active labour market polices in new EU member states is only half as important as the one in EU-15 countries (0.54 versus 0.23 percent of GDP, respectively). The cross country differences are substantial. Some countries devote an important share of GDP to ALMP (Bulgaria and Poland), but others (Estonia, Romania) allocate less funds. Some run a large set of various programs, but in others the set of available programs is more restricted (Estonia, Romania, Hungary).

Another indicator of the extent of active labour market policy can be developed when considering the share of unemployed persons participating in those programmes. In

[10] See Anspal and Vork [2007] who establish a comparison of the generosity of passive labour market policy, defining this latter in terms of expenditure (in percent of GDP) normalized by the per cent unemployment rate.

Figure 1.5: Expenditure and Participation in ALMP programmes



Source: EUROSTAT. Notes: (1) Expenditure on ALMP is expressed in percent of GDP. (2) Participation is given as the ratio of average (monthly) inflows into the programmes to the average number of unemployed.

terms of coverage, Hungary, Slovakia, Latvia, and Lithuania are at European level: here about 4 percent of active job seekers participate in ALMP programmes. In Bulgaria the participation indicator even exceeds the European average (6 percent), but in Poland , high expenditure on ALMP is mainly related to a high number of job seekers, and not to their intense involvement in the programmes.

The allocation of funds and resources across different programme types has also varied, and so did the implementation strategies. Heterogenous choices have been dictated by the cross country patterns of labour market development. Thus skill mismatch in the Baltic region accented training. The necessity to stimulate low labor demand and to help individuals in coping with insufficient job opportunities, as in Slovakia and Slovenia, or to integrate the discouraged workers in the labour market, as in Bulgaria and Hungary, explain the dominant role of subsidized employment and self-employment enhancing programmes and direct job creations schemes.

In Lithuania and Slovenia the allocation of funds is balanced across 3 main programme types (training, job subsidies and direct job creation).

As in EU-15, but at much more important scale, in Latvia and Estonia the focus was placed on labour training: about 70 percent of all allocated funds are devoted in these countries to the promotion of individual employability of the unemployed through training.

In Lithuania training and public jobs receive equal attention, but in Bulgaria and Slovenia the focus is mostly on direct job creation in the public sector (with second option on wage subsidies in Slovenia).

By contrast, in the Czech Republic, Slovakia, Hungary and Romania the subsidized employment in private sector and self-employment are privileged (second emphasis on public jobs in Slovakia and Romania). In Poland the funds are mainly allocated to the integration of disabled unemployed, while in terms of coverage training is the most important measure.

1.3 Theoretical and empirical effects of ALMP

Active labour market policy is a central element of employment related economic policy in both and founding and new EU member countries. We review in what follows the expected theoretical and empirical effects on this type of measures.

Active labour market policy works through various channels[11].

First, they can increase the speed and the effectiveness of the **matching process**: by reducing the skill (training programmes) or location (mobility programmes) mismatch between labour supply and labour demand; by reducing the frictions related to information imperfection (job placement programmes) in the labour market; by enhancing

[11] See Calmfors [1994], Calmfors et al. [2002] for a detailed exposition

self confidence, motivation and search intensity of the unemployed (job seeker clubs) or by making their search more efficient (job search assistance and counseling). It should however be noted that in the short run ALMP can be associated with negative **lock in effect**, implying that participation in a programme reduces the individual's search effort. In fact, the unemployed may be expected to devote less time and efforts to job search while undergoing training or while being occupied at temporary public job.

Second, accelerated matching process increases the number of hires per time period, thus reducing the average expected cost of vacancy posting. This can create incentives for the firms to post more vacancies in the labour market, thus **increasing labour demand** and pushing the employment level upwards.

Third, ALMP may be helpful in maintaining labour participation and preventing long term unemployed from discouragement, thus increasing the **employment on population** ratios[12].

Fourth, by enhancing human capital of programme participants or preventing it from distortion ALMP may also have positive **productivity effects** and in the same time contribute in **reducing the risk of future unemployment** for the participants.

Fifth, through the effects on employment, ALMP may generate positive income to **state budget** through taxes and decrease its social expenses through reduced unemployment benefit claims.

While aggregate effects of ALMP can be diverse, *a priori* positive on employment /population but ambiguous on wages, the programs may also have **unintended effects** on other individuals than participants[13]. Displacement, substitution and deadweight effects are the impacts often evoked when referring to the negative side of the ALMP programmes.

[12] The employment on labour force ratio will naturally decline due to the increase in labour supply.

[13] Many interactions can occur: shorter expected vacancy duration and increased bargaining power of the firm due to increased labor supply may induce a downward pressure on wages. Increased human capital of programme participants increases their competitiveness and may result in higher reservation wages, which may even offset employment effects. At the same time it may also be possible that stronger competition for jobs reduces real wages.

Displacement occurs when subsidized firms gain in competitiveness in the goods market and crowd out the unsubsidized firms from the market. The employment is therefore displaced from one type of firms to another, but this does not involve any net employment creation.

Substitution, can be viewed as displacement within the firm: with the intention to reduce labour costs, employers substitute nonsubsidized by subsidized workers, without any additional creation of employment.

The **deadweight loss** occurs when the state finances the creation of jobs, that would anyway be created and even in the absence of the programme.

One should however be reminded that apart from economic positive or negative effects, ALMP programmes may have an important social impact: by proposing job opportunity for those who have difficulties in integrating and performing at the labor market (long terms unemployed, disabled, women after maternity leave, senior unemployed) ALMP prevent social exclusion of these groups, maintains the motivation and mental well being of the individuals.

While theoretical effects of ALMP programmes are promising, their actual efficiency in stimulating labour market is often questioned. The experience of ALMP implementing in European countries is long (especially in Nordic countries). The interest of policymakers and scholars in measuring the effectiveness has been increasing during past decades and a certain number of evaluations have already been performed. Their results are however contrasting, depending on the type of the programs, the country and the period of their implementation, as well as the groups of unemployed concerned. For example, the impact of training programmes is sometimes reported negative (welfare benefit recipients in Denmark (Bolvig et al. [2003]) or Norway (Loretzen and Dahl [2005]), young unemployed in Finland (Hamalainen and Ollikainen [2004])), sometimes positive (unemployed in Belgium (Cockx [2003]), West Germany (Lechner et al. [2004]) or Estonia (Leetmaa and Vork [2003])) and often insignificant. Also the results of evaluations concerning the impact of job creation schemes and subsidized employment are conflicting: positive for young unemployed in Belgium (Cockx and Gobel [2004]) or long term unemployed in Germany (Eichler and Lechner [2002]), but insignificant for other groups of German unemployed (Hujer et al. [2004]).

In front of such controversy, Kluve [2007] pools together the results of 95 evaluation studies in Europe with the aim to detect systematic elements in the evaluation results. Apparently, there is a link between the type of the programme and its efficiency. Training displays modest positive or insignificant effects, the efficiency of public direct job creation is higher but also modest, while private sector incentives (wage subsidies and start up loans) and services and sanctions programme (job search assistance and counseling combined with sanctions for non-compliance) perform the best. In terms of targeting, the programs focused on young unemployed seem to perform worse than the policies designed for adults.

Indeed, the context of the transition countries is peculiar: apart from being designed as a tool for unemployment and mismatch reduction, ALMP have also played the role of reallocating mechanism from low productive to high productive sectors. Therefore one can expect different results of evaluation. However, due to the lack of adequate data, those are very rare: we can only list Leetmaa and Vork [2003] on Estonian data, and Kluve et al. [2002] on data from Poland for microeconomic studies and Boeri and Burda [1996], Munich et al. [1999] for Czech or Slovak Republics and Puhani [1999] for Poland for macroeconomic studies. One of the aims of this thesis is to add a contribution to the evaluations of ALMP in transition context.

1.4 Structure of the thesis

This thesis consists of three main parts: the first one assesses the functioning and the efficiency of aggregate and regional labour markets in several countries of Central and Eastern Europe, while the second and the third ones investigate, respectively, the role of active policies in improving the performance in the labour market and in enhancing individual employability.

Chapter 2 performs the analysis of the labour market functioning in transition - EU accession context through the estimation of aggregate matching functions on monthly panel data (1999-2006) from regional labour offices of State Employment Agencies in Latvia, Estonia and Slovenia. The relevance of the matching function approach for labour market analysis and policy evaluation in Central and Eastern European countries lies in the ability to model the presence of frictions in the labour market and has been supported by numerous studies employing this methodology (Burda [1993],Boeri and Burda [1996], Profit [1997], Burda and Profit [1996], Munich et al. [1999], Galuscak and Munich [2005], Puhani [1999]). The existing literature however, seldom goes beyond the basic matching function specification, which may omit some important patterns and interactions in the process of worker-firm matching. We address the possible misspecification of the matching function in two ways. First, following Coles and Smith [1998], Gregg and Petrongolo [2005] and Coles and Petrongolo [2003], we allow for stock-flow specification of the matching process. Second, based on the evidence from European labour markets (Burda and Profit [1996], Burgess and Profit [2001], Ahtonen [2005]), we allow for spatial interactions between regions in terms of worker and job flows, while standard matching functions assume that regional labour markets (possibly heterogeneous), are isolated.

The results bring light on the dynamics of aggregate and regional labour markets in selected new EU member states. They allow performing the diagnostics of labour market efficiency in terms of worker-firm matching, exploiting regional and country differences, the changes over time (we compare pre to post EU enlargement periods), measuring the importance of spatial spill over effects in matching and examining the sensibility of aggregate matching performance to the changes in labour supply and labour demand.

Chapter 3 evaluates the macroeconomic impact of active labour market policy programs, in particular of labour training programme, on employment, by estimating the augmented matching function. When the matching function is augmented by the variables, which measure the participation of unemployed in active labour market policy programs, it allows determining how the unemployed participation in such programs improves this efficiency of the matching process at the aggregate level.

Monthly panel data (1999-2006) data from regional labor offices of the State Employment Agency of Latvia (SEAL) are used to evaluate the efficiency of unemployed occupational training in Latvia and its regions. The correct specification of the matching function is obtained by allowing for stock-flow patterns in the matching process. The results will allow to quantify the aggregate outcomes of ALMP and to assess temporal evolution is programme efficiency (by comparing pre EU accession to post accession periods) or its regional distribution. The estimation results are further employed to perform a costs-benefit analysis and investigate the financial feasibility of the program.

The above analysis assesses the aggregate impact of unemployed training, but does not allow more careful evaluation of effects of programs on individual employability of job seekers. In this order, the microeconomic evaluation of active labour market policy programs is held in **chapter 4**.

We apply the "propensity score matching" methodology developed by Rosenbaum and Rubin (1983), Heckman, Lalonde and Smith (1999). This evaluation methodology consists in contrasting two groups of individuals, treated and non-treated by programmes, with otherwise similar characteristics in terms of gender, education, age, for example. Then the difference in their labour market outcome in terms of re-employment is considered.

Primary data files provided by the State Employment Agency of Latvia are used to construct the individual database of unemployed and programme participants (381 844 job seekers in total). Available data allow evaluating the following programs: (i) unemployed occupational training (vocational training, re-qualification and rising of qualifications); (ii) state language training for non - Latvians; (iii) modular training programme (training in foreign language, computer literacy, project management and business operation, driving).

We measure the impact of participation in each of those programs on the unemployed chances to be employed within 6, 9, 12, 18 and 24 months after the date of registration and assess temporal developments in programme efficiency by separating the unemployed pool in three groups according to the year of registration with SEAL (2003, 2004 or 2005 - 2006).

Moreover, we examine heterogeneity in programme effect across different socio - demographic (gender, age, education) and regional groups. We also test the sensitivity of our results to the so called "hidden" bias, related to the potential effect of unobservable variables (motivation, for example) on treatment assignment and unemployed outcome in the labour market.

Chapter 2

Matching and labour market efficiency through transition and EU accession

2.1 Introduction

During the phases of economic transformation - the transition from centrally planned to market economy and the accession to the European Union - all countries of Central and Eastern Europe, as well as the Baltic states, have witnessed remarkable changes in the structure and functioning of national economies[1].

First, the recession in the beginning of the 90's and parallel restructuring seriously limited the employment capacity of productive sectors, created high inflows into unemployment and inactivity and, in addition, induced an important mismatch (skill, geographical) between labour supply and labour demand.

[1]As mentioned we alternate the expressions - transition countries, accession countries or new EU member states - when refereing to ten Central and Eastern European countries (including the Baltic states), which have undergone the process of economic transition in the 90's and have recently joint the European Union - the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia as well as Bulgaria and Romania.

Further, CEEB transition countries reached a substantial progress in reforms, stabilized their economies and and displayed rapid economic growth. While aggregate unemployment declined to reasonable levels, the development of regional markets followed heterogenous paths, leading to strong disparities in terms of economic development, working and living conditions and access to employment.

Finally, the accession to the EU in 2004 and 2007 have contributed to sustain the economic growth and to improve social conditions. At the same time it also facilitated labour mobility within the EU. Very high migratory flow of workers from new to old EU member states, along persisting skill and qualification mismatch in the labour markets of these former, raise a full set of new concerns related to a forthcoming shortage of adequate labour in the region.

The aim of this chapter is to analyze the dynamics of aggregate and regional labour markets through the last decade in several new EU member states. The analysis is performed using the matching function approach, which since the 80's has become one of predominant stands in macroeconomics and labor economics. The matching function, which formally relates available job seekers to vacant jobs in the labour market and produces new hires as output, allows to account for the presence of frictions in the labour market. Frictions typically arise from the existence in the labour market of some inadequacy (in terms of information, geographical location, or qualifications) between buyers (employers) and sellers (job seekers). In transition countries, where the structure of the economy and the skills required to match with labour demand have significantly changed through last 15 years, frictions are indeed important. The relevance of the matching function approach for labour market analysis and policy evaluation in Central and Eastern European countries has been supported by numerous studies employing this methodology in transition context: Burda [1993], Boeri and Burda [1996], Profit [1997], Burda and Profit [1996], Munich et al. [1999], Galuscak and Munich [2005] for Czech and Slovak Republics, Puhani [1999] for Poland, Dmitrijeva and Hazans [2007] for Latvia.

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 the matching process[2]. A likely reason why these wealth of theoretical tools have been under-utilized in the 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 [2005] 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. The evidence from transition countries usually features very high vacancy turnover rates and significant correlations between hires and new vacancies, hence giving rise to the question on the true nature of the matching process. Can it be described by the standard stock-stock matching function (used in the previous studies on transitional labour markets), or should a more detailed specification be called for? To answer this question and to avoid the misspecification while performing the analysis of the aggregate efficiency of the labour market, we will employ both stock-stock and stock-flow specifications of the matching function.

Another misspecification of the matching process may come from the assumption that regional labour markets, which in recent literature ar often considered as heterogenous, are isolated. Meanwhile the evidence from European labour markets (see Burda and Profit [1996], Burgess and Profit [2001], Ahtonen [2005]) shows that the interactions between regions in terms of worker and job flows may be important. We address this issue by allowing for spatial spillover effects in the process of worker-firm matching.

We estimate the matching functions using the data from Latvian and Slovenian regions,

[2] See Petrongolo and Pissarides [2001] for a detailed survey.

as well as aggregated Estonian data. The estimation results allow performing the diagnostics of labour market efficiency in terms of worker-firm matching, exploiting regional and country differences, the dynamics and changes over time (we compare pre to post EU enlargement periods), measuring the importance of spatial spillovers in matching and also examining the sensibility of aggregate matching performance to the changes in labor supply and labor demand.

The reminder of the chapter is organized as follows. Section 2.2 presents the standard matching function, gives more intuition on different types of matching (stock-flow matching) and describes how spatial interactions between regions can be integrated in the analysis of labour market efficiency (spatially augmented matching function). Section 2.3 describes data and variables used in the analysis. Section 2.4 discusses the estimation procedure, section 2.5 displays the results. Section 2.6 concludes and provides policy suggestions.

2.2 The matching function

2.2.1 Standard matching function

In a labour market with search frictions (originating from information imperfections, underdevelopment of insurance markets, low labour mobility, high individual heterogeneity, high qualification mismatch and other similar factors), 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) $M_{i,t}$ in locality i (region, district, municipality)[3] at period t (week, month, quarter, year) to the numbers of unemployed job

[3]We alternate these notions further in the text when designing a geographically distinct areas within a country. Such word manipulation should not introduce any source of confusion since in this chapter we only use one level of regional disaggregation for each country.

seekers $U_{i,t}$ and available job vacancies $V_{i,t}$ in the same location[4] and time.

When employing the simplest version of the matching function *(i)* one treats the pool of unemployed and vacancies as homogenous, *(ii)* assumes that the beginning of month *stocks* of unemployed and vacancies determine the outflows to employment, *(iii)* considers regional markets as separated and *(iv)* 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:

$$M_{i,t} = A_{i,t} m(U_{i,t}, V_{i,t}), \quad \text{where } m_U > 0, m_V > 0 \tag{2.1}$$

We specify the matching function by a Cobb-Douglas form[5].

$$M_{i,t} = A_{i,t} \left(U_{i,t}\right)^{\alpha_U} \left(V_{i,t}\right)^{\alpha_V} \tag{2.2}$$

After a logarithmic transformation of both sides, one obtains the regression equation, where the mismatch parameter can be transformed in order to capture the efficiency of matching over time (by including time fixed effects λ_t) [6] and across regions (by including region fixed effects μ_i), to include the effects of k various macroeconomic factors and to allow for random variations in hiring:

$$\ln A_{i,t} = \alpha_0 + \mu_i + \lambda_t + \alpha_{Z^1} Z^1_{i,t} + ... + \alpha_{Z^k} Z^k_{i,t} + \varepsilon_{i,t}.$$

The resulting regression equation is the following:

$$\ln M_{i,t} = \alpha_0 + \alpha_U \ln U_{i,t} + \alpha_V \ln V_{i,t} + \alpha_{Z^1} Z^1_{i,t} + ... + \alpha_{Z^k} Z^k_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2.3}$$

[4]We introduce the presence of spatial inter-regional effects in section 2.2.3.

[5]Despite the absence of convincing micro-foundations for such functional form, it is widely used by empirical research and has become "standard" specification in the estimation of the matching function (see Petrongolo and Pissarides [2001]).

[6]The details of how the time periods are controlled can be found in section 2.4, where the specifications of estimated models are developed. Generally we include seasonal (quarterly) dummies and annual trend.

It can be rewritten in a more compact way as:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2.4}$$

Hence the vector $X_{i,t}$ contains main explanatory variables of the matching function $X_{i,t} = [\ \ln U_{i,t} \quad \ln V_{i,t}]$ and $\alpha_X = [\ \alpha_U \quad \alpha_V]'$ contains the corresponding coefficients to estimate. Similarly, the k-dimensional vector $Z_{i,t}$ contains the variables used to define the macroeconomic context $Z_{i,t} = [\ Z_{i,t}^1 \quad ... \quad Z_{i,t}^k]$ and $\alpha_Z = [\ \alpha_{Z^1} \quad ... \quad \alpha_{Z^1}]'$ contains the corresponding coefficients.

The parameters α_U and α_V can be interpreted as elasticities of matches (outflows from unemployment to employment) with respect to the size of unemployment and vacancy pools. Thus one percent increase in the number of unemployed, available for matching in the beginning of the period would increase the number of matches (new hires) realized during this period by α_U percent. Using the definition of the elasticity, $\alpha_U = (\partial M/M)/(\partial U/U)$, it is possible - by multiplying the elasticity by (M/U) - to define the marginal effect $(\partial M/\partial U)$, that indicates the number of additional matches produced if the stock of unemployed increases by one unity. The interpretation is symmetrical with regard to the elasticity α_V.

The estimated elasticities can also give a measure of the extent of externalities existing in the matching process. In fact, α_U measures the positive externality from searching workers to firms and α_V - the positive externality caused by firms on job seekers. By contrast, $(\alpha_U - 1)$ measures the negative externality (congestion) caused by the unemployed on other unemployed persons and $(\alpha_V - 1)$ the congestion caused by searching firms on other firms. Higher elasticities imply thus less congestion and more positive externalities (see Petrongolo and Pissarides [2001])[7].

[7] To see this point consider the average probability for the unemployed to find a job during a reference time period (transition probability or hazard rate). This probability is given by $h_U = M/U$. Similarly the average probability of a vacancy to be filled in a reference period is $h_V = M/V$. Using the Cobb-Douglas form of the matching function it comes that $h_U = AU^{(\alpha_U - 1)}V^{\alpha_V}$ and $h_V = AU^{\alpha_U}V^{(\alpha_V - 1)}$. Therefore, wherever enlarging the pool of unemployed will rise the average job-finding probability is defined by the sigh of $\partial h_U/\partial U$ and thus depends on $(\alpha_U - 1)$. The effect of enlarged unemployment pool on average vacancy transition rate $\partial h_V/\partial U$ depends on α_U.

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. When the returns to scale are constant, a proportional increase in inputs (unemployed and vacancy number) augments the output (new hires) in the same proportion. But when the returns to scale are decreasing, for example, output grows slower than input.

The diagnostics of the return to scale in the matching function is one of the central questions in the empirical analysis of worker-firm matching. On one hand, the homogeneity (constancy of the returns to scale) ensures the existence of a unique equilibrium in a model of equilibrium unemployment with endogenous search effort (see Petrongolo and Pissarides [2001]), while increasing returns to scale make room for multiple equilibria. On the other hand, the magnitude of the returns to scale allows to draw conclusions on the aggregate efficiency of the matching process.

The empirically estimated matching functions often display constant or slightly decreasing returns to scale in developed countries. For example Burda and Wyplosz [1994] report decreasing returns to scale for France, Germany, Spain and U.K., while Pissarides [1986] and Layard et al. [1991] find constant returns for U.K. The results are more diverse for transition countries and new EU member states. Instable and rapidly changing macroeconomic context has certainly made its contribution - the results vary across countries, but also across time: Burda [1993] finds decreasing returns to scale in Czech Republic and Slovakia in time period from 1990 to 1992, while Munich et al. [1999] show that for the period from 1979 to 1984 the returns to scale in matching are rather increasing in this region.

2.2.2 Particular forms of the matching process: stock-flow matching

While the standard matching function, described above, is extensively used for labour market diagnostics in various contexts, Coles and Smith [1998], followed by Gregg and Petrongolo [2005] and Coles and Petrongolo [2003], suggest that a traditionally employed simple matching function, which treats matching process as random and determines the outflow from unemployment by beginning of period stocks of unemployed and vacancies, may be misspecified. Observing a very high vacancy turnover rate in European labour markets (new vacancies are filled rapidly, within a reference period, and do not appear in end - period stocks), the authors state and show on U.K. data that not only stocks but also inflows of new vacancies and unemployed during the reference period intensively participate in the matching process. 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 [2005] 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 in the labour market may result in matching between stocks and flows. Basic intuition underlying this theoretical model is provided below, 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 etc.) 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 in 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 than stock-stock matching.

If the economic agents adopt a selective search strategy the matching process is no longer random. Gregg and Petrongolo [2005] and Coles and Petrongolo [2003] state that a correctly specified matching function should include both beginning of month stocks of unemployed and vacancies and their inflows during the month.

The stock-flow specification of the matching function has recently been employed by

Dmitrijeva and Hazans [2007] on Latvian data and by Galuscak and Munich [2005] on the data from Czech Republic. These studies show that in the context of a transition economy the misspecification from omitting flow variables in the matching function can be important and suggest a stock-flow matching function to be the only relevant specification for describing a hiring process in these economies. However a stock flow pattern in the matching may not result here from the differentiation between old *versus* new vacancies by the unemployed, but from the dominant role of labour demand. In transition economies labour demand is often low and the number of job vacancies is smaller than the number of unemployed: the vacancies are thus filled very rapidly. For example in Latvia, the size of the vacancy stock in the beginning of the month is systematically smaller than the size of vacancy inflow during the month (see tables 2.6, 2.7). This suggests that most of vacancies are filled within one month and thus do not appear in next month's stock. Therefore the outflows from unemployment mainly result from the matches realized between inflowing vacancies and previous period's unmatched unemployed (unemployed stock).

With regard to the estimation of the stock-flow version of the matching function, it is suitable to retain a basic specification originally proposed by Coles and Smith [1998]. We use, 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:

$$\ln M_{i,t} = \alpha_0 + \alpha_{SU} \ln U_{i,t}^S + \alpha_{SV} \ln V_{i,t}^S + \alpha_{FU} \ln U_{i,t}^F + \alpha_{FV} \ln V_{i,t}^F + \qquad (2.5)$$
$$+ \alpha_{Z^1} Z_{i,t}^1 + ... + \alpha_{Z^k} Z_{i,t}^k + \mu_i + \lambda_t + \varepsilon_{i,t}$$

where α_{SU} and α_{SV} are elasticities with respect to the size of the stocks U^S and V^S, while α_{FU} and α_{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.

The equation 2.5 can still be written as previously in a following compact form:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2.6}$$

The vector $X_{i,t}$ still englobe the main explanatory variables or the matching function, but their number has now doubled (we include not only stocks but also inflows of unemployed and vacancies): $X_{i,t} = [\ \ln U_{i,t}^S \quad \ln U_{i,t}^F \quad \ln V_{i,t}^S \quad \ln V_{i,t}^F]$. The dimension of the vector α_X has also increased - it now contains four parameters to estimate $\alpha = [\ \alpha_{SU} \quad \alpha_{SV} \quad \alpha_{FU} \quad \alpha_{FV}]'$. With this exception , all other components are equivalent to those in equation 2.4.

Equations 2.3 and 2.5, corresponding to stock-stock and stock-flow versions of the equation 2.6 - the empirical matching function - will be estimated on administrative data from several new EU member states (Latvia, Estonia, Slovenia) and for several time periods. The estimation results will allow performing the diagnostics of the labour market functioning and monitoring its efficiency in terms of firm-unemployed matching across different time periods and regions. We will address the particularities in the matching process in former transition countries and discuss the stability of this process through EU accession. We will also assess the sensibility of outflows from unemployment to the changes in labour supply and labour demand. The results are displayed in section 2.5.

2.2.3 Spatially augmented matching function: regional spillovers

As previously discussed, an aggregate economy can rarely be considered as a single market or a collection of homogenous micro-markets. When the process of job matching is not homogenous across space, a common practice in empirical literature is to consider the aggregate labour market as a collection of spatially distinct and heterogenous labour markets that can suffer from many frictions. A panel or cross section of regions, municipalities, statistical or administrative units is therefore often used in order to estimate the aggregate matching function [8].

Moreover, it is possible that the heterogenous micro-markets do not develop separately but interact with each other. Economic conditions affecting one region may affect the neighboring regions as well. Unemployed, that are searching for work are not likely to restrict their search to one labour office district; they extend their search to other districts as well. As both commuting and migration are possible outcomes of the job search process of workers, spatial externalities are involved in the matching process. Including a spatial dimension in the econometric analysis of matching function is therefore a necessary step in the assessment of the process of worker-firm matching.

While job search across spatially distinct labour markets is brought in by a job search models of migration (Hughes and McCormick [1994]), the individual decision to stay or leave the home region is, however, completely ignored in the standard matching or flow approach to labour market analysis (see Petrongolo and Pissarides [2001]). Burda and Profit [1996] have pioneered in addressing this issue by developing a model of non-sequential search over space and providing the empirical evidence of the relevance of spatial interaction in job search for the Czech economy. Burgess and Profit [2001] provide the evidence for existence of spatial externalities in job matching across travel-to-work areas in the United Kingdom, while Petrongolo and Wasmer [1999] found weak cross-regional spillovers for Britain and France. Recently, Lopez-Tamayo et al. [2000] established the evidence for the relevance of the spatial dimension in matching workers to vacant jobs for Spanish regions, while Fahr and Sunde [2006a] and Fahr and Sunde [2006b] investigated spatial interactions in the matching process for West German planning regions in the time period from 1980 to 1997.

When a standard matching model is extended in order to allow for spatial spillovers,

[8] See section 2.4 for more details.

it can be referred to as a *spatially augmented matching function*. The key assumption is that regional job matching does not only depend on local stocks (and inflows in a stock-flow setting) of unemployed workers and job openings. Unemployed workers from neighboring or other spatially distinct labour markets will compete with local job searchers for vacant posts. Naturally, also local job seekers can apply for job vacancies in neighboring areas. The spatially augmented matching function can be written:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + X^*_{i,t}\alpha^*_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2.7}$$

As previously, the vector $X_{i,t}$ collects the main explanatory variables or the matching function (stocks and flows of unemployed and vacancies), while the vector $X^*_{i,t}$ consists of *foreign* versions of those variables and measures the spatial spillovers. Thus if

$$X_{i,t} = [\ \ln U^S_{i,t} \quad \ln U^F_{i,t} \quad \ln V^S_{i,t} \quad \ln V^F_{i,t}]$$

then

$$X^*_{i,t} = [\ \ln U^{*S}_{i,t} \quad \ln U^{*F}_{i,t} \quad \ln V^{*S}_{i,t} \quad \ln V^{*F}_{i,t}\ ]\ .$$

External variables in $X^*_{i,t}$ are defined here as weighted averages of the corresponding variable $X_{i,t}$ observed over neighboring regions. Thus W being the spatial weights matrix, $X^*_{i,t} = W \otimes X_{i,t}$ or equivalently:

$$U^{*S}_{i,t} = \sum_{j=1}^{N} w_{i,j} U^S_{j,t} \text{ and } U^{*F}_{i,t} = \sum_{j=1}^{N} w_{i,j} U^F_{j,t}$$
$$V^{*S}_{i,t} = \sum_{j=1}^{N} w_{i,j} V^S_{j,t} \text{ and } V^{*F}_{i,t} = \sum_{j=1}^{N} w_{i,j} V^F_{j,t}$$

We use a simple specification for weights $w_{i,j} = J_i^{-1}$ if regions i and j are neighboring and 0 otherwise. For each region i, J_i is the number of contentent regions (we chose to attribute the same weight to all neighbor). Two regions are considered neighboring if they share a common border or if one of them is surrounded by the other, as it may be the case when the administrative data distinguishes the cities and their surrounding areas. Furthermore, we do not consider a region to be neighbor to itself.

The magnitude of spatial spillovers

The magnitude of the effects of external variables may differ across regions. The asymmetry in spatial spillovers may be related to the differences between local and foreign unemployment rates. In fact, the job seekers tend to widen their search radius and search more intensively in neighboring areas if local unemployment is high comparing to the surrounding areas. Following Burgess and Profit [2001], the asymmetry in spatial spillovers can be accounted for by using the unemployment rate ratio index (URR), which is constructed as the ratio of local unemployment rate in the region (as denominator) and a weighted average of the unemployment rates in neighboring regions (as numerator). For a given region i, a high value of URR indicates that the region i is surrounded by municipalities where the unemployment is much higher than local, while a low value of URR witnesses the opposite : the region i is surrounded by a low unemployment area. The regions are then sorted according to URR and two dummy variables are created: HR (high unemployment rate around) takes the value of 1 for the regions in the top of the distribution (usually 10-15 %, we take 4 regions in Latvia and 2 regions in Slovenia) and LR (low unemployment rate around) picks out the regions from the bottom of the distribution (4 Latvian and 2 Slovenian regions). When the basic spillover variables are multiplied by these dummies and included into the model; we get:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + X^*_{i,t}\alpha^*_X + X^{*HR}_{i,t}\alpha^{*HR}_X + X^{*LR}_{i,t}\alpha^{*LR}_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2.8)$$

Basic spillover is now decomposed in spillovers from high relative unemployment areas ($X^{*HR}_{i,t}$), low relative unemployment areas ($X^{*LR}_{i,t}$) and spillovers from the areas with similar unemployment context ($X^*_{i,t}$).

The magnitude of spillovers can also be related to the population density in the region itself. In order to analyze such an asymmetry the basic spillover can be separated into the spillovers to dense regions and spillovers to the rest of the regions. In this order a dummy variable POP is constructed: it takes value one if the population density in the region i is higher than the average in the country and 0 otherwise. The spillover variables are multiplied by this indicator and included into the model. The estimated matching function takes then the following form:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + X^*_{i,t}\alpha^*_X + X^{*POP}_{i,t}\alpha^{*POP}_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (2.9)$$

The equations 2.7 - 2.9 can be rewritten in a more compact way as:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + X^*_{i,t}\alpha^*_X + X^{*ASYM}_{i,t}\alpha^{*ASYM}_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (2.10)$$

where vector $X^*_{i,t}$ includes the basic spillover for the variables contained in the vector of main explanatory variables $X_{i,t}$ and the vector $X^{*ASYM}_{i,t}$ collects the variables expressing possible asymmetry of spillovers: $X^{*ASYM}_{i,t}$ may be empty if the magnitude of the effects is supposed invariant, $X^{*ASYM}_{i,t} = [\; X^{*HR}_{i,t} \quad X^{*LR}_{i,t} \;]$ if the effects are supposed to vary with the unemployment context in neighboring areas, or $X^{*ASYM}_{i,t} = [X^{*POP}_{i,t}]$ if these rather depend on the local population density.

The equation 2.10 in different specifications (those are given in section 2.4) is estimated on administrative data from two new EU member states (Latvia, Slovenia). The results are displayed and discussed in section 2.5.

2.3 Data and Variables

Data used in this chapter originates from databases of State Employment Services of three new EU member countries (State Employment Agency of Latvia (SEAL), Employment Service of Slovenia (ESS) and Estonian Labour Market Board (ELMB)[9]), Central Statistical Bureau of Latvia and EUROSTAT. Latvian data covers 33 Latvian administrative regions[10] from January 1999 to July 2006 on monthly basis. Slovenian

[9] We would like to thank Grieta Tentere and Ilze Berzina from SEA, Viljem Spruk from ESS and Aimi Kalvist from ELMB for cooperation in provision of necessary data.

[10] NUTS 4 level division

data covers 12 regions corresponding to regional location of ESS offices[11] for a period from January 2000 to December 2006 on a monthly basis. Estonian data is geographically aggregated (it is only available for the whole country) and covers on a monthly basis a period from January 2003 to December 2006[12].

The following variables are used in the analysis:

(i) the **stock of unemployed** U^S which is given as the number of registered unemployed at the beginning of the month; *(ii)* the **flow of unemployed** U^F which refers to the number of individuals entering the registered 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 registered by National Public Employment Service (SEAL,ELMB, ESS) during the month; *(v)* **outflows** or matches M measured by the number of registered unemployed exiting to employment during a month; *(vi)* an **additional labour demand indicator** Z which describes regional[13] macroeconomic and labour market context. It corresponds to the monthly growth in secondary employment - number of individuals having not only principal but also secondary job[14]. *(vi)* **other regional indicators** including data on population density in regions, local unemployment rates and spatial properties of the observation units.

More detailed description of variables, data coverage and sources is given in table 2.8 in the appendix. The descriptive statistics on regional panel data and also on aggregate data is summarized in tables 2.7 and 2.6. The maps indicating the geographical location of Latvian and Slovenian regions are displayed by figures 2.4 and 2.5 in appendix. Let us now clarify some points concerning definitions and patterns of certain variables as well as relations between them.

[11] In Slovenia regional division of ESS offices does not correspond exactly to the geographical separation in statistical regions. However, it corresponds roughly to NUTS 3 level division.

[12] Time coverage for the data on secondary employment is shorter: until June 2006 for Latvia and October 2006 for Estonia and Slovenia.

[13] Or national, when regional data are not available.

[14] It is reasonable to suppose that macroeconomic context is more favorable, labour demand is higher and access to employment to easier in the localities where high proportion of population is employed at secondary job.

2.3.1 Main components of the matching function: unemployed, vacancies and outflows to jobs

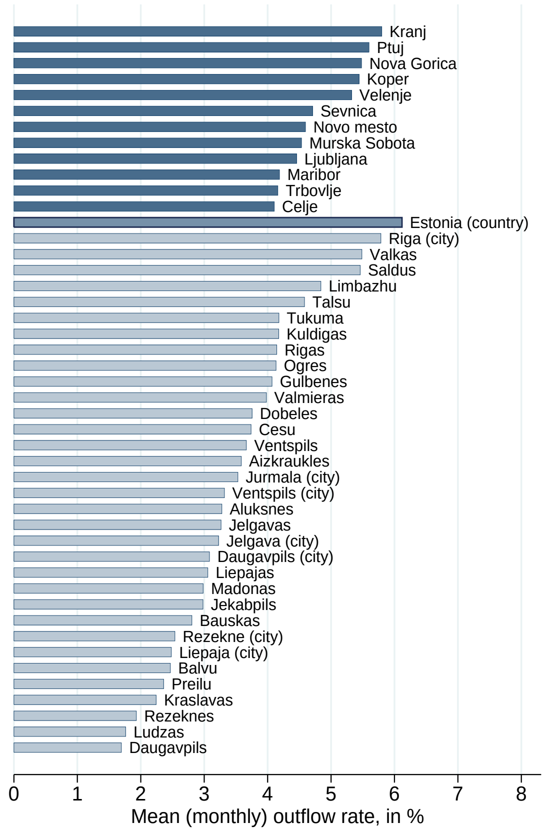
Unemployment data covers only registered job seekers (there is no information on non-registered job seekers available on monthly basis). This may be thought as a serious limitation of our analysis since empirical evidence from transition economies (see Boeri [2001], Boeri and Terrell [2002], Hazans [2005]) 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 labour force.

This limitation, however, is unlikely to bias our results for several reasons. First, our dependent variable (outflows from unemployment to employment) only concerns outflows from the pool of registered unemployed. Second, in Latvia and Estonia, vacancy data cover job announcements placed through Public Employment Service (SEAL in Latvia and ELMB in Estonia) and thus in the first place available to registered unemployed. For Slovenia the situation is slightly different: here all the employers are enforced by law to register all free jobs at the Employment Service of Slovenia. Therefore data cover all job vacancies in Slovenia[15].

Another issue related is the adequacy between unemployed and vacancy data concerns the qualification structure of the matching pools. For example in Latvia, the share of registered unemployed with manual occupation is above 80 percent. 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 (see Dmitrijeva and Hazans [2007]). From this perspective, the matching function estimated in this study refers to a segment of the labour market which to large extent excludes high skilled blue collar occupations.

[15] However, ESS has several publication procedure types to distinguish across job vacancy types. For example only job vacancies for which employer desires a public announcement are available to general public. Employers can also indicate whether the cooperation with ESS is wanted in order to fill the vacancy (the share is such vacancies is about 1/3 of all job vacancies).

Figure 2.1: Mean outflow rate in Latvia (by region), Slovenia (by region) and Estonia



Source: Author's calculations based on data series from State Employment Agency of Latvia, Estonian Labour Market Board and Employment Service of Slovenia. Reported rates are averages of transition rates over available time period (see table 2.8).

Concerning the outflows from unemployment or matches, here (and in what follows) we mean by outflow the reported outflows to jobs from the pool of registered unemployed[16].

Data reveal that outflow rates - ratio of the number of registered unemployed finding jobs during a month to the beginning of month number of registered unemployed - were comparable across three analyzed countries: on average 3 percent in Latvia, 5 percent

[16]It is possible that some outflows to jobs may not be reported to the Public Employment Service by the ex-unemployed. While we do not have a reliable estimate of the scope of the problem (under-reporting) in Estonia and Slovenia, in Latvia the problem has been fixed in 2003 by using information from tax authorities. There is evidence that less than 25% of outflows to jobs in Latvia were not reported. Plausibly, the rate of under-reporting was of the similar order in other countries and did not vary significantly across districts and time periods, and hence we believe this problem does not cause bias in our results.

in Slovenia and 6 percent in Estonia. The figure 2.1 displays mean transition rates for each of the 33 regions of Latvia, for 12 regions of Slovenia and for Estonia (as a whole country).

In Latvia the highest rate of outflows from unemployment to employment is observed in the capital city Riga, in Saldus and Valkas districts, with 5 to 6 percent of registered unemployed finding a job every month. As above mentioned, Estonia witnesses a 6 percent outflow rate while in Slovenia, Kranj, Ptuj, Nova Gorika , Koper and Velenje regional offices of ESS top the distribution of transitions from unemployment to jobs with 5 to 6 percent rates[17]. The regions with the weakest performance in terms of outflows to jobs are Ludzas Rezeknes and Daugavpils - three Latvian districts where outflow rates do not exceed 2 percent for the period from 1:1999 to 07:2006. By contrast in Slovenia, even in the worst performing areas (Maribor, Triborvje, Celje regional offices of ESS) the mean outflow rate still exceeds 4 percent.

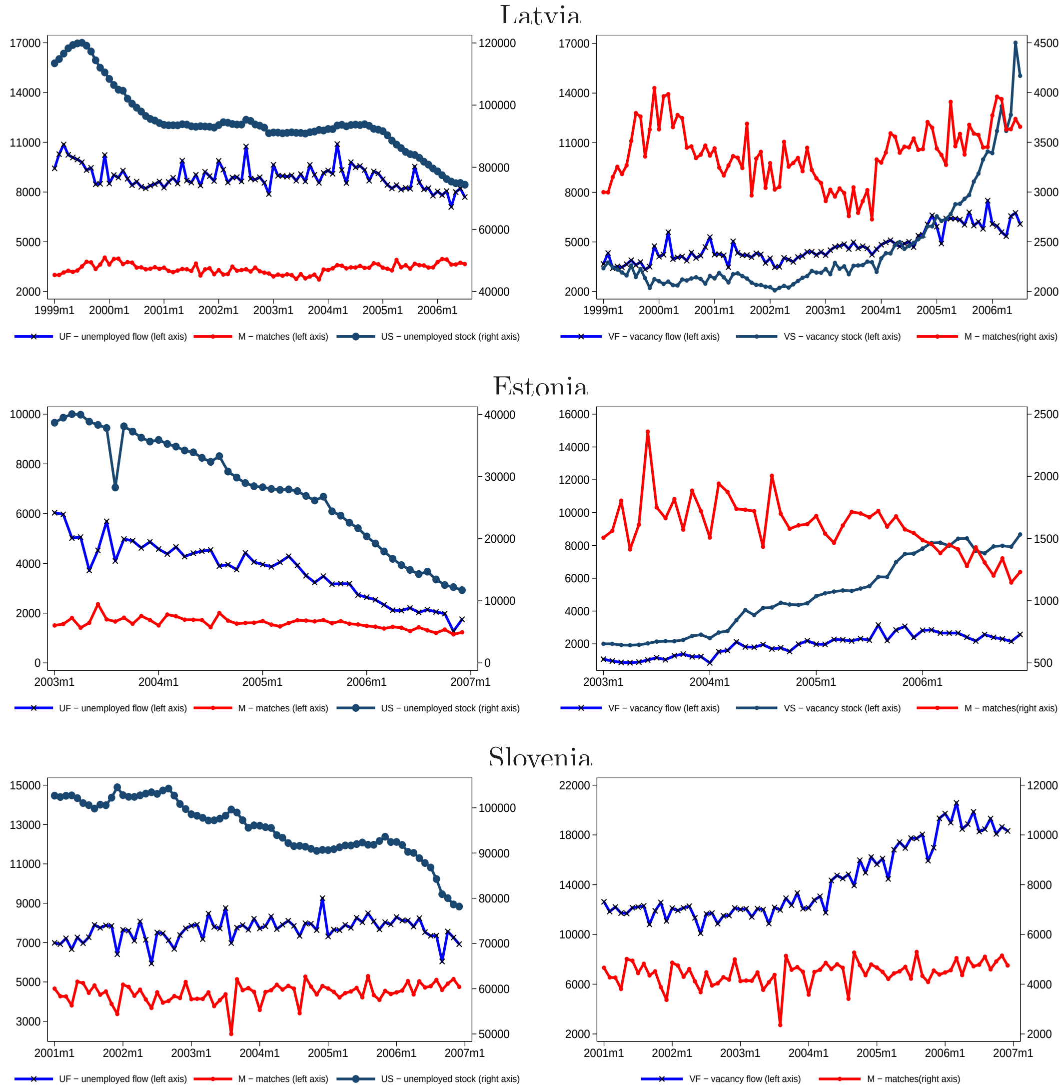
Figure 2.2 shows the aggregate dynamics of matches, unemployed and vacancy stocks and flows in Latvia, Estonia and Slovenia. Outflows from unemployment (matches, new hires) seem to be quite sensitive to the movements in vacancy inflows in Latvia and to the movements in the inflow of new unemployed in Slovenia.

More intuition on the role of flow variables can be derived from table 4[18], which shows the turnover rates and correlations between different variables.

[17]The distribution is certainly smoother across Slovenian regions, comparing to Latvia. It should, however, be noted that the degree of spatial disaggregation of Latvian data is higher (NUTS 4 for Latvia, and NUTS 3 for Slovenia).

[18]The correlations, displayed in Table 2.1 are calculated on the variables transformed in order to remove heterogeneity in regional labour market size and to account for seasonal and trend effects in variables. For Latvia and Slovenia the transformations are performed as follows. For each variable $X_{i,t}$ the corresponding transformed variable $\Delta\overline{\widetilde{X}}_{i,j}$ is constructed as follows: $\widetilde{X}_{i,t} = X_{i,t}/U^S_{i,t}$ is variable divided by region specific beginning of month stock of unemployed; $\overline{\widetilde{X}}_{i,j}$ is annual mean of $\widetilde{X}_{i,t}$ for every year j within each region i; $\overline{\overline{\widetilde{X}}}_i$ is the average of annual means $\overline{\widetilde{X}}_{i,j}$ within each region i; and $\Delta\overline{\widetilde{X}}_{i,j} = \overline{\widetilde{X}}_{i,j} - \overline{\overline{\widetilde{X}}}_i$ is the deviation of region specific annual averages from the $\overline{\overline{\widetilde{X}}}_i$. For Estonia only national aggregated data is available. Therefore the correlations are calculated on the variables purified for for seasonal and trend effects.

Figure 2.2: The dynamics of unemployment, vacancies and outflows to employment



Source: State Employment Agency of Latvia, Estonian Labour Market Board and Employment Service of Slovenia. Data seasonally adjusted (X11).

In Latvia and Estonia, the correlation between matches and vacancy inflow is higher than the one with vacancy stock. The correlation between the outflow to employment and the inflow of new unemployed is high in Latvia, but low and statistically insignificant in Estonia. In Slovenia, by contrast, both monthly inflow of unemployed and inflow of new vacancies are correlated to the outflow from unemployment to jobs.

The observed unemployed turnover rate (ratio of the inflow to the stock) is 0.09 in Latvia, 0.13 in Estonia and 0.08 in Slovenia. Monthly inflows into unemployment in Latvia, Estonia and Slovenia are actually important, but small relative to extremely high stock of unemployed[19]. In contrast, vacancy turnover rates are much higher: aggregate vacancy turnover rate is 0.44 in Estonia and 1.29 in Latvia (while the rate calculated on Latvian regional units exceeds 5)[20]. This suggests that vacancies are filled very rapidly in Latvia and Estonia, and especially in some of Latvian regions. The above statement, reinforced by reported correlations between outflows to jobs and other variables, confirms the importance of inflow variables (new vacancies, new unemployed) in the process of demand-supply matching in the labour market, approving its relevance for our analysis.

Table 2.1: **Correlations and turnover rates**

	Latvia	**Estonia**	**Slovenia**
	Correlations of number of matches (M) with :		
Inflow of unemployed (U^F)	0.46***	0.19	0.59***
Inflow of vacancies (V^F)	0.59***	0.89***	0.82***
Stock of vacancies (V^S)	0.47***	0.76**	-
			Mean values of:
Vacancy monthly turnover rate (V^F/V^S)	5.69 (1.29)	(0.44)	-
Unemployed monthly turnover rate (U^F/U^S)	0.09 (0.09)	(0.13)	0.08 (0.08)
Monthly hiring rate (M/U^S)	0.03 (0.04)	(0.06)	0.05 (0.05)

Source: Calculations based on data from Latvian State Employment Agency, Estonian Labour Market Board and Employment Service of Slovenia. Notes: (1) Correlations are calculated on the variables transformed in order to remove heterogeneity in regional labour market size as well as for seasonal and trend effects in variables (see footnote below). (2) Calculations are made on monthly data for the time periods covered with data (see table 2.8). (3) Reported turnover rates are time averages of monthly rates (the length of available time period for each country is specified in table 2.8). (4) Reported turnover rates are averages of regional rates, while the rates calculated from aggregated data are reported in parentheses. (5) ***, **, * - correlations significantly different from zero at 1,5,10 percent level respectively.

[19]This is due to high frequency of inflow data. Annual inflow into unemployment is indeed higher: in year 2004, for example, both the stock of registered unemployed and yearly inflow were of the same scale in three countries : about 6-7 percent of the population aged 15 to 64 years in Latvia, from 4 to 6 percent in Estonia and 7 percent in Slovenia.

[20]It is not possible to calculate the vacancy turnover rate for Slovenia since the data on vacancy stocks is not produced by ESS, it only produces data on vacancy inflow.

2.4 Estimation procedure

2.4.1 Estimated models

Let us first recall the relationships that we estimate in this study. In order to monitor the main patterns and efficiency of the labour market in terms of worker-firm matching in three new EU member states, we estimate the matching function given by equation 2.6. The developments on the stock-flow matching and the evidence supplied by descriptive statistics raise the question of the relevance of the standard matching function in the case of transition-accession economies. We address this issue by estimating the equation 2.6 in both stock-stock and stock-flow settings. As mentioned above the difference lies in the specification of the main explanatory variables when estimating the matching function (either only unemployed and vacancy stocks on RHS or both stocks and inflows of unemployed and vacancies on RHS).

Estimated model 1: Standard matching function

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t}$$

for stock-stock $X_{i,t} = [\ \ln U_{i,t} \quad \ln V_{i,t}\ ]$ and for stock-flow $X_{i,t} = [\ \ln U^S_{i,t} \quad \ln U^F_{i,t} \quad \ln V^S_{i,t} \quad \ln V^F_{i,t}\ ]$

Finally, we allow for interactions between the regions and estimate a spatially augmented matching function, corresponding to the equation 2.10 in section 2.2.3.

Estimated model 2: Spatially augmented stock-flow matching function

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + X^*_{i,t}\alpha^*_X + X^{*ASYM}_{i,t}\alpha^{*ASYM}_X + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t}$$

for context based asymmetry $X^{*ASYM}_{i,t} = [\ X^{*HR}_{i,t} \quad X^{*LR}_{i,t}\ ]$, for density based $X^{*ASYM}_{i,t} = [X^{*POP}_{i,t}]$

2.4.2 Estimation procedure and related issues

When estimating the matching function from the data, several issues are to be controlled for in order to avoid possible bias, which may be related to data contents and structure (aggregation bias), to (mis)specification of estimated models or to built-in endogeneity in the matching function.

Since Pissarides [1986], early studies on empirical matching functions were realized on aggregate time series data (Layard et al. [1991] on British data, Blanchard and Diamond [1989] on US data, Burda and Wyplosz [1994] on French, German, Spanish and U.K. data). This is due to the fact that equilibrium unemployment theory (delivering the matching function as its central element) aims at describing the macroeconomic behavior of unemployment. In addition, it is easier to collect the aggregate (national) data on hirings, unemployment and vacancies. However, such spatial aggregation is only possible under the assumption that search frictions are homogeneous across the observation units (regions, municipalities, TTWA [21], for instance.) and therefore may impose strong and presumably counter-factual assumptions on the form of the matching function. Coles and Smith [1996] cross-sectional analysis on England and Wales has revealed the importance of demographic factors in estimating the matching function and cautioned researchers for the existence of regional heterogeneity, which was entirely neglected by the studies on the aggregate time series data. The necessity to control for spatial heterogeneities (both observable and unobservable) across observation units and to correct possible aggregation bias, along with the substantial difficulty with making inferences from the aggregate time series, has led many authors to shift their focus from aggregate to geographically disaggregate data (panels or cross sections). Anderson and Burgess [2000] estimate the matching function for four US states and 20 industries; Burgess and Profit [2001] for 303 TTWA in U.K.; Burda and Profit [1996] and Boeri and Burda [1996] for 76 districts of Czech Republic. The main parameters estimated in the matching function are the elasticities of new hires with respect to unemployment

[21] TTW stands for Travel To Work Areas.

and vacancy pools. Those being affected by potential bias, the results from estimations conducted on aggregate time series and the ones proceeded on panel data may diverge with respect to the returns to scale in the estimated matching function.

While using cross section time series data (CSTS) for the estimation of the matching function considerably reduces the possibility for spatial aggregation bias, it also enriches the study with analysis opportunities: allows exploring spatial and time variations in the matching. Nonetheless, using cross sectional time series data also requires an appropriate estimation technique. CSTS typically exhibit non-spherical error structure, which does not conform to OLS assumptions: there are high chances for the residuals to be group-wise heteroscedastic, contemporaneously and serially correlated. Two methods can be used to bring necessary corrections: 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 (see Beck and Katz [1995]). 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). In this study the estimations based on both Parks-Kmenta and Beck-Katz methods are reported.

Another source of bias in the estimated coefficients of the matching function may be related to temporal aggregation problem which arises when discrete time data are used to describe continuous time processes. Indeed, the matching function describes the process that takes place continuously in spatially distinct locations (regions, municipalities, TTWA), while discrete data for observation units are used to estimate the matching function. Therefore flow variables (outflows from unemployment to employment, vacancy outflow from posted to filled) are estimated as functions of stock conditioning variables (stock of unemployed, vacancies), which changes during the reference time period. In addition, the dependent variable itself is mismeasured, since, for example, the outflow from unemployment englobe the outflows from the stock of unemployed and the outflow from the inflow into unemployment. For the time period, even as short as as quarter this can lead to the outflow greater than the initial stock. One of the possible solutions includes inflow variables on the RHS of the estimated matching function (as a fraction of inflow added to the stock variables or as a part of a stock-flow matching mechanism). Another solution to the temporal aggregation problem is purely mechanical and consists in using as high disaggregate data as possible (high frequency data). Benett et al. [1994] show that the size of the temporal aggregation bias in the estimated matching elasticity is a linear function of the measurement interval and the bias is not important when the frequency of the data is monthly or higher. Taking into account the above issues, the data used for this study is the highest available highly disaggregated in both spatial and time dimensions (monthly time series from regional units are used), and we use the estimation techniques appropriate for such data structure.

Turning to other estimation issues, a common, but rarely highlighted in the related literature, problem in empirical estimation of the matching function concerns possible built-in endogeneity of explanatory variables. In fact, current and past outflows to employment (matches) predetermine the stocks of unemployed and vacancies in the beginning of the next period. In this case the assumption of the strict exogeneity of regressors (conditional on the unobserved effect), does not hold. Meanwhile, matches partially determine both current period's errors and next period's stocks of unemployed and vacancies. Therefore errors are correlated only with future (but not current and past) values of regressors, which imply that a weaker assumption on sequential exogeneity of explanatory variables (conditional on unobserved effect) is still verified. Following Wooldridge [2002], when the times series process is appropriately stable and weakly dependent, it is possible to show that the inconsistency of using fixed effects is of order $1/T$ under sequential exogeneity assumption. Thus, when T is large (which is our case), the bias in fixed effect estimator is likely very small. Moreover, it can also be shown under the same conditions, that for $T > 2$, fixed effect estimator can have less bias than a first difference estimator, as $N \to \infty$ (see Wooldridge [2002], p.302). We therefore prefer fixed effects over first difference methods, in the estimation of the matching function. Meanwhile, it seems that the size of the endogeneity problem is minimal in application to our case. The descriptive statistics exercise on sample data shows that the stock of unemployed $U^S_{i,t+1}$ has weaker correlation with current matches $M_{i,t}$ than with its' other components (current inflows, outflows other that matches) and the contribution of $M_{i,t}$ to $U_{i,t+1}$ relative to other contributing variables is also weak.

The last point concerns the specification of the model. When important explanatory variables or interactions are omitted in the specification the results are naturally biased. To correctly specify the matching process, we estimate both stock-stock and stock-flow matching models. We control for heterogeneity in observation units by including in all estimated models regional fixed effects, annual time trend and seasonal (quarterly) dummy variables. Region fixed effects capture unobserved region-specific factors, remove average region effect and focus the model on within region variation over time. Time trend and seasonal dummies capture the effect of macroeconomic factors, remove seasonality, and purify the between (inter-regional) component of variation from time specific effects. In order to incorporate the macroeconomic and labour market context, we use the additional indicator for labour demand, expressed as the growth in secondary employment.

Eventually we allow for interactions between spatially separated units by adding spatial spillovers in matching.

Let us now turn to the detailed description of estimated specifications.

Stock-stock and stock-flow matching functions:

- **Specification [I]**: We first estimate the specification, which includes main explanatory variables (stocks and flows of unemployed and vacancies), region dummies (for Latvia 33 regions, reference region - Riga city; for Latvia pooled with Estonia -34 regions, omitted region - Riga city; for Slovenia 12 regions, omitted region is Celje(Savinjska)), time dummies (quarters, omitted first quarter) and time trend (year).

- **Specification [II]**: baseline specification [I] augmented by the use of the additional labour demand indicator. This indicator is expressed as the growth in secondary employment. For Latvia and Latvia pooled with Estonia, the indicator varies across regions and time (giving the changes in local labour demand), while for Slovenia data is aggregate and the indicator varies only across time.

- **Specification [III]**: is only estimated for Latvia. To make sure the results are not affected by influential observations related to capital city Riga - where unemployed stock values are a lot higher than elsewhere - we run a previous specification ([II]), but exclude Riga city from the sample (in this case Riga district is used as a reference).

- **Specification [VI]**: is only estimated for Latvia. We use the time dimension of the data in order to learn whether the changes in employment legislation have affected matching efficiency in Latvia. In 1999-2003 several major changes, which could have influenced labour supply (or search effort of unemployed) and labour demand, have occurred. These regard the level of unemployment benefit and the amount of legal minimum wage. The average level of unemployment benefit has dropped by 15 percent in August 2000 (when benefit amount calculation rules became harsher) and has raised by 15 percentage oints in February 2003 (when the ceiling on benefit amount was removed). The specification [VI] shows the effect of changes in the unemployment benefit amount. It adds to the baseline specification [II] two step dummy variables: one for the period after August 1st, 2000 and another for the period after February 1st 2003.

- **Specification [V]**: is only estimated for Latvia. Shows the effect of changes in the minimum wage amount in Latvia. This amount was raised by 20 percent in July 2001 and by 17 percent in January 2003, by 14 percent in January 2004, by 13 percent in January 2006. We add to specification [II] step dummy variables for the above changes: first for the period after July 1st 2001, second for the period after January 1st 2003, third for the period after January 1st 2004 and then the fourth for the period after January 1st 2006.

For Latvia the specifications [I] - [V] are estimated both by GLS and PCSE, for both stock-stock and stock-flow models and for three time periods: overall time period 1:1999 to 07:2006, time period prior the EU accession 1:1999 to 04:2004, time period after the EU enlargement 05:2004 - 07:2006. This gives the total of 60 regressions, the results of which are reported in tables 2.9 -2.14 (see appendix).

For Latvia pooled with Estonia, we estimate the specifications [I] and [II] by GLS and PCSE for both stock-stock and stock-flow models and for three time periods (overall time period 1:2003 to 07:2006, time period prior the EU accession 1:2003 to 04:2004, time period after the EU enlargement 05:2004 - 07:2006). This gives the total of 24 regressions, the results being reported in tables 2.15 -2.16.

For Slovenia, we estimate the specifications [I] and [II] by GLS and PCSE for a semi stock-flow models [22] and for three time periods (overall time period 1:2000 to 12:2006, time period prior the EU accession 1:2000 to 04:2004, time period after the EU enlargement 05:2004 - 12:2006). This gives the total of 12 regressions, the results being reported in table 2.17.

[22] The model estimated for Slovenia, due to data availability problems, lies in between the stock-stock and stock-flow models: it includes unemployed stocks and flows and only vacancy flows. Therefore it will be referred to as a *semi stock-flow model*.

The main results are compared in a synthetic result tables 2.2, 2.3 and 2.4.

Spatially augmented matching functions:

- **Specification [VI]**: The specification, without spillover effects but showing the differences in matching efficiency in the areas bordering with other countries. For Latvia 4 regions groups are distinguished, those on the border with Estonia (4 regions), with Russia (3 regions), with Byelorussia (3 regions), with Lithuania (8 regions). The grouping will be maintained in all other spatial specifications. For Slovenia 3 groups of regions are distinguished: those bordering with Italy (3 regions), with Croatia (7 regions) and with Austria (4 regions). The bordering with Hungary is not considered as it only concerns 1 region. The grouping is not maintained in other specifications: almost all regions of Slovenia are bordering with some country, thus grouping is not being informative. Apart from grouping the regions according to their location, this specification is idem to specification [II] above.

- **Specification [VII]**: The specification including spillover effects from neighboring regions.

- **Specification [VIII]**: The specification including spillover effects from neighboring regions, and decomposing the overall spillover in the spillover from high unemployment ratio areas, from low unemployment ratio areas and from the areas with similar unemployment context.

- **Specification [IX]**: The specification including spillover effects from neighboring regions, and decomposing the overall spillover in spillover to high density and normal density areas.

For Latvia the specifications [VI] - [IX] are estimated by both GLS and PCSE, for a stock-flow models, for three time periods (total, prior the EU accession and after the EU enlargement). This gives the total of 24 regressions, the results being reported in tables 2.18 -2.20.

For Slovenia, we estimate the specifications [VI] - [IX] by GLS and PCSE for a semi stock-flow model and for three time periods (total, before and after the EU accession). This gives the total of 24 regressions, the results being reported in tables 2.21 -2.21.

The main results are compared in a synthetic result table 2.5[23].

2.5 Estimation results

We can now turn to the discussion of the estimation results. As above mentioned, we estimate the matching function in three settings representing stock-stock matching function, stock-flow matching function and a spatially augmented stock-flow matching functions.

While all estimation results can be found in annex tables, we provide a summary of regression results in tables 2.2, 2.3 and 2.4 below [24].

Table 2.2: **Estimation results: stock-stock matching function.**

	Latvia			Latvia pooled with Estonia		
Period : Dep.var: ln Matches (outflows from registered unemployment to employment)	Total GLS [II]	Before EU GLS [II]	After EU GLS [II]	Total GLS [II]	Before EU GLS [II]	After EU GLS [II]
ln unemployed (stock)	**0.737***** [0.066]	**0.948***** [0.078]	**1.026***** [0.189]	**0.686***** [0.090]	**0.878***** [0.186]	**0.927***** [0.154]
ln vacancies (stock)	**0.029***** [0.007]	**0.003** [0.009]	**0.025**** [0.012]	**0.014** [0.010]	**0.017** [0.016]	**0.023*** [0.012]
Indicator for local labour demand	**0.797***** [0.069]	**0.886***** [0.071]	**-0.014** [0.326]	**0.723***** [0.152]	**1.129***** [0.162]	**0.108** [0.306]
Time trend (annual)	**0.032***** [0.004]	**0.012**** [0.005]	**0.169***** [0.028]	**0.112***** [0.011]	**0.145***** [0.023]	**0.162***** [0.026]
Constant	**-64.871***** [8.604]	**-27.481**** [11.122]	**-342.773***** [56.924]	**-224.9** [21.744]	**-292.9** [46.226]	**-327.8** [53.468]
Regional dummies (test)	1504***	1192***	1294***	1504***	1111***	1374***
Quarterly dummies (test)	102***	84***	64***	97***	66***	67***
Returns to scale	0.77	0.95	1.05	0.70	0.90	0.95
Constant returns to scale, test	11.96***	0.39	0.07	11***	0.32	0.11
Observations	2738	1954	784	1304	493	811
Regions	33	33	33	34	34	34

Generally, the absence of region and time specific effects is always rejected. All reported tests indicate the presence of serial correlation and groupwise heteroscedasticity in disturbances, both in traditional stock-stock and stock-flow matching functions for all

[23] As previously we report here the results of estimation of the preferred specification (VIII).

[24] To synthesize, we display here only the results of estimations for a preferred specification (specification [II]).

countries, while the autocorrelation in Slovenian data seems to be much weaker that in the data concerning the Baltic states.

Table 2.3: **Estimation results: stock-flow matching function.**

	Latvia			Latvia pooled with Estonia		
Period :	Total	Before EU	After EU	Total	Before EU	After EU
Dep.var: ln Matches	GLS	GLS	GLS	GLS	GLS	GLS
(outflows from registered unemployment to employment)	[II]	[II]	[II]	[II]	[II]	[II]
ln unemployed (stock)	**0.681*** **	**0.947*** **	**0.926*** **	**0.587*** **	**0.802*** **	**0.821*** **
	[0.062]	[0.074]	[0.180]	[0.089]	[0.177]	[0.142]
ln unemployed (flow)	**0.047***	**0.037**	**0.049**	**0.142*** **	**0.223*** **	**0.04**
	[0.029]	[0.033]	[0.054]	[0.040]	[0.055]	[0.050]
ln vacancies (stock)	**0.030*** **	**0.002**	**0.037*** **	**0.021** **	**0.01**	**0.035*** **
	[0.007]	[0.008]	[0.012]	[0.010]	[0.015]	[0.012]
ln vacancies (flow)	**0.203*** **	**0.206*** **	**0.198*** **	**0.195*** **	**0.236*** **	**0.206*** **
	[0.011]	[0.013]	[0.020]	[0.016]	[0.026]	[0.020]
Indicator for local labour demand	**0.749*** **	**0.825*** **	**-0.152**	**0.598*** **	**0.869*** **	**0**
	[0.066]	[0.067]	[0.298]	[0.147]	[0.156]	[0.279]
Time trend (annual)	**0.017*** **	**0.009***	**0.130*** **	**0.087*** **	**0.093*** **	**0.118*** **
	[0.004]	[0.005]	[0.027]	[0.011]	[0.023]	[0.025]
Constant	**-36**	**-22.2**	**-264.3**	**-176**	**-190**	**-240**
	[8.098]	[10.414]	[55.648]	[21.779]	[44.882]	[50.911]
Regional dummies (test)	762***	745***	632***	713***	509***	694***
Quarterly dummies (test)	75***	75***	43***	68***	51***	42***
Returns to scale	0.96	1.19	1.21	0.95	1.27	1.10
Constant returns to scale, test	0.33	5.92**	1.1	0.32	2.1	0.42
Observations	2737	1953	784	1304	493	811
Regions	32	32	32	34	34	34

Considering the main components of the matching function, the estimation results show that in Latvia and Estonia the outflows from unemployment are driven 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 vacancy stock is statistically insignificant in most specifications and the effect of the inflow of unemployed is relatively weak. Also in Slovenia the

Table 2.4: **Estimation results: semi stock-flow matching function.**

	Slovenia		
Period :	Total	Before EU	After EU
Dep.var: ln Matches	GLS	GLS	GLS
(outflows from registered unemployment to employment)	[II]	[II]	[II]
ln unemployed (stock) :	**0.581*** **	**0.661*** **	**0.929*** **
	[0.095]	[0.152]	[0.217]
ln unemployed (flow):	**0.234*** **	**0.237*** **	**0.238*** **
	[0.031]	[0.043]	[0.044]
ln vacancies (flow):	**0.595*** **	**0.688*** **	**0.399*** **
	[0.037]	[0.060]	[0.061]
Indicator for labour demand	**0.278** **	**0.131**	**1.230*** **
	[0.111]	[0.129]	[0.244]
Time trend (annual)	**-0.033*** **	**-0.037*** **	**0.021**
	[0.005]	[0.008]	[0.017]
Constant	**61.08*** **	**67.28*** **	**-49.76**
	[10.804]	[17.141]	[34.974]
Regional dummies (test)	246***	148***	78***
Quarterly dummies (test)	154***	109***	50***
Returns to scale	1.41	1.59	1.57
Constant returns to scale, test	15***	13***	6**
Observations	972	612	360
Regions	12	12	12

matching process is better described by a stock- flow matching function, rather than by a traditional stock-stock one. The stock of unemployed and the inflow of vacancies very intensively participate in match creation, but, in contrast with the Baltic states, also the inflow of unemployed plays an important role in explaining the outflows from unemployment.

The efficiency of the matching process

The aggregate efficiency of the matching process can be analyzed by considering the returns to scale of the estimated matching function.

Generally, constant returns to scale can not be rejected when examining the non-augmented matching functions on Latvian data and the pooled data from Latvia and Estonia. However, the returns to scale are higher when employing a stock -flow version of the matching function. By contrast, in Slovenia, the returns to scale in the matching function are rather increasing.

The degree of homogeneity of the matching function (expressing returns to scale) is slightly increasing over time in Latvia: comparing to the earlier period of time, returns to scale are higher after Latvia's accession to the EU. When the matching function is estimated on pooled Latvian-Estonian data or on Slovenian data the returns to scale are decreasing over time.

Regarding the effect of the changes in employment legislation, which have been evaluated for Latvia, the results suggest a negative relationship between the generosity of labour market institutions and the performance of the economy in terms of matching. Higher unemployment benefits reduce search intensity (effort) of the unemployed, while higher minimum wage reduce the pool of available jobs. The effect on the number of outflows from unemployment is therefore negative.

Labour supply and labour demand

The role of labour supply (demand) in creation of new matches in the labour market can be analyzed by considering the elasticity of outflows from unemployment to employment with respect to unemployed (vacancy) stocks and inflows. We will use the results of the estimation for the stock-flow matching function for Latvia (table 2.3, columns 2 and 3) and semi stock-flow matching function for Slovenia (table 2.4, columns 2 and 3).

Consider first the results for Latvia in the period before EU enlargement (estimation period from 1:1999 to 04:2004). Generally the elasticity of outflows with respect to the size of unemployed pool (stock) varies around 0.95 across various specifications (table 2.13). The estimation results of a preferred specification (II) (table 2.3, 3rd column) show that one percent increase in unemployed stock, raises the outflow from unemployment by 0.947 percent. In the period from 1:1999 to 4:2004 the average number of unemployed in Latvia (see table 2.6) was 98.8 thousand people: one percent increase in unemployed stock is equivalent to adding 988 extra persons to the number of unemployed. Similarly, the number of outflows from unemployment was 3303 on average and a 0.947 percent increase is equivalent to 31 extra matches per month. One new match can thus be created in the labour market if the number of unemployed increases by 988/31=32 persons (on average by 1 in each of Latvian regions).

The elasticity of outflows with respect to the inflow of unemployed is relatively weak (around 0.05) and often statistically insignificant, suggesting that Latvian unemployed are rarely re-employed within the first month after their registration with SEAL.

We now consider the role of job vacancies in creation of new matches in Latvia. The elasticity of outflows with respect to the stock of vacancies varies around 0.03 (table 2.13) and is equal to 0.002 in the above considered specification (table 2.3, 2nd column). Increasing the vacancy stock by 1 percent, 30 additional vacancies (see table 2.6), will result in a 0.002 percent increase in monthly outflow from unemployment, equivalent to 0.07 new matches. Weak elasticity of vacancy stock is closely related to a very high vacancy rotation in Latvian labour market: the majority of inflowing vacancies are filled within a month and remaining vacancies are in most part unsuitable for matching (due to their low quality or narrow specialization).

On the contrary, the elasticity of hiring with respect to new (inflowing) vacancies is always statistically significant and varies around 0.2. Using the above specification (table 2.3, 3rd column), it can be concluded that if the number of new job vacancies increases by 42 (1 percent), the number of new matches will increase by 7 (0.206 percent). Thus for creating one new match the number of new job offers should be increased by 6: outflows are quite sensitive to the changes in the number of new job offers (inflows)[25].

Summing up the characteristics of the matching process in the period before EU enlargement in Latvia: 6 additional new vacancies (inflowing) are equivalent, in terms of match creation, to 32 additional unemployed in stock. One new vacancy is thus equivalent to 5 unemployed. We can conclude that generally, in that period the role of labour demand in creating new matches has been much more important than the role of labour supply.

The dynamics of the role of labour supply and labour demand in the matching process can be analyzed by comparing the estimation results for two time periods: before and after the May 1st 2004. While even after the EU enlargement labour demand still dominates labour supply in Latvian labour market, the results feature the development of a new trend: after Latvia's accession to the EU the role of labour demand in the matching process becomes weaker, but the role of labour supply increases (partially due to high migratory outflows of Latvian workers to other EU member states, see Rutkaste [2006]).

After the 1st May 2004 the effect of new vacancies on match creation decreases (staying though statistically significant), while the vacancy stock variable, that previously did not have any explanatory power, becomes statistically significant. The elasticity of the outflow with respect to the inflow of new unemployed increases suggesting that the matching process is becoming more and more sensitive to the changes in labour supply.

[25] 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-labour force.

Replicating the previous calculations it can be shown that in the period from 5:2004 to 7:2006 one new (inflowing) vacancy was worth three unemployed (in terms of match creation).

The indicator for local labour demand has in general a positive and significant effect on the outflows from unemployment, but in the period after Latvia's accession to the EU this factor looses its statistical significance. This suggests that more job vacancies are now placed through SEAL and the role of registered vacancies in determining the outflow to employment from the pool of registered unemployed also becomes more important.

When Estonia is included into the estimation sample the results stay qualitatively the same: main components of the matching function are stock of unemployed and inflow of new vacancies. In both periods before and after EU enlargement the labour demand dominates labour supply, but the role of labour demand weakens over time (one vacancy is worth seven unemployed when considering the time period before 1st May 2004, while after this date, one vacancy is equivalent to three unemployed).

Let us now discuss the pattern and dynamics in worker-firm matching in Slovenia. As mentioned above, the data on vacancy stocks is not produced by the Employment Service of Slovenia. The other three components of the matching function -the stock of unemployed, the inflow of unemployed and the inflow of new vacancies - intensively participate in determining the outflow from unemployment to jobs.

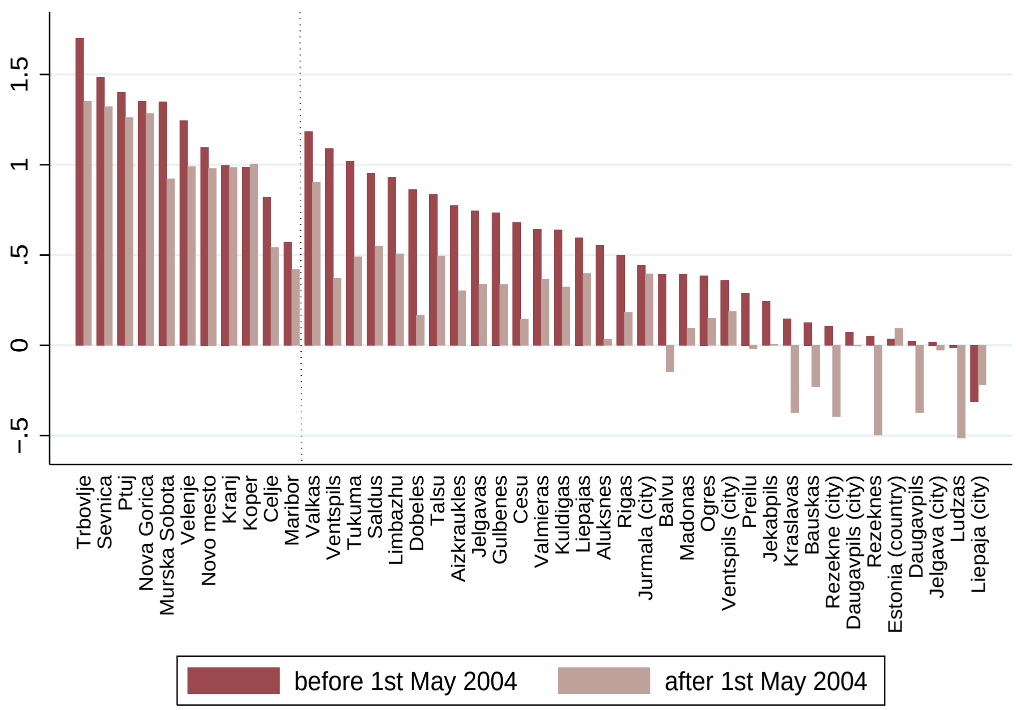
In the period before the EU enlargement the role of labour demand has been important. One additional match could be created in Slovenia by increasing the stock of unemployed by 34 persons, by adding 7 new individuals into the inflow of unemployed or by posting only 4 new vacancies. Thus in terms of match creation one vacancy can be compared to 9 unemployed in stock or to (almost) 2 inflowing unemployed. The trend towards shifting the dominance in match creation from demand to supply side is even more pronounced in Slovenia than it is in the Baltic States. After 1st may 2004, the number of additional unemployed (stock) necessary for increasing hires by one is

21, while the number of required additional vacancies is now 9. One vacancy has as much importance in match creation as 2 unemployed.

Regional heterogeneity in matching

The efficiency of matching significantly vary across space. Figure 2.3 displays the efficiency of matching in various Latvian (including Estonia in the panel) and Slovenian regions. The comparison is based on regression coefficients derived when estimating the stock-flow matching function (in preferred specification [II]) on a panel of Latvian regions and Estonia (in this case the comparison is made with Riga city) and separately on a panel of Slovenian regions (in this case the reference region is Ljubljana). Generally speaking the lowest matching efficiency has been observed in Liepaja, Jel-

Figure 2.3: Regional efficiency of matching in Latvia, Estonia and Slovena



Source: Author's calculations based on data series from State Employment Agency of Latvia, Estonian Labour Market Board and Employment Service of Slovenia. Time periods is available time period covered with data (see table 2.8).

gava, Rezeknes and Daugavpils cities, Ludzas, Daugavpils and Rezeknes regions. Most of these regions are located in depressed eastern part of Latvia and display the lowest levels of development and economic activity. The highest efficiency characterized Valkas, Saldus, Limbazhu regions. The results confirm that, while in general the performance in these regions is better than the one in the capital city Riga, the efficiency gap (in favor of three regions) seems to decrease with time. In Estonia, the matching efficiency is not different from the one in the capital city of Latvia (Riga). In Slovenia, the regional distribution in terms of matching efficiency does not vary significantly over time. The central region of Ljubljana is not performing better than on average. The regions with the weakest performance in terms of matching are Celje and Maribor and those with the best performance are Tribovolje and Sevnica. Whereas Maribor and Celje areas display the highest unemployment rates in the country (13 to 14 percent in January 2006), the unemployment indicators in Trivolje and Sevnica areas are also above national's average (12 percent in these areas *versus* 10,5 national average in January 2006). At the same time, Celje and Maribor areas are situated at Koper-Ljubljana-Maribor development axis and contain the above average developed municipalities in terms population, economic activity, social conditions, while Trivolje and Sevnica mostly contain below average developed municipalities. In terms of specialization, Trivolje is industrial region, but Sevnica has agricultural orientation. It is therefore difficult to attribute higher matching efficiency in Trivolje and Sevnica to any of the above factors.

Regional differences in matching may be explained by several other factors: heterogeneity in unemployed skills and their adequacy to labour demand, differences in unemployment involvement in various active labour market policy programs, varying efficiency of such programmes, or, also, differences in skills and efficiency of staff in different SEAL regional units (which are in charge of job placements and unemployed assignment to ALMP programmes).

Numerous studies have also tried to relate the regional performance in terms of matching to population density in the region. Coles and Smith [1996] state that in the areas with dense pool of unemployed and firms, traders would be in a close proximity and thus enjoy communication with less effort and at lower costs. Therefore matching process would be faster and unemployed/vacancy transition rates consequently higher in the regions with dense population of workers and firms. Kano and Ohta [2005], by contrast, find the empirical evidence for matching efficiency to be decreasing with population density. They argue that in dense areas, the heterogeneity of both firms (in terms of hiring standards and wage structures) and unemployed (in terms of skills and reservation wages) is high and matches are therefore more difficult to arise.

Investigating the role of population density in the matching process from our sample, it turns that in Latvia regional distribution of matching efficiency is not related to population density in the regions, while in Slovenia matching efficiency seems to be lower in dense areas.

The economic activity and the efficiency of the labour market can also be related to the geographical position of the region. For example the regions bordering with other countries may perform better than central regions, because of their involvement in intensive cross-border cooperation (trade, transit or other exchange activities between countries). At the same time, those regions, can also perform worse that the average, because of their remoteness from big cities, insufficient infrastructure, etc. We have examined this issue by introducing in the estimated specification of the matching function the dummy variables grouping the Latvian and Slovenian districts according to their geographical position *vis-a-vis* to other countries. The results show that both in Latvia and Slovenia, closeness to the border negatively affects the efficiency of matching, whereas this effect seems to become weaker in Slovenia after the accession to the EU (at least at Italian and Austrian borders).

Spatial effects

We now turn to the discussion of the estimation results of spatially augmented matching function. Due to the structure of available data, the spatial effects can only be estimated for Latvia and Slovenia.

When spatial interactions are allowed for in the estimated matching function, the

Table 2.5: **Estimation results: Spatially augmented matching function.**

	Latvia			**Slovenia**		
Period :	Total	Before EU	After EU	Total	Before EU	After EU
Dep.var: ln Matches	GLS	GLS	GLS	GLS	GLS	GLS
(outflows from registered unemployment to employment)	[VIII]	[VIII]	[VIII]	[VIII]	[VIII]	[VIII]
ln unemployed (stock) :	**0.749*****	**0.932*****	**0.862*****	**0.718*****	**0.812*****	**1.107*****
	0.07	0.085	0.212	0.1	0.147	0.245
ln unemployed (flow):	**0.022**	**0.013**	**0.027**	**0.028**	**0.025**	**0.067**
	0.032	0.036	0.06	0.051	0.067	0.071
ln vacancies (stock):	**0.022*****	**0.004**	**0.032*****			
	0.007	0.008	0.012			
ln vacancies (flow):	**0.184*****	**0.186*****	**0.198*****	**0.372*****	**0.438*****	**0.271*****
	0.011	0.013	0.02	0.048	0.062	0.073
Indicator for local labour demand	**0.762*****	**0.802*****	**-0.133**	**0.288*****	**0.013**	**1.257*****
	0.065	0.066	0.29	0.11	0.125	0.24
Time trend (annual)	**0.003**	**-0.001**	**0.076****	**-0.032*****	**-0.017***	**0.002**
	0.004	0.005	0.032	0.007	0.01	0.019
Constant	**-6.8**	**-1.0**	**-154*****	**53.4*****	**21.1**	**-14.7**
	8.811	11.486	66.256	14.926	21.667	39.529
	Neighbouring region variables					
	Overall spillover effect					
ln (W x unemployed (stock)	(-)			(+)	(+)	
ln (W x unemployed (flow)	(+)	(+)		(+)	(+)	(+)
ln (W x vacancies (stock)	(+)					
ln (W x vacancies (flow)	(+)	(+)	(+)	(+)	(+)	(+)
	Spillovers from high unemployment ratio areas					
ln (W x unemployed (stock)		(+)				
ln (W x unemployed (flow)	(-)				(-)	
ln (W x vacancies (stock)		(+)				
ln (W x vacancies (flow)			(-)			
	Spillovers from low unemployment ratio areas					
ln (W x unemployed (stock)			(+)		(-)	
ln (W x unemployed (flow)	(-)					
ln (W x vacancies (stock)	(-)					
ln (W x vacancies (flow)					(+)	
	Effects from high population density areas					
POP x ln (W x unemployed (stock)			(-)		(-)	
POP x ln (W x unemployed (flow)		(+)		(-)	(-)	(-)
POP * ln (W x vacancies (stock)						
POP * ln (W x vacancies (flow)	(-)	(-)	(-)			
Regional dummies (test)	385***	389***	331***	218***	170***	55***
Quarterly dummies (test)	79***	76***	23***	136***	77***	53***
Returns to Scale	0.67	1.02	2.00	1.76	1.64	1.95
Constant returns to scale, test	0.81	0	1.81	1.85	0.69	0.57
Observations	2679	1898	781	972	612	360
Regions	33	33	33	12	12	12

matching process can be specified as unemployed stock-vacancy flow matching for both countries. For Latvia the specification remains robust to the introduction of new spatial variables. For Slovenia, by contrast, there is a qualitative change in the results: the inflow of new unemployed, which previously has intensively contributed to determining the flow of new hires, has now lost its explanatory power due to the inclusion of spatial effects.

Spatial spillovers exist and are statistically significant in both countries. In Latvia the inflow of new vacancies in the neighboring areas positively affects local outflows to employment, while the increase in foreign unemployment decreases local outflows to jobs (mostly in the time period before Latvia's accession to EU), suggesting that unemployed search indeed and actively in the neighboring areas. This finding is in line with the results brought by Ahtonen [2005] for Finland and witnesses the effect of congestion caused by job seekers from neighboring areas. The foreign stock of vacancies and inflow into unemployment have positive influence on the matches, but this effect is not robust to specification choice and is mostly present in the time period before Latvia's accession to the EU.

In Slovenia, the foreign variable, that always increases local outflows to jobs is the inflow into the pool of unemployed workers. Together with the positive influence of foreign stock of unemployed (not always, but in most cases, statistically significant) this suggests the existence of positive externalities relied to increased number of traders at the "market place", which can presumably reduce the search costs for unemployed and employers. The posting of job offers in neighboring areas also positively influences local exits from unemployment, but especially in the pre-EU period when the role of labour demand was more important.

Regarding the asymmetry of spatial effects, in Slovenia the positive influence of new vacancies in surrounding regions is even stronger if these neighboring areas also display an unemployment rate much lower than the domestic one . However this asymmetry is only observed in the time period before the EU enlargement. The same applies to the asymmetry found in the effect of the inflow of unemployed from the areas with high unemployment rate and in the effect of the stock of unemployed from low unemployed regions: these are only statistically significant in the period before May 2004.

In Latvia, the asymmetry of spillovers seems to be weak. Meanwhile, spillovers from foreign unemployed inflow seems to be lower whenever the unemployment situation in the neighboring area is different from the domestic one (disregarding the sense).

As to the effects of population density, when the region itself is dense the foreign inflow of vacancies lowers local matches in Latvia, while in Slovenia this effect is observed for unemployed inflow.

2.6 Conclusions

We investigate the process of worker-firm matching in three new EU member states (Latvia, Slovenia and Estonia) by estimating the aggregate matching function.

We first assess the correct specification of 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 and recent empirical findings of Dmitrijeva and Hazans [2007], we estimate both stock-stock and stock-flow matching functions.

When estimating the matching function in its traditional stock-stock setting either on Latvian or on combined Latvian and Estonian data, 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 other Central and Eastern European 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 the 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 and Estonia 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 and Estonian labour market do not result from differentiation between old versus new vacancies by the unemployed, but from dominant role of labour demand. Generally speaking the above findings suggest a stock-flow setting to be the only relevant for describing a matching process in a high unemployment - low labour demand environment, typical for the transition countries.

Also in Slovenia the matching process is better described by a stock-flow matching function, than by a traditional stock-stock function. Similarly to Baltic States, stock of unemployed and the inflow of vacancies participate very intensively in match creation in Slovenia. Meanwhile, the inflow of unemployed, which does not play an important role in matching process in Latvia, significantly contributes to explaining the outflows from unemployment in Slovenia.

Thus, while the patterns of the matching process are different between the Baltic states and Slovenia, in both cases a stock-flow matching function is the most appropriate for describing this process.

Comparing the aggregate efficiency of the matching process, Slovenian labour market seems to be less subject to frictions, comparing to the Baltic States. This is supported by the fact that the returns to scale in the matching function are constant in Latvia and Estonia and increasing in Slovenia. Regarding the temporal dynamics, the efficiency of the labour market in terms of worker-firm matching is increasing over time in Latvia but seems to decrease in Estonia and Slovenia.

The improvement in the efficiency of matching over time in Latvia can be partially explained by increasing efficiency of active labour market policy programs. It can also point to the reduction of macroeconomic mismatch and imbalances (better adequacy to labour demand of education and skills of Latvian population, higher labour mobility, ect.) or / and on the development of other factors, that speed up the matching process.

In Latvia, Estonia and Slovenia the role of labour demand in creating new hires is very important. However, the results also feature the development of a new trend: after the EU accession the role of labour demand in the matching process becomes weaker, but the role of labour supply substantially increases. This trend is the most pronounced in Slovenia.

Cross-region comparisons reveal that matching efficiency has been heterogenous across space. In Latvia matching is least efficient in depressed eastern part of Latvia (Rezeknes and Daugavpils cities, Ludzas, Daugavpils and Rezeknes regions) and in Liepaja and Jelgava cities, while the highest efficiency characterized Valkas, Saldus, Limbazhu regions. In Estonia, the matching efficiency is not different from the one in the capital city of Latvia (Riga). In Slovenia the regions with the weakest performance in terms of matching are Celje and Maribor and those with the best performance are Tribovolje and Trevnica.

In Latvia regional distribution of matching efficiency can not be attributed to the population density in the regions, but in Slovenia matching efficiency seems to be lower in the areas, where the population density is high.

Following Burda and Profit [1996], Burgess and Profit [2001], Ahtonen [2005] we also allow for spatial interactions in the matching process. We estimate spatially augmented matching function on Latvian and Slovenian data and show that spatial spillovers exist and are statistically significant in both countries. In Latvia the inflow of new vacancies in the neighboring areas positively affects local outflows to employment, while the increase in foreign unemployment decreases local outflows to jobs (mostly in the time period before Latvia's accession to EU), suggesting that unemployed widen their search to the neighboring areas. In Slovenia local outflows to jobs increase with the inflows into unemployment in neighboring regions.

Since the magnitude of spatial spillover effects can vary across regions, we investigate whether it is affected by the unemployment rate difference between local and neighboring regions. We also analyze wherever the spillovers to the regions with high population density are different from the ones to other regions.

While in Latvia the asymmetry of spillovers is weak, in Slovenia the extent of spillovers seem to vary depending on economic context in neighboring regions. The effects, however, are statistically significant only in the period before EU enlargement.

Population density also matters for the magnitude of a spillover for some variables: foreign inflow of vacancies lowers local hires in dense regions of Latvia, while in Slovenia local matches are negatively affected by the inflow of new unemployed in neighboring regions, if local population density is higher than national average.

2.7 Appendices

Table 2.6: **Descriptive statistics, aggregated data**

Variable	**Mean**	**S.d.**	**Min**	**Max**	**Obs.**	**Mean**	
	Latvia 1:1999 - 07:2006					**(a)**	**(b)**
Matches	3377	527	2520	4832	91	3303	3554
Stock of unemployed	94733	10951	73333	121760	91	98801	85092
Inflow of unemployed	8901	953	6699	11679	91	9095	8442
Stock of vacant jobs	4596	3166	1721	16378	91	2985	8417
Inflow of vacant jobs	4725	1139	2575	7829	91	4216	5931
Secondary job	51416	10544	36324	72089	90	45551	65852
	Estonia 1:2003 - 12:2006					**(a)**	**(b)**
Matches	1601	398	674	2435	48	1756	1523
Stock of unemployed	27902	9205	11989	43606	48	37518	23094
Inflow of unemployed	3730	1289	1352	7348	48	4926	3133
Stock of vacant jobs	4968	2389	1707	9210	48	2249	6327
Inflow of vacant jobs	1928	788	623	3804	48	1197	2293
Secondary job	21572	2841	16700	29200	46	23275	20663
	Slovenia 1:2000 - 12:2006					**(a)**	**(b)**
Matches	4537	899	2172	7279	84	4521	4562
Stock of unemployed	97045	7548	78303	116243	84	101788	89339
Inflow of unemployed	7522	1876	4353	11770	84	7353	7796
Inflow of vacant jobs	14076	3116	9098	22699	84	12139	17223
Secondary job	24009	6939	12700	37300	82	19702	31473

Notes: Variables are aggregated for all regions, frequency - monthly. Means (a) and (b) refer to mean values of the variables for two time periods: (a) - before April 2004, (b) - after this date.

Table 2.7: **Descriptive statistics on panel data (regions)**

Variable	**Mean**	**Variation**	**S.d.**	**Min**	**Max**	**Obs.**	
	Latvia: time period 01:1999 - 07:2006						
Matches (Outflows	102	overall	170	5	1478	Nit	3003
from unemployment		between	169	20	1027	Ni	33
to employment)		within	37	-200	553	Nt	91
Stock of unemployed	2871	overall	3029	419	26369	Nit	3003
		between	3000	551	18089	Ni	33
		within	670	-908	11151	Nt	91
Inflow of unemployed	270	overall	405	30	3567	Nit	3003
		between	404	54	2447	Ni	33
		within	75	-415	1390	Nt	91
Stock of vacant jobs	139	overall	681	0	11566	Nit	3003
		between	562	2	3258	Ni	33
		within	398	-1961	8448	Nt	91
Inflow of vacant jobs	143	overall	440	0	4767	Nit	3003
		between	427	16	2507	Ni	33
		within	131	-973	2403	Nt	91
Secondary job	2751	overall	8842	191	72089	Nit	2970
		between	8778	274	51416	Ni	33
		within	1857	-12341	23424	Nt	90
	Slovenia: time period 01:2000 - 12:2006						
Matches (Outflows	378	overall	236	45	1216	Nit	1008
from unemployment		between	221	163	866	Ni	12
to employment)		within	104	-76	870	Nt	84
Stock of unemployed	8087	overall	5235	2507	24121	Nit	1008
		between	5375	2991	19406	Ni	12
		within	947	3846	12802	Nt	84
Inflow of unemployed	627	overall	413	123	2365	Nit	1008
		between	381	261	1515	Ni	12
		within	193	24	1477	Nt	84
Inflow of vacant jobs	1173	overall	1181	138	7431	Nit	1008
		between	1166	288	4633	Ni	12
		within	383	-806	3971	Nt	84
Secondary job	24009	overall	6900	12700	37300	Nit	984
		between				Ni	1
		within				Nt	82

Notes: (1)N_{it} - total observation number; N_i - number of regions; N_t - number of time periods (months). (2) 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 2.8: **Data description and sources**

Variable	**Country**	**Nr. of months**	**Nr. of regions**	**Description**	**Source**
Matches	Latvia	91 (01:1999-07:2006)	33 (regional units of SEAL)	Outflows from registered	SEAL
	Estonia	48 (01:2003-12:2006)	1 (aggregate data)	unemployment to employment.	ELMB
	Slovenia	84 (01:2000-12:2006)	12 (regional units of ESS)		ESS
Stock of unemployed	Latvia	91 (01:1999-07:2006)	33 (regional units of SEAL)	End-month stock of registered	SEAL
	Estonia	48 (01:2003-12:2006)	1 (aggregate data)	unemployed.	ELMB
	Slovenia	84 (01:2000-12:2006)	12 (regional units of ESS)		ESS
Inflow of unemployed	Latvia	91 (01:1999-07:2006)	33 (regional units of SEAL)	Monthly inflow into registered	SEAL
	Estonia	48 (01:2003-12:2006)	1 (aggregate data)	unemployed.	ELMB
	Slovenia	84 (01:2000-12:2006)	12 (regional units of ESS)		ESS
Stock of vacant jobs	Latvia	91 (01:1999-07:2006)	33 (regional units of SEAL)	End-month stock of vacant jobs,	SEAL
	Estonia	48 (01:2003-12:2006)	1 (aggregate data)	posted through SEAL/ELMB	ELMB
	Slovenia	Not available (ESS does not perform accounting of vacancy stocks)			ESS
Inflow of vacant jobs	Latvia	91 (01:1999-07:2006)	33 (regional units of SEAL)	Monthly inflow of new vacancies,	SEAL
	Estonia	48 (01:2003-12:2006)	1 (aggregate data)	posted through SEAL/ELMB.	ELMB
	Slovenia	84 (01:2000-12:2006)	12 (regional units of ESS)	Total monthly inflow of new vacancies	ESS
				(registration with ESS is obligatory).	
Secondary job	Latvia	90 (01:1999-06:2006)	33 (regional units of SEAL)	Average number of employed	SCBL
	Estonia	46 (01:2003-10:2006)	1 (aggregate data)	at secondary job.	EUROSTAT
	Slovenia	82 (01:2000-10:2006)	1 (aggregate data)		EUROSTAT
Unemployment rates	Latvia	1 (12:2005)	33 (regional units of SEAL)	Regional unemployment rate	SEAL
	Slovenia	12 (01:2006-12:2006)	12 (regional units of ESS)		ESS
Population density	Latvia	1 (12:2005)	33 (regional units of SEAL)	Regional unemployment rate	CSBL
	Slovenia	1 (annual for 2005)	12 (statistical regions)		SORS

Notes: (1) SEAL: State Employment Agency of Latvia; ELMB: Estonian Labour Market Board; ESS: Employment Service of Slovenia; CSBL: Central Statistical Bureau of Latvia; SORS: Statistical Office of the Republic of Slovenia. (2) Secondary job data: Original monthly data is only available for Latvia for the period 1999 2003, in all other cases quarterly data is interpolated to monthly.

Table 2.9: **Latvia - Estimation results: stock-stock matching function (time period 01:1999 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]	PCSE [V]
ln unemployed (stock)	**0.727*** **	**0.737*** **	**0.759*** **	**0.747*** **	**0.769*** **	**0.746*** **	**0.759*** **	**0.764*** **	**0.775*** **	**0.805*** **
	[0.068]	[0.066]	[0.068]	[0.066]	[0.065]	[0.115]	[0.107]	[0.106]	[0.101]	[0.098]
ln vacancies (stock)	**0.025*** **	**0.029*** **	**0.030*** **	**0.027*** **	**0.015** **	**0.022** **	**0.026*** **	**0.026*** **	**0.024** **	**0.012**
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.010]	[0.010]	[0.010]	[0.010]	[0.009]
Indicator for local labour demand		**0.797*** **	**0.799*** **	**0.792*** **	**0.810*** **		**0.770*** **	**0.771*** **	**0.763*** **	**0.783*** **
		[0.069]	[0.070]	[0.069]	[0.069]		[0.134]	[0.134]	[0.134]	[0.132]
Time trend (annual)	**0.033*** **	**0.032*** **	**0.033*** **	**0.036*** **	**0.028*** **	**0.032*** **	**0.032*** **	**0.032*** **	**0.036*** **	**0.029*** **
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.011]	[0.010]	[0.010]	[0.010]	[0.010]
Constant	**-65.64*** **	**-64.87*** **	**-66.93*** **	**-71.91*** **	**-57.65*** **	**-65.22*** **	**-65.01*** **	**-66.15*** **	**-72.98*** **	**-59.23*** **
	[8.979]	[8.604]	[8.695]	[8.929]	[9.126]	[22.492]	[19.596]	[19.534]	[19.889]	[21.238]
UBA 1 (after 01/08/2000)				**0.039***					**0.044**	
				[0.022]					[0.061]	
UBA 2 (after 01/02/2003)				**-0.081*** **					**-0.086**	
				[0.021]					[0.059]	
MWA1 (after 01/07/2001)					**-0.02**					**-0.022**
					[0.021]					[0.058]
MWA2 (after 01/01/2003)					**-0.103*** **					**-0.109***
					[0.022]					[0.060]
MWA3 (after 01/01/2004)					**-0.014**					**-0.033**
					[0.023]					[0.063]
MWA4 (after01/01/2006)					**0.163*** **					**0.174** **
					[0.030]					[0.083]
Regional dummies (test)	1372***	1504***	998***	1635***	1743***	2333***	2805***	1375***	3008***	3282***
Quarterly dummies (test)	79***	102***	110***	112***	117***	11**	16***	17***	18***	20***
Returns to Scale	0.75	0.77	0.79	0.77	0.78	0.77	0.78	0.79	0.80	0.82
Constant returns to scale, test	13***	11.96***	9.31***	11.41***	10.65***	4**	4.03**	3.82*	3.89*	3.45*
Observations	2769	2738	2648	2738	2738	2769	2738	2648	2738	2738
Regions	33	33	32	33	33	33	33	32	33	33
Coefficient of determination R2						0.87	0.87	0.87	0.87	0.88
Heteroscedasticity, test	898.6***	892***	643***	886***	820***					
Autocorrelation, test	20.9***	20.10***	19.59***	19.52***	18.98***					

Table 2.10: **Latvia - Estimation results: stock-stock matching function (time period 01:1999 - 04:2004)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]	PCSE [V]
ln unemployed (stock)	**0.936*****	**0.948*****	**0.983*****	**1.003*****	**0.901*****	**0.980*****	**0.991*****	**1.005*****	**1.050*****	**0.949*****
	[0.083]	[0.078]	[0.080]	[0.081]	[0.079]	[0.145]	[0.126]	[0.125]	[0.121]	[0.121]
ln vacancies (stock)	**0.003**	**0.003**	**0.004**	**0.004**	**0.002**	**-0.004**	**-0.003**	**-0.003**	**-0.003**	**-0.005**
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Indicator for local labour demand		**0.886*****	**0.889*****	**0.872*****	**0.894*****		**0.841*****	**0.842*****	**0.827*****	**0.843*****
		[0.071]	[0.071]	[0.071]	[0.070]		[0.131]	[0.130]	[0.130]	[0.129]
Time trend (annual)	**0.014****	**0.012****	**0.012****	**0.021*****	**0.01**	**0.014**	**0.012**	**0.012**	**0.021**	**0.009**
	[0.006]	[0.005]	[0.005]	[0.006]	[0.007]	[0.016]	[0.012]	[0.012]	[0.013]	[0.016]
Constant	**-30.59****	**-27.48****	**-28.13****	**-44.19*****	**-22.69**	**-31.02**	**-27.28**	**-27.61**	**-45.253***	**-19.93**
	[12.200]	[11.122]	[11.156]	[12.478]	[14.523]	[31.833]	[24.663]	[24.485]	[27.101]	[32.721]
UBA 1 (after 01/08/2000)				**0.047****					**0.059**	
				[0.020]					[0.051]	
UBA 2 (after 01/02/2003)				**-0.036***					**-0.037**	
				[0.021]					[0.055]	
MWA1 (after 01/07/2001)					**0.004**					**0.007**
					[0.020]					[0.052]
MWA2 (after 01/01/2003)					**-0.051****					**-0.043**
					[0.024]					[0.063]
MWA3 (after 01/01/2004)					**0.074****					**0.084**
					[0.035]					[0.089]
Regional dummies (test)	1027***	1192***	786***	1251***	1261***	2459***	2878***	1331***	3067***	3034***
Quarterly dummies (test)	58***	84***	92***	91***	91***	9**	16***	17***	18***	18***
Returns to Scale	0.94	0.95	0.99	1.01	0.90	0.98	0.99	1.00	1.05	0.94
Constant returns to scale, test	0.53	0.39	0.03	0.01	1.50	0.03	0.01	0.00	0.15	0.21
Observations	1954	1954	1890	1954	1954	1954	1954	1890	1954	1954
Regions	33	33	32	33	33	33	33	32	33	33
Coefficient of determination R2						0.89	0.90	0.90	0.90	0.90
Heteroscedasticity, test	468.1***	551***	534***	542***	571***					
Autocorrelation, test	14.7***	13.57***	13.02***	13.39***	13.25***					

Table 2.11: **Latvia - Estimation results: stock-stock matching function (time period 05:2004 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [V]
ln unemployed (stock)	**0.965*****	**1.026*****	**1.082*****	**1.157*****	**1.086*****	**1.130*****	**1.151*****	**1.198*****
	[0.188]	[0.189]	[0.194]	[0.195]	[0.311]	[0.316]	[0.317]	[0.321]
ln vacancies (stock)	**0.020***	**0.025****	**0.023***	**0.023***	**0.018**	**0.021**	**0.02**	**0.019**
	[0.012]	[0.012]	[0.012]	[0.012]	[0.015]	[0.015]	[0.015]	[0.015]
Indicator for local labour demand		**-0.014**	**-0.02**	**-0.055**		**0.253**	**0.256**	**0.209**
		[0.326]	[0.328]	[0.325]		[0.469]	[0.470]	[0.461]
Time trend (annual)	**0.137*****	**0.169*****	**0.186*****	**0.137*****	**0.169*****	**0.197*****	**0.204*****	**0.165****
	[0.026]	[0.028]	[0.029]	[0.030]	[0.059]	[0.063]	[0.064]	[0.078]
Constant	**-276.92*****	**-342.77*****	**-376.44*****	**-278.92*****	**-341.59*****	**-399.76*****	**-413.49*****	**-335.67****
	[54.509]	[56.924]	[59.359]	[61.062]	[120.446]	[128.056]	[129.060]	[157.550]
MWA4 (after01/01/2006)				**0.107*****				**0.093**
				[0.040]				[0.125]
Regional dummies (test)	1344***	1294***	952***	1352***	485169***	22081***	1206***	1502***
Quarterly dummies (test)	60***	64***	70***	68***	9**	10**	11***	11**
Returns to Scale	0.99	1.05	1.10	1.18	1.10	1.15	1.17	1.22
Consant returns to scale, test	0.01	0.07	0.29	0.83	0.11	0.23	0.29	0.46
Observations	815	784	758	784	815	784	758	784
Regions	33	33	32	33	33	33	32	33
Coefficient of determination R2					0.93	0.94	0.93	0.94
Heteroscedasticity, test	347.7***	338***	258***	397***				
Autocorrelation, test	8.7***	7.86***	7.67***	8.06***				

Table 2.12: **Latvia - Estimation results: stock-flow matching function (time period 01:1999 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]	PCSE [V]
ln unemployed (stock)	**0.658*** **	**0.681*** **	**0.699*** **	**0.673*** **	**0.713*** **	**0.713*** **	**0.730*** **	**0.735*** **	**0.730*** **	**0.767*** **
	[0.063]	[0.062]	[0.064]	[0.062]	[0.061]	[0.102]	[0.096]	[0.096]	[0.092]	[0.089]
ln unemployed (flow)	**0.049***	**0.047***	**0.034**	**0.048***	**0.062****	**0.003**	**0.004**	**0.001**	**0.004**	**0.02**
	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.046]	[0.043]	[0.043]	[0.043]	[0.042]
ln vacancies (stock)	**0.027*** **	**0.030*** **	**0.030*** **	**0.026*** **	**0.017****	**0.022****	**0.025*** **	**0.026*** **	**0.022****	**0.012**
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.009]	[0.009]	[0.009]	[0.009]	[0.008]
ln vacancies (flow)	**0.209*** **	**0.203*** **	**0.202*** **	**0.203*** **	**0.199*** **	**0.190*** **	**0.188*** **	**0.188*** **	**0.189*** **	**0.184*** **
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.016]	[0.015]	[0.015]	[0.015]	[0.014]
Indicator for local labour demand		**0.749*** **	**0.748*** **	**0.748*** **	**0.762*** **		**0.737*** **	**0.737*** **	**0.734*** **	**0.750*** **
		[0.066]	[0.066]	[0.066]	[0.065]		[0.118]	[0.118]	[0.117]	[0.116]
Time trend (annual)	**0.016*** **	**0.017*** **	**0.018*** **	**0.019*** **	**0.015*** **	**0.021****	**0.021****	**0.021****	**0.023*** **	**0.019****
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.010]	[0.008]	[0.008]	[0.008]	[0.009]
Constant	**-34.74*** **	**-36.01*** **	**-38.021*** **	**-39.74*** **	**-32.40*** **	**-43.83****	**-44.34*** **	**-45.31*** **	**-49.00*** **	**-40.88****
	[8.372]	[8.098]	[8.179]	[8.460]	[8.649]	[19.714]	[17.031]	[16.995]	[17.294]	[18.445]
UBA 1 (after 01/08/2000)				**0.017**					**0.017**	
				[0.021]					[0.053]	
UBA 2 (after 01/02/2003)				**-0.083*** **					**-0.097***	
				[0.020]					[0.051]	
MWA1 (after 01/07/2001)					**0.004**					**-0.007**
					[0.020]					[0.050]
MWA2 (after 01/01/2003)					**-0.096*** **					**-0.108****
					[0.021]					[0.052]
MWA3 (after 01/01/2004)					**-0.017**					**-0.028**
					[0.022]					[0.054]
MWA4 (after01/01/2006)					**0.139*** **					**0.148****
					[0.028]					[0.072]
Regional dummies (test)	714***	762***	654***	789***	831***	1220***	1268***	901***	1340***	1441***
Quarterly dummies (test)	52***	75***	80***	78***	84***	8**	14***	15***	15***	17***
Returns to Scale	0.94	0.96	0.96	0.95	0.99	0.93	0.95	0.95	0.94	0.98
Constant returns to scale, test	0.68	0.33	0.26	0.55	0.02	0.4	0.25	0.25	0.31	0.03
Observations	2768	2737	2647	2737	2737	2768	2737	2647	2737	2737
Regions	33	32	33	33	33	33	32	33	33	33
Coefficient of determination R2						0.87	0.87	0.87	0.88	0.88
Heteroscedasticity, test	980.7***	1011***	709***	974***	973***					
Autocorrelation, test	20.6***	20.09***	19.54***	19.47***	18.97***					

Table 2.13: **Latvia - Estimation results: stock-flow matching function (time period 01:1999 - 04:2004)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]	PCSE [V]
ln unemployed (stock)	**0.931*****	**0.947*****	**0.985*****	**0.979*****	**0.938*****	**0.971*****	**0.988*****	**1.001*****	**1.025*****	**0.971*****
	[0.078]	[0.074]	[0.075]	[0.075]	[0.074]	[0.129]	[0.114]	[0.113]	[0.109]	[0.110]
ln unemployed (flow)	**0.038**	**0.037**	**0.024**	**0.04**	**0.041**	**-0.005**	**-0.001**	**-0.005**	**0.001**	**-0.001**
	[0.034]	[0.033]	[0.033]	[0.033]	[0.033]	[0.052]	[0.046]	[0.046]	[0.046]	[0.046]
ln vacancies (stock)	**0.002**	**0.002**	**0.003**	**0.003**	**0.001**	**-0.007**	**-0.006**	**-0.006**	**-0.006**	**-0.007**
	[0.009]	[0.008]	[0.008]	[0.008]	[0.008]	[0.010]	[0.009]	[0.009]	[0.009]	[0.009]
ln vacancies (flow)	**0.216*****	**0.206*****	**0.202*****	**0.207*****	**0.207*****	**0.187*****	**0.182*****	**0.180*****	**0.183*****	**0.182*****
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.019]	[0.017]	[0.017]	[0.017]	[0.017]
Indicator for local labour demand		**0.825*****	**0.825*****	**0.818*****	**0.834*****		**0.801*****	**0.801*****	**0.791*****	**0.803*****
		[0.067]	[0.067]	[0.067]	[0.066]		[0.115]	[0.115]	[0.114]	[0.114]
Time trend (annual)	**0.010***	**0.009***	**0.009***	**0.018*****	**0.016****	**0.011**	**0.01**	**0.01**	**0.019***	**0.014**
	[0.005]	[0.005]	[0.005]	[0.006]	[0.007]	[0.014]	[0.010]	[0.010]	[0.011]	[0.014]
Constant	**-23.337****	**-22.159****	**-23.081****	**-40.247*****	**-36.175*****	**-25.943**	**-23.773**	**-23.959**	**-43.558***	**-31.183**
	[11.266]	[10.414]	[10.452]	[11.527]	[13.638]	[27.856]	[21.299]	[21.181]	[23.109]	[28.339]
UBA 1 (after 01/08/2000)				**0.027**					**0.034**	
				[0.018]					[0.043]	
UBA 2 (after 01/02/2003)				**-0.062*****					**-0.067**	
				[0.019]					[0.047]	
MWA1 (after 01/07/2001)					**0.018**					**0.013**
					[0.018]					[0.044]
MWA2 (after 01/01/2003)					**-0.078*****					**-0.071**
					[0.023]					[0.055]
MWA3 (after 01/01/2004)					**0.005**					**0.035**
					[0.033]					[0.077]
Regional dummies (test)	668***	745***	628***	770***	759***	1281***	1468***	1012***	1528***	1546***
Quarterly dummies (test)	50***	75***	81***	80***	66***	9**	17***	18***	19***	16***
Returns to Scale	1.19	1.19	1.21	1.23	1.19	1.15	1.16	1.17	1.20	1.15
Constant returns to scale, test	5**	5.92**	7.05**	7.96	5.4**	1.02	1.69	1.89	2.86*	1.48
Observations	1953	1953	1889	1953	1953	1953	1953	1889	1953	1953
Regions	33	32	33	33	33	33	32	33	33	33
Coefficient of determination R2						0.90	0.91	0.91	0.91	0.91
Heteroscedasticity, test	652.4***	779***	755***	793***	815***					
Autocorrelation, test	14.9***	14.24***	13.7***	13.96***	13.88***					

Table 2.14: **Latvia - Estimation results: stock-flow matching function (time period 05:2004 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [V]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [V]
ln unemployed (stock)	**0.867*****	**0.926*****	**0.972*****	**1.037*****	**1.014*****	**1.053*****	**1.070*****	**1.112*****
	[0.177]	[0.180]	[0.183]	[0.187]	[0.277]	[0.281]	[0.281]	[0.288]
ln unemployed (flow)	**0.062**	**0.049**	**0.044**	**0.046**	**0.021**	**0.008**	**0.005**	**0.004**
	[0.052]	[0.054]	[0.055]	[0.054]	[0.090]	[0.092]	[0.092]	[0.091]
ln vacancies (stock)	**0.033*****	**0.037*****	**0.036*****	**0.034*****	**0.032****	**0.036*****	**0.035****	**0.034****
	[0.011]	[0.012]	[0.012]	[0.012]	[0.013]	[0.014]	[0.014]	[0.014]
ln vacancies (flow)	**0.205*****	**0.198*****	**0.201*****	**0.197*****	**0.194*****	**0.192*****	**0.193*****	**0.192*****
	[0.019]	[0.020]	[0.020]	[0.020]	[0.026]	[0.027]	[0.027]	[0.027]
Indicator for local labour demand		**-0.152**	**-0.169**	**-0.188**		**0.175**	**0.173**	**0.135**
		[0.298]	[0.300]	[0.296]		[0.411]	[0.411]	[0.403]
Time trend (annual)	**0.102*****	**0.130*****	**0.141*****	**0.100*****	**0.127****	**0.151*****	**0.156*****	**0.121***
	[0.026]	[0.027]	[0.028]	[0.029]	[0.051]	[0.054]	[0.054]	[0.066]
Constant	**-209.287*****	**-264.281*****	**-287.838*****	**-206.659*****	**-260.087****	**-308.200*****	**-318.329*****	**-248.947***
	[53.243]	[55.648]	[57.351]	[59.298]	[103.708]	[109.544]	[109.979]	[133.363]
MWA4 (after01/01/2006)				**0.095****				**0.085**
				[0.037]				[0.108]
Regional dummies (test)	642***	632***	570***	638***	13214***	39894***	5482***	6876***
Quarterly dummies (test)	42***	43***	48***	46***	7.7*	9**	9**	9**
Returns to Scale	1.17	1.21	1.25	1.31	1.26	1.29	1.30	1.34
Constant returns to scale, test	0.73	1.1	1.55	2.33	0.79	0.92	1.01	1.22
Observations	815	784	758	784	815	784	758	784
Regions	33	32	33	33	33	32	33	33
Coefficient of determination R2					0.94	0.94	0.94	0.94
Heteroscedasticity, test	380.8***	423***	407***	475***				
Autocorrelation, test	8.1***	7.44***	7.18***	7.5***				

Table 2.15: **Latvia and Estonia - Estimation results: stock-stock matching function**

	Time period 01:2003 - 07:2006				Time period 01:2003 -04:2004				Time period 05:2004 - 07:2006			
Dep.var: ln Matches (outflows from registered unemployment to emp.)	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]
ln unemployed (stock)	**0.658*** **	**0.686*** **	**0.665*** **	**0.691*** **	**0.848*** **	**0.878*** **	**0.957**	**0.985*** **	**0.853*** **	**0.927*** **	**0.979*** **	**1.046*** **
	[0.091]	[0.090]	[0.180]	[0.171]	[0.211]	[0.186]	[0.000]	[0.289]	[0.154]	[0.154]	[0.252]	[0.256]
ln vacancies (stock)	**0.007**	**0.014**	**0.001**	**0.006**	**0.008**	**0.017**	**-0.009**	**-0.003**	**0.018**	**0.023***	**0.015**	**0.018**
	[0.010]	[0.010]	[0.013]	[0.013]	[0.017]	[0.016]	[0.000]	[0.019]	[0.012]	[0.012]	[0.015]	[0.015]
Indicator for local labour demand		**0.723*** **		**0.737*** **		**1.129*** **		**0.876*** **		**0.108**		**0.335**
		[0.152]		[0.266]		[0.162]		[0.281]		[0.306]		[0.424]
Time trend (annual)	**0.104*** **	**0.112*** **	**0.114*** **	**0.121*** **	**0.140*** **	**0.145*** **	**0.128**	**0.139***	**0.130*** **	**0.162*** **	**0.162*** **	**0.192*** **
	[0.011]	[0.011]	[0.029]	[0.028]	[0.026]	[0.023]	[0.000]	[0.076]	[0.025]	[0.026]	[0.058]	[0.062]
Constant	**-208.9**	**-224.9**	**-228.1**	**-243.4**	**-282.2**	**-292.9**	**-258.6**	**-280.5**	**-261.7**	**-327.8**	**-327.1**	**-387.6**
	[21.744]	[21.744]	[59.512]	[57.846]	[51.429]	[46.226]	[0.000]	[152.829]	[51.072]	[53.468]	[117.937]	[126.408]
Regional dummies (test)	1508***	1504***	6199***	6123***	1004***	1111***		9720***	1417***	1374***	47379***	29653***
Quarterly dummies (test)	83***	97***	10**	14***	41***	66***		8**	62***	67***	9**	10**
Returns to scale	0.66	0.70	0.67	0.70	0.86	0.90	0.95	0.98	0.87	0.95	0.99	1.06
CRS, test	13***	11***	3.5*	3.2*	0.46	0.32		0	0.69	0.11	0	0.06
Observations	1335	1304	1335	1304	493	493	493	493	842	811	842	811
Regions	34	34	34	34	34	34	34	34	34	34	34	34
Coef. of det. R2			0.94	0.94			0.96	0.97			0.96	0.96
Heteroscedasticity, test	649.0***	608.5***			685.1***	1130.1***			337.7***	314.4***		
Autocorrelation, test	10.0***	9.4***			2.2**	1.6*			8.7***	7.8***		

Table 2.16: **Latvia and Estonia - Estimation results: stock-flow matching function**

Dep.var: ln Matches (outflows from registered unemployment to emp.)	Time period 01:2003 - 07:2006				Time period 01:2003 -04:2004				Time period 05:2004 - 07:2006			
	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]
ln unemployed (stock)	**0.552*** **	**0.587*** **	**0.618*** **	**0.640*** **	**0.786*** **	**0.802*** **	**0.852*** **	**0.884*** **	**0.755*** **	**0.821*** **	**0.915*** **	**0.976*** **
	[0.090]	[0.089]	[0.167]	[0.161]	[0.194]	[0.177]	[0.260]	[0.254]	[0.140]	[0.142]	[0.227]	[0.229]
ln unemployed (flow)	**0.153*** **	**0.142*** **	**0.122* **	**0.115* **	**0.253*** **	**0.223*** **	**0.260*** **	**0.245*** **	**0.048**	**0.036**	**0.008**	**-0.001**
	[0.040]	[0.040]	[0.067]	[0.065]	[0.057]	[0.055]	[0.089]	[0.083]	[0.049]	[0.050]	[0.086]	[0.087]
ln vacancies (stock)	**0.016* **	**0.021** **	**0.01**	**0.015**	**0.004**	**0.011**	**-0.007**	**-0.003**	**0.031*** **	**0.035*** **	**0.030** **	**0.034** **
	[0.009]	[0.010]	[0.011]	[0.012]	[0.016]	[0.015]	[0.018]	[0.018]	[0.011]	[0.012]	[0.013]	[0.014]
ln vacancies (flow)	**0.203*** **	**0.195*** **	**0.194*** **	**0.190*** **	**0.255*** **	**0.236*** **	**0.225*** **	**0.213*** **	**0.213*** **	**0.206*** **	**0.199*** **	**0.197*** **
	[0.016]	[0.016]	[0.023]	[0.023]	[0.026]	[0.026]	[0.039]	[0.037]	[0.019]	[0.020]	[0.026]	[0.027]
Indicator for local labour demand		**0.598*** **		**0.600** **		**0.869*** **		**0.640*** **		**0.004**		**0.268**
		[0.147]		[0.239]		[0.156]		[0.246]		[0.279]		[0.374]
Time trend (annual)	**0.080*** **	**0.087*** **	**0.093*** **	**0.099*** **	**0.085*** **	**0.093*** **	**0.082**	**0.089**	**0.091*** **	**0.118*** **	**0.118** **	**0.143*** **
	[0.011]	[0.011]	[0.026]	[0.025]	[0.024]	[0.023]	[0.074]	[0.063]	[0.024]	[0.025]	[0.050]	[0.053]
Constant	**-162.6**	**-176**	**-187.3**	**-200.2**	**-174.8**	**-190.2**	**-168.6**	**-184.3**	**-186.1**	**-240.1**	**-239.7**	**-291**
	[21.596]	[21.779]	[52.852]	[51.606]	[48.169]	[44.882]	[147.377]	[126.489]	[48.434]	[50.911]	[101.583]	[107.810]
Regional dummies (test)	711***	713***	3347***	2803***	472***	509***	8473***	18725***	705***	694***	17576***	5444***
Quarterly dummies (test)	62***	68***	9**	12***	35***	51***	4.66	7.8*	41***	42***	7.2*	8**
Returns to scale	0.92	0.95	0.94	0.96	1.30	1.27	1.33	1.34	1.05	1.10	1.15	1.21
CRS, test	0.6	0.32	0.11	0.06	2.1	2.1	1.4	1.54	0.1	0.42	0.44	0.8
Observations	1335	1304	1335	1304	493	493	493	493	842	811	842	811
Regions	34	34	34	34	34	34	34	34	34	34	34	34
Coef. of det. R2			0.92	0.93			0.97	0.97			0.96	0.96
Heteroscedasticity, test	543.0***	504.0***			1172.4***	1977.5***			367.2***	367.6***		
Autocorrelation, test	9.8***	9.5***			2.5***	2.2**			8.0***	7.4***		

Table 2.17: **Slovenia - Estimation results: semi stock-flow matching function**

	Time period 01:2000 - 12:2006				Time period 01:2000 -04:2004				Time period 05:2004 - 12:2006			
Dep.var: ln Matches (outflows from registered unemployment to emp.)	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]	GLS [I]	GLS [II]	PCSE [I]	PCSE [II]
ln unemployed (stock)	**0.559*****	**0.581*****	**0.570*****	**0.597*****	**0.683*****	**0.661*****	**0.720*****	**0.701*****	**0.662*****	**0.929*****	**0.688****	**0.902*****
	[0.094]	[0.095]	[0.110]	[0.105]	[0.152]	[0.152]	[0.182]	[0.183]	[0.195]	[0.217]	[0.348]	[0.350]
ln unemployed (flow)	**0.200*****	**0.234*****	**0.193*****	**0.227*****	**0.231*****	**0.237*****	**0.231*****	**0.236*****	**0.184*****	**0.238*****	**0.171***	**0.227****
	[0.031]	[0.031]	[0.063]	[0.064]	[0.043]	[0.043]	[0.082]	[0.082]	[0.043]	[0.044]	[0.095]	[0.095]
ln vacancies (flow)	**0.593*****	**0.595*****	**0.582*****	**0.584*****	**0.698*****	**0.688*****	**0.685*****	**0.677*****	**0.372*****	**0.399*****	**0.352*****	**0.363*****
	[0.037]	[0.037]	[0.068]	[0.068]	[0.059]	[0.060]	[0.089]	[0.088]	[0.061]	[0.061]	[0.103]	[0.104]
Indicator for labour demand		**0.278****		**0.264**		**0.131**		**0.113**		**1.230*****		**1.185***
		[0.111]		[0.282]		[0.129]		[0.305]		[0.244]		[0.691]
Time trend (annual)	**-0.029*****	**-0.033*****	**-0.029****	**-0.032*****	**-0.035*****	**-0.037*****	**-0.038****	**-0.040****	**0.019**	**0.021**	**0.023**	**0.027**
	[0.005]	[0.005]	[0.011]	[0.011]	[0.008]	[0.008]	[0.018]	[0.019]	[0.017]	[0.017]	[0.042]	[0.042]
Constant	**53.85*****	**61.08*****	**53.021****	**60.061*****	**62.76*****	**67.28*****	**69.16***	**72.74***	**-41.82**	**-49.76**	**-50.8**	**-59.99**
	[10.957]	[10.804]	[22.684]	[22.353]	[16.845]	[17.141]	[36.995]	[37.499]	[35.246]	[34.974]	[84.717]	[85.668]
Regional dummies (test)	236***	246***	179***	182***	154***	148***	118***	119***	70***	78***	122***	115***
Quarterly dummies (test)	142***	154***	26***	29***	108***	109***	23***	24***	34***	50***	4.82	7.1*
Returns to scale	1.35	1.41	1.34	1.41	1.61	1.59	1.64	1.61	1.22	1.57	1.21	1.49
CRS, test	11***	15***	6**	10***	15***	13***	11***	10***	1.11	6**	0.29	1.53
Observations	996	972	996	972	612	612	612	612	384	360	384	360
Regions												
Coef. of det. R2			0.91	0.91			0.91	0.91			0.96	0.97
Heteroscedasticity, test	92.1***	96.6***			50.8***	55.1***			37.8***	80.5***		
Autocorrelation, test	0.60	0.20			1.3*	1.5*			2.1**	2.1**		

Table 2.18: **Latvia - Estimation results: Spatially augmented stock-flow matching function (time period 01:1999 - 07:2006).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	**0.681*** **	**0.721*** **	**0.749*** **	**0.721*** **	**0.730*** **	**0.750*** **	**0.753*** **	**0.770*** **
	0.062	0.068	0.07	0.07	0.096	0.083	0.083	0.086
ln unemployed (flow)	**0.047***	**0.03**	**0.022**	**0.03**	**0.004**	**-0.011**	**-0.02**	**-0.008**
	0.029	0.032	0.032	0.032	0.043	0.037	0.037	0.037
ln vacancies (stock)	**0.030*** **	**0.023*** **	**0.022*** **	**0.023*** **	**0.025*** **	**0.018** **	**0.017** **	**0.017** **
	0.007	0.007	0.007	0.007	0.009	0.008	0.008	0.008
ln vacancies (flow)	**0.203*** **	**0.186*** **	**0.184*** **	**0.183*** **	**0.188*** **	**0.172*** **	**0.171*** **	**0.166*** **
	0.011	0.011	0.011	0.011	0.015	0.013	0.013	0.013
Indicator for local labour demand	**0.749*** **	**0.749*** **	**0.762*** **	**0.736*** **	**0.737*** **	**0.740*** **	**0.750*** **	**0.729*** **
	0.066	0.065	0.065	0.065	0.118	0.112	0.112	0.11
Time trend (annual)	**0.017*** **	**0.002**	**0.003**	**0**	**0.021** **	**0.005**	**0.006**	**0.004**
	0.004	0.004	0.004	0.004	0.008	0.009	0.009	0.009
Constant	**-36.0*** **	**-4.2**	**-6.8**	**-0.4**	**-44.3*** **	**-11.7**	**-12.4**	**-6.7**
	8.098	8.825	8.811	8.864	17.031	18.087	17.924	17.576
Indicators for common border with:								
Estonia	**0.279**	**-0.1**	**-0.017**	**-1.236**	**-0.438*** **	**0.089**	**0.145**	**-1.434**
	0.201	0.161	0.164	1.258	0.131	0.293	0.294	1.528
Russia	**-0.644*** **	**-0.256*** **	**0.794**	**-0.395*** **	**-0.01**	**-0.563*** **	**-0.542*** **	**-0.566*** **
	0.07	0.075	1.904	0.091	0.25	0.069	0.07	0.071
Byelorussia	**0.16**	**-0.161**	**-0.784**	**-1.549**	**-0.611*** **	**-0.003**	**-0.403** **	**-1.586**
	0.17	0.132	1.891	1.27	0.07	0.197	0.197	1.6
Lithuania	**-0.085**	**-0.545*** **	**0.127**	**-0.448*** **	**-0.199**	**-0.831*** **	**-0.553** **	**-2.151**
	0.178	0.112	1.912	0.069	0.256	0.096	0.239	1.569
Neighbouring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		**-0.274*** **	**-0.301*** **	**-0.271*** **		**-0.276***	**-0.265***	**-0.286***
		0.095	**0.104**	**0.105**		**0.141**	**0.143**	**0.161**
ln (W x unemployed (flow))		**0.075***	**0.139*** **	**0.058**		**0.082**	**0.144***	**0.079**
		0.043	**0.049**	**0.053**		**0.067**	**0.076**	**0.079**
ln (W x vacancies (stock))		**0.033*** **	**0.042*** **	**0.015**		**0.032** **	**0.041** **	**0.011**
		0.009	**0.011**	**0.013**		**0.014**	**0.017**	**0.019**
ln (W x vacancies (flow))		**0.118*** **	**0.118*** **	**0.200*** **		**0.122*** **	**0.125*** **	**0.213*** **
		0.014	**0.016**	**0.021**		**0.019**	**0.021**	**0.029**
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			**0.151**				**0.16**	
			0.242				**0.25**	
ln (W x unemployed (flow))			**-0.203** **				**-0.233** **	
			0.099				**0.106**	
ln (W x vacancies (stock))			**0.014**				**0.013**	
			0.021				**0.023**	
ln (W x vacancies (flow))			**-0.026**				**-0.014**	
			0.033				**0.035**	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			**-0.001**				**-0.338**	
			0.228				**0.248**	
ln (W x unemployed (flow))			**-0.181***				**-0.163**	
			0.107				**0.117**	
ln (W x vacancies (stock))			**-0.096*** **				**-0.106*** **	
			0.026				**0.029**	
ln (W x vacancies (flow))			**0.037**				**0.011**	
			0.044				**0.049**	
Effects from high population density areas								
POP x ln (W x unemployed (stock))				**-0.101**				**-0.11**
				0.147				**0.185**
POP x ln (W x unemployed (flow))				**0.026**				**0.039***
				0.018				**0.021**
POP x ln (W x vacancies (stock))				**0.017**				**-0.018**
				0.072				**0.088**
POP x ln (W x vacancies (flow))				**-0.136*** **				**-0.151*** **
				0.026				**0.032**
Regional dummies (test)	536***	392***	385***	371***	910***	732***	574***	596***
Quarterly dummies (test)	75***	74***	79***	72***	14***	16***	16***	16***
Returns to Scale	0.96	0.91	0.67	0.76	0.95	0.89	0.30	0.72
Constant returns to scale, test	0.33	0.85	0.81	2.8*	0.25	0.41	2.6	2.31
Observations	2737	2679	2679	2679	2737	2679	2679	2679
Coefficient of determination R2					0.87	0.88	0.88	0.89
Heteroscedasticity, test	1010.6***	992.6***	953.2***	967.3***				
Autocorrelation, test	20.1***	18.3***	18.2***	18.6***				

Table 2.19: **Latvia - Estimation results: Spatially augmented stock-flow matching function (time period 01:1999 - 04:2004).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	0.947***	0.973***	0.932***	0.976***	0.988***	0.968***	0.899***	0.961***
	0.074	0.083	0.085	0.085	0.114	0.105	0.105	0.107
ln unemployed (flow)	0.037	0.017	0.013	0.016	-0.001	-0.018	-0.027	-0.016
	0.033	0.035	0.036	0.035	0.046	0.042	0.042	0.042
ln vacancies (stock)	0.002	0.003	0.004	0.003	-0.006	-0.006	-0.006	-0.007
	0.008	0.008	0.008	0.008	0.009	0.009	0.009	0.009
ln vacancies (flow)	0.206***	0.188***	0.186***	0.185***	0.182***	0.164***	0.162***	0.160***
	0.013	0.013	0.013	0.013	0.017	0.016	0.016	0.016
Indicator for local labour demand	0.825***	0.795***	0.802***	0.789***	0.801***	0.775***	0.789***	0.768***
	0.067	0.066	0.066	0.066	0.115	0.11	0.109	0.108
Time trend (annual)	0.009*	0.003	-0.001	0.003	0.01	0.006	0.002	0.005
	0.005	0.005	0.005	0.005	0.01	0.011	0.011	0.011
Constant	-22.2**	-10.3	-1.0	-9.6	-23.8	-16.8	-8.8	-15.8
	10.414	11.383	11.486	11.521	21.299	22.694	22.655	22.455
Indicators for common border with:								
Estonia	0.312*	0.303	-3.976	0.886	0.573	-0.019	0.382	1.864
	0.187	0.186	2.425	1.452	0.359	0.139	0.358	1.77
Russia	0.375*	-0.082	4.111*	0.249	-0.475***	0.078	6.468**	-0.353***
	0.212	0.089	2.414	1.446	0.071	0.309	2.617	0.128
Byelorussia	-0.537***	-0.486***	-4.330*	0.303	0.122	-0.486***	-6.998***	1.418
	0.071	0.091	2.43	1.465	0.256	0.142	2.629	1.848
Lithuania	0.18	0.13	3.899	0.402	-0.637***	-0.112	-0.237	-0.499***
	0.204	0.206	2.406	1.444	0.095	0.299	0.296	0.113
Neighboring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		-0.187*	-0.186	-0.206*		-0.086	-0.028	-0.137
		0.11	0.121	0.122		0.162	0.172	0.182
ln (W x unemployed (flow))		0.075	0.116**	0.058		0.086	0.13	0.068
		0.05	0.057	0.061		0.074	0.085	0.087
ln (W x vacancies (stock))		-0.011	-0.018	-0.034*		-0.013	-0.019	-0.036
		0.012	0.015	0.017		0.015	0.019	0.022
ln (W x vacancies (flow))		0.114***	0.116***	0.154***		0.118***	0.120***	0.169***
		0.016	0.019	0.024		0.022	0.025	0.032
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			0.513*				0.5	
			0.296				0.318	
ln (W x unemployed (flow))			-0.118				-0.172	
			0.118				0.131	
ln (W x vacancies (stock))			0.061**				0.061**	
			0.027				0.029	
ln (W x vacancies (flow))			-0.009				0.003	
			0.043				0.045	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			-0.465				-0.792**	
			0.307				0.332	
ln (W x unemployed (flow))			-0.105				-0.085	
			0.124				0.138	
ln (W x vacancies (stock))			-0.051				-0.062	
			0.038				0.042	
ln (W x vacancies (flow))			0.035				0.009	
			0.053				0.059	
Effects from high population density areas								
POP x ln (W x unemployed (stock))				0.026				0.173
				0.172				0.212
POP x ln (W x unemployed (flow))				0.042*				0.049*
				0.023				0.027
POP x ln (W x vacancies (stock))				0.044				0.054
				0.083				0.1
POP x ln (W x vacancies (flow))				-0.069**				-0.086**
				0.031				0.037
Regional dummies (test)	599***	401***	389***	349***	987***	775***	581***	487***
Quarterly dummies (test)	75***	79***	76***	78***	17***	21***	21***	22***
Returns to Scale	1.19	1.17	1.02	1.19	1.16	1.21	0.69	1.35
Constant returns to scale, test	6**	2.6	0	1.36	1.69	1.13	0.33	2.58
Observations	1953	1898	1898	1898	1953	1898	1898	1898
Coefficient of determination R2					0.91	0.92	0.90	0.91
Heteroscedasticity, test	779.5***	765.7***	735.0***	727.9***				
Autocorrelation, test	14.2***	13.5***	13.4***	13.7***				

Table 2.20: **Latvia - Estimation results: Spatially augmented stock-flow matching function (time period 04:2004 - 07:2006).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	**0.926*****	**0.838*****	**0.862*****	**0.846*****	**1.053*****	**1.027*****	**1.034*****	**1.023*****
	0.18	0.208	0.212	0.211	0.281	0.258	0.259	0.26
ln unemployed (flow)	**0.049**	**0.014**	**0.027**	**0.048**	**0.008**	**-0.035**	**-0.027**	**0.002**
	0.054	0.06	0.06	0.06	0.092	0.07	0.07	0.069
ln vacancies (stock)	**0.037*****	**0.032*****	**0.032*****	**0.036*****	**0.036*****	**0.029****	**0.028****	**0.036*****
	0.012	0.012	0.012	0.012	0.014	0.013	0.013	0.013
ln vacancies (flow)	**0.198*****	**0.192*****	**0.198*****	**0.199*****	**0.192*****	**0.189*****	**0.190*****	**0.190*****
	0.02	0.02	0.02	0.019	0.027	0.025	0.026	0.025
Indicator for local labour demand	**-0.152**	**-0.179**	**-0.133**	**-0.107**	**0.175**	**0.158**	**0.199**	**0.067**
	0.298	0.289	0.29	0.285	0.411	0.401	0.401	0.379
Time trend (annual)	**0.130*****	**0.079****	**0.076****	**0.052**	**0.151*****	**0.096**	**0.094**	**0.086**
	0.027	0.032	0.032	0.033	0.054	0.064	0.063	0.061
Constant	**-264.3*****	**-160.3****	**-154.3****	**-102.1**	**-308.2*****	**-195.8**	**-190.4**	**-168.3**
	55.648	66.866	66.256	67.677	109.544	131.227	129.554	124.072
Indicators for common border with:								
Estonia	**1.182****	**-0.487****	**7.751***	**-6.037****	**0.193**	**0.489**	**0.433**	**-8.063****
	0.538	0.199	4.303	2.983	0.326	0.728	0.745	3.479
Russia	**0.679**	**0.532**	**-7.696***	**-5.770****	**0.315**	**-0.206**	**-0.162**	**-0.189**
	0.548	0.547	4.374	2.902	0.598	0.206	0.209	0.271
Byelorussia	**-1.034*****	**-0.962*****	**7.397***	**-1.043*****	**-0.621*****	**-0.087**	**-0.052**	**-0.701**
	0.195	0.226	4.348	0.261	0.108	0.408	0.417	0.479
Lithuania	**0.86**	**0.541**	**-7.694***	**-5.812****	**0.548**	**-0.13**	**-0.107**	**-8.262****
	0.583	0.582	4.37	2.931	0.688	0.31	0.31	3.322
Neighbouring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		**-0.159**	**-0.377**	**-0.106**		**-0.32**	**-0.477**	**-0.135**
		0.29	**0.301**	**0.318**		**0.386**	**0.399**	**0.423**
ln (W x unemployed (flow))		**0.049**	**0.076**	**-0.036**		**0.083**	**0.128**	**0.022**
		0.081	**0.094**	**0.098**		**0.142**	**0.156**	**0.16**
ln (W x vacancies (stock))		**0.035***	**0.028**	**0.024**		**0.031**	**0.028**	**0.014**
		0.019	**0.024**	**0.026**		**0.026**	**0.032**	**0.038**
ln (W x vacancies (flow))		**0.097*****	**0.114*****	**0.273*****		**0.096*****	**0.106*****	**0.295*****
		0.024	**0.029**	**0.038**		**0.032**	**0.036**	**0.058**
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			**0.102**				**0.048**	
			0.367				**0.369**	
ln (W x unemployed (flow))			**0.08**				**-0.013**	
			0.167				**0.176**	
ln (W x vacancies (stock))			**0.024**				**0.018**	
			0.038				**0.042**	
ln (W x vacancies (flow))			**-0.117****				**-0.084**	
			0.05				**0.054**	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			**1.051****				**0.723**	
			0.5				**0.552**	
ln (W x unemployed (flow))			**-0.203**				**-0.329**	
			0.191				**0.202**	
ln (W x vacancies (stock))			**0.005**				**-0.01**	
			0.053				**0.061**	
ln (W x vacancies (flow))			**0.098**				**0.073**	
			0.074				**0.082**	
Effects from high population density areas								
POP x				**-0.745****				**-0.935****
ln (W x unemployed (stock))				**0.342**				**0.376**
POP x				**0.032**				**0.042**
ln (W x unemployed (flow))				**0.036**				**0.041**
POP x				**0.119**				**0.017**
ln (W x vacancies (stock))				**0.136**				**0.164**
POP x				**-0.262*****				**-0.294*****
ln (W x vacancies (flow))				**0.046**				**0.061**
Regional dummies (test)	404***	386***	331***	384***	8393***	4408***	4301***	8755***
Quarterly dummies (test)	43***	22***	23***	20***	9**	5.1	5.3	5.38
Returns to Scale	1.21	1.10	2.00	0.43	1.29	1.10	1.44	0.28
Constant returns to scale, test	1.1	0.11	1.81	2.31	0.92	0.04	0.25	2.04
Observations	784	781	781	781	784	781	781	781
Coefficient of determination R2					0.94	0.95	0.94	0.93
Heteroscedasticity, test	422.9***	373.1***	523.7***	198.0***				
Autocorrelation, test	7.4***	6.3***	6.0***	5.9***				

Table 2.21: **Slovenia - Estimation results: Spatially augmented semi-stock-flow matching function (time period 01:2000 - 12:2006).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	**0.581*****	**0.675*****	**0.718*****	**0.700*****	**0.597*****	**0.695*****	**0.741*****	**0.718*****
	0.095	0.091	0.1	0.094	0.105	0.092	0.099	0.095
ln unemployed (flow)	**0.234*****	**0.023**	**0.028**	**0.015**	**0.227*****	**0.002**	**0.008**	**-0.005**
	0.031	0.05	0.051	0.051	0.064	0.045	0.046	0.045
ln vacancies (flow)	**0.595*****	**0.375*****	**0.372*****	**0.373*****	**0.584*****	**0.350*****	**0.347*****	**0.349*****
	0.037	0.048	0.048	0.048	0.068	0.045	0.045	0.045
Indicator for local labour demand	**0.278****	**0.292*****	**0.288*****	**0.291*****	**0.264**	**0.298**	**0.295**	**0.296**
	0.111	0.109	0.11	0.109	0.282	0.269	0.269	0.268
Time trend (annual)	**-0.033*****	**-0.033*****	**-0.032*****	**-0.033*****	**-0.032*****	**-0.034****	**-0.033****	**-0.034****
	0.005	0.007	0.007	0.007	0.011	0.013	0.014	0.013
Constant	**61.752*****	**56.170*****	**53.411*****	**56.825*****	**60.723*****	**57.108****	**54.318***	**58.627****
	10.769	14.481	14.926	14.501	22.365	27.685	28.673	27.865
Indicators for common border with:								
Italy	**-0.398*****				**-0.385*****			
	0.044				0.072			
Croatia	**-0.139*****				**-0.138*****			
	0.041				0.046			
Austria	**-0.092**				**-0.092**			
	0.065				0.075			
Neighbouring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		**0.393****	**0.433****	**0.540*****		**0.410***	**0.459***	**0.523****
		0.158	**0.187**	**0.186**		**0.225**	**0.271**	**0.24**
ln (W x unemployed (flow))		**0.279*****	**0.291*****	**0.378*****		**0.314*****	**0.334*****	**0.407*****
		0.059	**0.062**	**0.07**		**0.082**	**0.085**	**0.096**
ln (W x vacancies (flow))		**0.366*****	**0.362*****	**0.379*****		**0.401*****	**0.393*****	**0.399*****
		0.059	**0.063**	**0.069**		**0.097**	**0.101**	**0.112**
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			**-0.402**				**-0.433**	
			0.397				**0.273**	
ln (W x unemployed (flow))			**-0.062**				**-0.092***	
			0.081				**0.056**	
ln (W x vacancies (flow))			**0.016**				**0.024**	
			0.103				**0.072**	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			**0.011**				**-0.01**	
			0.279				**0.234**	
ln (W x unemployed (flow))			**-0.047**				**-0.056**	
			0.084				**0.067**	
ln (W x vacancies (flow))			**0.043**				**0.043**	
			0.111				**0.095**	
Effects from high population density areas								
POP x				**-0.344**				**-0.313**
ln (W x unemployed (stock)				**0.235**				**0.192**
POP x				**-0.161*****				**-0.167*****
ln (W x unemployed (flow)				**0.059**				**0.049**
POP x				**-0.035**				**-0.007**
ln (W x vacancies (flow)				**0.074**				**0.067**
Regional dummies (test)	177***	249***	218***	247***	146***	247***	162***	213***
Quarterly dummies (test)	154***	138***	136***	140***	29***	27***	26***	27***
Returns to Scale	1.41	2.11	1.76	1.85	1.41	2.17	1.76	1.90
Constant returns to scale, test	15***	34***	1.85	13***	10***	13***	2.69	7***
Observations	972	972	972	972	972	972	972	972
Coefficient of determination R2					0.91	0.89	0.89	0.87
Heteroscedasticity, test	96.6***	32.3***	30.4***	36.0***				
Autocorrelation, test	0.20	0.80	0.80	0.90				

Table 2.22: **Slovenia - Estimation results: Spatially augmented semi-stock-flow matching function (time period 01:2000 - 04:2004).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	0.661***	0.770***	0.812***	0.861***	0.701***	0.819***	0.863***	0.887***
	0.152	0.142	0.147	0.147	0.183	0.146	0.145	0.149
ln unemployed (flow)	0.237***	-0.002	0.025	-0.017	0.236***	-0.017	0.009	-0.031
	0.043	0.066	0.067	0.066	0.082	0.063	0.065	0.063
ln vacancies (flow)	0.688***	0.472***	0.438***	0.467***	0.677***	0.449***	0.420***	0.445***
	0.06	0.062	0.062	0.062	0.088	0.062	0.063	0.062
Indicator for local labour demand	0.131	0.007	0.013	-0.003	0.113	0.005	0.007	-0.007
	0.129	0.127	0.125	0.126	0.305	0.285	0.28	0.284
Time trend (annual)	-0.037***	-0.017*	-0.017*	-0.014	-0.040**	-0.018	-0.018	-0.016
	0.008	0.01	0.01	0.01	0.019	0.019	0.019	0.019
Constant	68.162***	19.191	21.105	17.063	73.653**	21.252	23.893	21.15
	17.068	21.409	21.667	21.55	37.46	39.463	39.462	39.625
Indicators for common border with:								
Italy	-0.533***				-0.523***			
	0.066				0.094			
Croatia	-0.181***				-0.188***			
	0.055				0.062			
Austria	-0.172*				-0.190*			
	0.097				0.114			
Neighbouring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		0.486*	0.789***	0.958***		0.493	0.836**	0.908**
		0.253	0.279	0.305		0.364	0.396	0.411
ln (W x unemployed (flow))		0.247***	0.288***	0.394***		0.289***	0.340***	0.428***
		0.082	0.085	0.097		0.107	0.109	0.127
ln (W x vacancies (flow))		0.595***	0.486***	0.456***		0.608***	0.487***	0.452**
		0.095	0.107	0.131		0.154	0.166	0.195
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			-0.957				-1.086***	
			0.618				0.411	
ln (W x unemployed (flow))			-0.183*				-0.194***	
			0.107				0.071	
ln (W x vacancies (flow))			0.312				0.270*	
			0.22				0.155	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			-0.758*				-0.866**	
			0.427				0.359	
ln (W x unemployed (flow))			-0.157				-0.179**	
			0.102				0.089	
ln (W x vacancies (flow))			0.544***				0.514***	
			0.202				0.19	
Effects from high population density areas								
POP x				-0.950**				-0.922***
ln (W x unemployed (stock))				0.384				0.342
POP x				-0.220***				-0.233***
ln (W x unemployed (flow))				0.077				0.07
POP x				0.215				0.276*
ln (W x vacancies (flow))				0.154				0.143
Regional dummies (test)	115***	172***	170***	170***	117***	147***	126***	136***
Quarterly dummies (test)	109***	75***	77***	75***	24***	17***	18***	18***
Returns to Scale	1.59	2.57	1.64	2.16	1.61	2.64	1.41	2.21
Constant returns to scale, test	13***	30***	0.69	12***	10***	12***	0.41	6**
Observations	612	612	612	612	612	612	612	612
Coefficient of determination R2					0.91	0.92	0.92	0.90
Heteroscedasticity, test	55.1***	16.1	13.9	17.8		.		
Autocorrelation, test	1.5*	2.7***	3.0***	2.8***				

Table 2.23: **Slovenia - Estimation results: Spatially augmented semi-stock-flow matching function (time period 04:2004 - 12:2006).**

Dep. Variable: ln Matches (outflows from registered unemployment to employment)	GLS [VI]	GLS [VII]	GLS [VIII]	GLS [IX]	PCSE [VI]	PCSE [VII]	PCSE [VIII]	PCSE [IX]
ln unemployed (stock)	**0.929***** 0.217	**1.110***** 0.233	**1.107***** 0.245	**1.088***** 0.235	**0.902***** 0.35	**1.026***** 0.217	**0.992***** 0.234	**0.992***** 0.216
ln unemployed (flow)	**0.238***** 0.044	**0.062** 0.068	**0.067** 0.071	**0.044** 0.069	**0.227**** 0.095	**0.032** 0.061	**0.036** 0.064	**0.019** 0.062
ln vacancies (flow)	**0.399***** 0.061	**0.277***** 0.071	**0.271***** 0.073	**0.288***** 0.072	**0.363***** 0.104	**0.247***** 0.065	**0.234***** 0.067	**0.257***** 0.065
Indicator for local labour demand	**1.230***** 0.244	**1.260***** 0.239	**1.257***** 0.24	**1.260***** 0.238	**1.185*** 0.691	**1.252*** 0.663	**1.258*** 0.667	**1.254*** 0.661
Time trend (annual)	**0.021** 0.017	**0.002** 0.019	**0.002** 0.019	**0.003** 0.019	**0.027** 0.042	**0.003** 0.048	**0.003** 0.048	**0.004** 0.048
Constant	**-48.953** 34.902	**-8.148** 38.541	**-14.668** 39.529	**-9.477** 38.403	**-59.276** 85.594	**-10.962** 97.479	**-18.586** 98.783	**-11.505** 97.366
Indicators for common border with:								
Italy	**-0.142**** 0.065				**-0.108** 0.103			
Croatia	**-0.205**** 0.086				**-0.181** 0.134			
Austria	**-0.224** 0.139				**-0.188** 0.224			
Neighbouring region variables								
Overall spillover effect								
ln (W x unemployed (stock))		**-0.503** **0.334**	**-0.551** **0.356**	**-0.615** **0.484**		**-0.419** **0.651**	**-0.558** **0.648**	**-0.398** **0.739**
ln (W x unemployed (flow))		**0.189**** **0.082**	**0.175**** **0.087**	**0.306***** **0.104**		**0.248**** **0.123**	**0.233*** **0.125**	**0.338**** **0.144**
ln (W x vacancies (flow))		**0.247**** **0.101**	**0.233**** **0.108**	**0.243*** **0.13**		**0.255** **0.185**	**0.245** **0.19**	**0.248** **0.209**
Additional spillovers from high unemployment ratio areas								
ln (W x unemployed (stock))			**-0.181** **0.796**				**0.026** **0.558**	
ln (W x unemployed (flow))			**-0.01** **0.11**				**-0.029** **0.076**	
ln (W x vacancies (flow))			**0.035** **0.168**				**0.044** **0.114**	
Additional spillovers from low unemployment ratio areas								
ln (W x unemployed (stock))			**0.585** **0.846**				**0.909** **0.58**	
ln (W x unemployed (flow))			**0.113** **0.133**				**0.097** **0.09**	
ln (W x vacancies (flow))			**0.101** **0.192**				**0.098** **0.136**	
Effects from high population density areas								
POP x **ln (W x unemployed (stock))**				**0.134** **0.538**				**-0.076** **0.377**
POP x **ln (W x unemployed (flow))**				**-0.152*** **0.086**				**-0.141**** **0.065**
POP x **ln (W x vacancies (flow))**				**-0.025** **0.124**				**-0.02** **0.089**
Regional dummies (test)	47***	75***	55***	75***	49***	123***	59***	110***
Quarterly dummies (test)	50***	52***	53***	55***	7.1*	8**	8**	8**
Returns to Scale	1.57	1.38	1.95	1.31	1.49	1.39	2.33	1.22
Constant returns to scale, test	6**	1.31	0.57	0.58	1.53	0.23	1.25	0.08
Observations	360	360	360	360	360	360	360	360
Coefficient of determination R2					0.97	0.96	0.96	0.96
Heteroscedasticity, test	80.5***	55.5***	53.2***	60.0***				
Autocorrelation, test	2.1**	2.0**	2.1**	2.0**				

Explanatory notes for tables 2.9 -2.23:

(1) GLS: Model estimated by Generalized Least Squares method. PCSE: Model estimated by Panel Corrected Standard Errors method.
(2) [I] - [V]: specifications (see section 2.4 for details); All models include regional and time (quarterly) dummies and time (annual) trend. Local labor demand indicator: growth in local (within region) secondary employment for Latvia and Estonia, growth in aggregate (national) secondary employment for Slovenia.
(3) UBA 1 - UBA 2 are time dummies for changes in unemployment benefit amount (UBA): UB1 1=1 starting from 1/08/2000 when UBA dropped from 50 to 43 Ls, UBA 2=1 starting from 01/02/2003 when UBA raised from 43 to 50Ls.
(4) MWA 1 - MWA 4 are time dummies for changes in minimum wage amount: MWA 1=1 starting from 1/07/2001, when minimum wage raised from 50 to 60 Ls, MWA 2=1 starting from 01/01/2003 when MWA raised from 60 to 70 Ls, MWA 3=1 starting from 01/01/2004 when MWA raised from 70 to 80 Ls, MWA 4=1 starting from 01/01/2006 when MWA raised from 80 to 90 Ls.
(5) Constant returns to scale (CRS), test: test for constant returns to scale in estimated matching function. Ho: α_{SU} + α_{FU}+ α_{SV} + α_{FV}=1 in stock-flow specification. Ho: α_{SU} + α_{SV} =1 in stock-stock specification. Ho: α_{SU} + α_{FU}+ α_{FV}=1 in semi stock-flow specification (Slovenia).
(6) [VI] - [IX] - specifications for a spatially augmented matching function (see section 2.4 for details); For Latvia, includes the indicators of common border with one of the following countries: Estonia, Russia, Byelorussia, Lithuania. For Slovenia, includes the indicators of common border with one of the following countries: Croatia, Italy, Austria. All models include regional and time (quarterly) dummies and time (annual) trend. Local labor demand indicator: growth in local (within region) secondary employment for Latvia and Estonia, growth in aggregate (national) secondary employment for Slovenia. The indicators for common border are included to all specifications for Latvia and to specification [VI] only for Slovenia.
(7) Constant returns to scale, test: test for constant returns to scale in estimated matching function. For spatially augmented matching function the returns to scale are measured as a sum of estimated elasticities of all main variables (local and foreign).
(8) Heteroscedasticity, test: modified Wald test for group wise heteroscedasticity (Greene 2000, pp.598).
(9) Autocorrelation, test - Baltagi test for autocorrelation.
(10) Standard errors in parentheses, for PCSE models standard errors corrected for heteroscedasticity,cross sectional correlation and panel specific AR1 are reported.
(11) ***, **, * - estimates significantly different from zero at 1,5,10 percent level respectively.

Figure 2.4: Latvian regions by unemployment rate in 2002

Figure 2.5: Slovenian regions, by ESS offices

Source: State Employment Agency of Latvia and Employment Service of Slovenia.

Chapter 3

Matching and macroeconomic effects of labour market policy

3.1 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. High inflows into unemployment coexisted with very low re-employment, this latter being blocked by insufficient labour demand in new developing sectors and high skill mismatch between labour supply and labour demand. In line with OECD suggestions and European experience a great importance has been given to Active Labour Market Policy (ALMP), *i.e.* employment stimulating programmes that usually include direct job creation, job subsidies, self-employment promotion, as well as labour training and re-qualification schemes. While the theoretical suitability of those programmes to transition context is obvious, their actual efficiency (both at macroeconomic and individual levels) crucially depends on correct targeting and implementation quality and is therefore often questioned. We aim to bring more light on this issue by performing the evaluation of active labour market policy programmes in case of Latvia, one of the transition economies which have recently joint the European Union. Our focus is on training oriented programs, which appear to be the main element of ALMP portfolio (in terms of allocated funds and participation) in a number of new EU member states and especially in the Baltic region.

The evaluation is performed both from the macroeconomic and microeconomic perspectives. We start here with the evaluation of aggregate effects of ALMP on transitions from unemployment to jobs through the estimation of an augmented matching function on cross section data from Latvian districts[1]. The microeconomic (individual) effects are investigated in chapter 4.

We describe the main developments in ALMP implementation in Latvia in section 3.2. The evaluation methodology is exposed in section 3.3, data, variables and estimation related issues are treated in sections 3.5 and 3.6. Section 3.7 displays the estimation results, while section 3.8 concludes.

3.2 Active labour market policy in Latvia

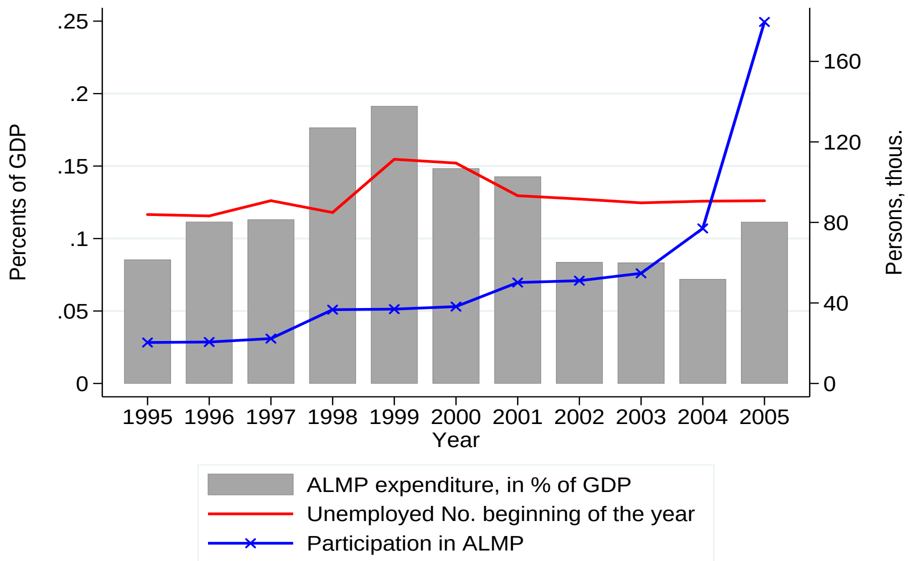
Active labour market policies are implemented in Latvia by the Ministry of Welfare through the State Employment Agency of Latvia (SEAL). Figure 3.1 displays the developments in ALMP participation and expenditures over the last decade.

The expenditure on active labour market policy programmes in Latvia varied around 0.10 - 0.15 percent of GDP, which is substantially lower than in EU-15 countries (0.5 percent of GDP in 2005), but is in line with the majority of new EU member states (0.20 percent of GDP on average). A decline in the ALMP expenditure (both in volume and as GDP share) is observed between 2002 and 2004. This was mainly due to budgetary reasons: in the anticipation of the possibility to involve the means of ESF (European Social Fund) in funding active labour market policy after Latvia's accession to the EU, the national budget was reduced. Starting from 2004 over 75 percent of ALMP expenditures were covered by ESF funding.

Very high participation in ALMP in 2005 is a purely statistical phenomenon, it is

[1] 33 NUTS 4 districts, as in chapter 2.

Figure 3.1: Unemployment, ALMP expenditure and participation



Source: Author's calculations based on the data from State Employment Agency of Latvia.

related to the reorganisation of SEAL activities. Starting from 2005 the training on job search methods and the consultations in carrier guidance and professional orientation (undergone by almost all unemployed) are proposed not only by SEAL, but also by contracted training institutions. In this case the participation in one of above activities is considered as short term training and is accounted under "Measures to Increase Competitiveness" (MIC), a programme, which also includes some longer training (state language, computer literacy, management, driving).

The following four types of active labour market policy programmes are generally proposed to unemployed by the State Employment Agency of Latvia:

- **Occupational training of unemployed**: vocational training, re-training and raising of qualifications.

- **Measures to increase competitiveness**: (i) short term training on carrier guidance and professional orientation, training on job search methods; (ii) modular training in state language (Latvian) and in other skills (foreign language, computer literacy, business related skills, driving).

- **Temporary job schemes**: short term employment in public sector, promotes working culture and experience and facilitates the insertion in the labour market of those who face difficulties with adapting to the requirements of labour demand.

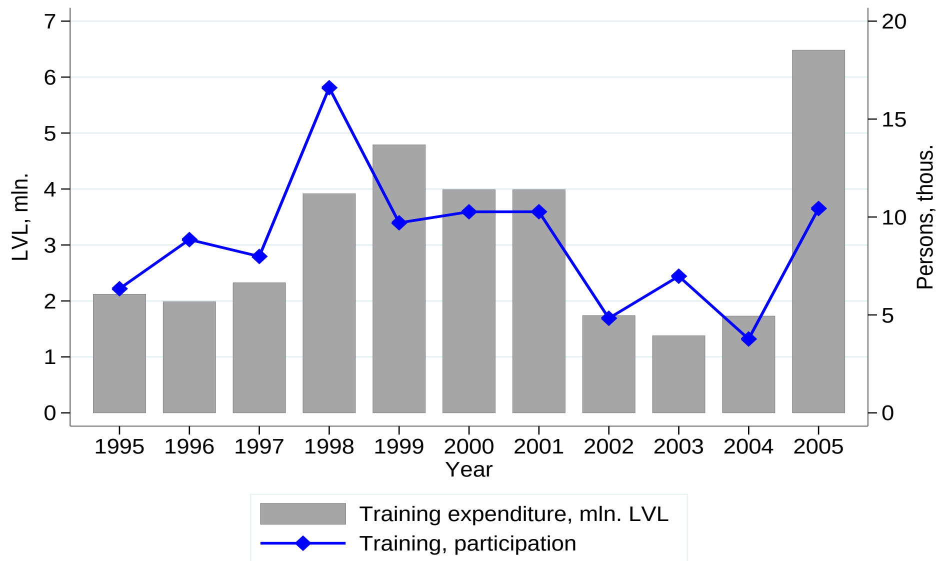
- **Measures for disadvantaged groups** (youth, pre-retirement age unemployed, long-term unemployed, disabled, woman after maternity leave): subsidized employment schemes, various training programmes and, since 2001, social enterprizes in the labour market to employ the less competitive unemployed.

In terms of expenditure, the main efforts of SEAL are oriented towards increasing the knowledge and skills of unemployed via training and encouraging unemployed to acquire new professions and find permanent jobs. In 2005, the major part of ALMP budget (almost 80 percent) was allocated to the implementation of unemployment training and the measures for competitiveness promotion among unemployed. The expenditure and corresponding participation trends are displayed by figure 3.2.

In Latvia, Estonia and Lithuania such a pattern is typical (more than a half of active labour market policy budget is usually devoted to labour training), while in the Czech Republic, Hungary, Bulgaria, Poland and Slovenia subsidized employment and direct job creation have mostly been promoted.

The dominant role of training programmes in the Baltic countries can be explained by the unemployment patterns in this region characterised by a strong mismatch between the *old* skills of the labour force and the *new* requirements of employers. In Latvia, most of the registered unemployed have general secondary or professional secondary education (two thirds in 2001 and 2002). At the same time, for the majority of them the education has been obtained before 1992 in the framework of a centrally-planned and industry oriented Soviet system. Apart from the need for update of often obsolete labour skills, jobs in manufacturing and services (sectors which employ about 90 percent

Figure 3.2: Training expenditure and participation



Source: Author's calculations based on the data from State Employment Agency of Latvia.

of Latvian wage-earners) often require at least basic knowledge of state and foreign languages, basic computer skills or skills in the work with office equipment. And these are largely absent among Latvian unemployed. A survey conducted among Latvian unemployed in February 2006 (see SEAL [2006]) reveals that almost 30 percent of unemployed do not have an occupation or have not worked or updated skills in their occupation within last 5 years. Over 30 percent of unemployed consider their skills in Latvian language as absent or very limited. About 60 and 75 percent of unemployed lack any computer skills or are not familiar with elementary office equipments (fax, coping machine), respectively. Finally, only 6 percent of unemployed evaluate their knowledge of English language as good.

In such context, the promotion of any of above mentioned skills can increase employability of job seekers. The occupational training stands however as the programme with the highest potential: while developing skills in a certain occupation, it indirectly promotes other related skills (communication and language, dealing with computer or other office equipment).

In this chapter we focus on the aggregate efficiency of occupational training programme in adjusting the skills of unemployed to labour demand, while the individual effects of this and other training programmes (modular training in state language and in other skills) will be evaluated in chapter 4.

3.3 The matching function as policy evaluation tool

The matching function[2], reflecting the efficiency of the labour 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 new hires arising in the labour market. The underlying idea is that active labour market policy programmes can speed up the matching process by enhancing the search intensity[3] of the unemployed or by adjusting their skills to the structure of labour demand. Becoming more "suitable" for employers and searching for jobs more intensively, programme participants find jobs more rapidly. At the aggregate level, this results in an increased number of new hires realized in the labour market during a reference period of time.

A model including policy variables among the possible determinants of job matches is referred to as the *augmented matching function*.

It can be written as[4]:

$$M = Am(\psi U, V) \tag{3.1}$$

where ψU denotes the search effective stock of unemployed. The average *search effectiveness* of the unemployed ψ is no longer considered as homogenous across individuals

[2] The matching function relates available job seekers to vacant jobs and produces new hires as output. Its extensive use in labour market analysis is relied to its ability to model frictions. See more details in chapter 2.

[3] When speaking about search intensity we mean unemployed search effort and implicitly his competence in search methods.

[4] We suppress region and time indices for now.

and it is assumed to be positively affected by the participation in active labour market policy programmes (Lehmann [1995], followed by Puhani [1999], Hagen [2003], Hujer et al. [2002]). For example the unemployed who have completed training are assumed to have higher search effectiveness if compared to their non-trained peers.

Search effectiveness can be seen as the ability of unemployed to find a match in a reference period. Search effectiveness is an increasing and concave function of *(i)* search intensity of the unemployed (his effort and competence in searching jobs), and *(ii)* his adequacy (in terms of skills) to the labour demand.

Participation in ALMP (especially in training programs) may increase search effectiveness of an unemployed individual in several ways: *(i)* by enhancing motivation and competence, which leads to more intensive search. *(ii)* by increasing the set of suitable jobs.

One might argue that, apart from direct effects of training, another reason for a more intense search may be that after programme completion unemployed also screen vacancies that they have missed during training period. However, this effect could be considered as negligible in Baltic region because, as highlighted by the analysis of the matching process (chapter 2), in Latvia and Estonia only new vacancies significantly contribute to match creation in the labour market.

In order to integrate the participation in ALMP programme in our analysis we relax the assumption of homogeneous unemployment pool, assume that different unemployed groups can have varying search effectiveness and then decompose the search effective stock of unemployed ψU.

Let R be the number of available active labour market policy programme combinations, then the total number of unemployed can be divided in $(1 + R)$ groups. First group contains the unemployed that do not participate in any of available programs: we denote the share of such unemployed in total number of unemployed by γ_0. The remaining unemployed form R groups according to their participation in different ALMP programmes[5]. The share of unemployed belonging to the group r in total number of unemployed is denoted by γ_r $(r = 1, 2, 3, ..., R)$. Naturally $(\gamma_0 + \gamma_1 + \gamma_2 + ... + \gamma_R = 1)$ or equivalently $(\gamma_0 = 1 - \sum_{r=1}^{r=R} \gamma_r)$.

We denote by ψ_r $(r = 1, 2, 3, ..., R)$ the search effectiveness of the unemployed who participate in one of active labour market policy programmes r, and by ψ_0 the search effectiveness of those who participate in none of the programs. Theoretically $\psi_0 < \psi_r$ should hold. This is tested empirically when estimating the augmented matching function.

Now the search effective stock of unemployed can be decomposed as:

$$\psi U = \psi_0 \gamma_0 U + \psi_1 \gamma_1 U + ... + \psi_R \gamma_R U \tag{3.2}$$

When denoting the r programme participants' relative search effectiveness by $\theta_r = \psi_r / \psi_0$, the equation 3.2 can be written as :

$$\psi U = [1 - \sum_{r=1}^{r=R} \gamma_r + \sum_{r=1}^{r=R} \theta_r \gamma_r] \psi_0 U \tag{3.3}$$

The augmented matching function is obtained from equation 3.1 by replacing the term $\psi U_{i,t}$ by its expression from 3.3.

When precising the form of the matching function (for example Cobb-Douglas $M = U^{\alpha_U} V^{\alpha_V}$), normalizing the search effectiveness of non-trained unemployed to 1 $(\psi_0 = 1)$ and applying the logarithmic transformation on the both sides, one obtains the equation 3.4, where the parameters, including θ_r (programme's r impact on unemployed search efficiency) can be estimated from the data.

$$\ln M = \ln A + \alpha_U \ln U + \alpha_V \ln V + \alpha_U \ln[1 - \sum_{r=1}^{r=R} \gamma_r + \sum_{r=1}^{r=R} \theta_r \gamma_r] \tag{3.4}$$

Estimation results would thus allow to determine wherever unemployed participation

[5]For example in case when only two programme types are available from State Employment Agency (A and B), the unemployed that have completed one or both of them may be divided in 3 groups: those that have completed a programme A only, a programme B only and both programmes A and B. The combination of programmes A and B can be considered as a separate program.

in the programme increases the number of transitions to jobs at the aggregate level.

3.4 Evaluation of unemployed training: application to Latvian case

The policy evaluation approach, described above, is based on the inclusion of economic policy variables in the matching function and the data on participation in active labour market policy programmes used when implementing this approach should be conform to certain requirements. For example, it is important to insure that, within the framework of the same programme, the contents and duration of the treatment is sufficiently homogenous.

We aim to assess the aggregate effects of ALMP in transition context on the example of Latvia. The available data from SEAL regional units (data structure is described in section 3.5) for the period from 1999 to 2006 provides the information on two major training oriented active labour market policy programmes in Latvia: unemployed occupational training (OT) (vocational training, re-training and rising of qualifications); "Measures to Increase Competitiveness" among unemployed (MIC). Only the data on unemployed occupational training is conform to the above requirement - as specified above MIC include some training (state and foreign language, computer literacy), but also include carrier guidance and orientation. Since the aggregate data does not allow to distinguish between these sub-types of MIC, we focus herein on the effects of the OT program, which is also the most important among ALMP in Latvia in terms of expenditure.

As mentioned above, we integrate the participation in training programmes in the analysis by supposing that the unemployed pool is composed by a fraction γ of trained individuals and a fraction $(1-\gamma)$ of untrained. Assuming that trained individuals have the search effectiveness ψ_T and non-trained ψ_{NT} , we can represent the search-effective stock of unemployed at the beginning of each time period t and in region i as follows:

$$\psi U_{i,t} = \gamma_{i,t}\psi_T U_{i,t} + (1-\gamma_{i,t})\,\psi_{NT} U_{i,t} \tag{3.5}$$

Let us denote the ratio of two search effectiveness (trained and non-trained) by $\theta = \psi_T / \psi_{NT}$. Including $\psi U_{i,t}$ into a Cobb-Douglas type matching function, normalizing the search effectiveness of non trained unemployed to unity and taking logarithms of both sides would give:

$$\ln M_{i,t} = \alpha_0 + \alpha_U \ln U_{i,t} + \alpha_V \ln V_{i,t} + \alpha_U \ln(1+\gamma_{i,t}(\theta-1)) + \alpha_{Z^1} Z^1_{i,t} + ... + \alpha_{Z^k} Z^k_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3.6}$$

The mismatch parameter is transformed in order to capture the efficiency of matching over time (by including time fixed effects λ_t)[6], across different regions (by including region fixed effects μ_i), to include the effects of k various macroeconomic factors and to allow for random variations in hiring:

$$\ln A_{i,t} = \alpha_0 + \mu_i + \lambda_t + \alpha_{Z^1} Z^1_{i,t} + ... + \alpha_{Z^k} Z^k_{i,t} + \varepsilon_{i,t}.$$

Equation 3.6, can be rewritten in a more compact way when collecting the main components of the matching function (unemployed, vacancies) in a vector $X_{i,t} = [\ \ln U_{i,t} \quad \ln V_{i,t}]$, the k variables used to define the macroeconomic context in a vector $Z_{i,t} = [\ Z^1_{i,t} \quad ... \quad Z^k_{i,t}]$.

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + \alpha_U \ln(1+\gamma_{i,t}(\theta-1)) + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3.7}$$

The vector $\alpha_X = [\ \alpha_U \quad \alpha_V]'$ contains the coefficients, corresponding to the variables in the vector $X_{i,t}$, while $\alpha_Z = [\ \alpha_{Z^1} \quad ... \quad \alpha_{Z^k}]'$ corresponding to those in vector $Z_{i,t}$.

The analysis performed in the chapter 2 indicates that the matching process in Latvia is better described by a stock-flow, rather than by a stock-stock matching function. In order to avoid misspecification, we will include unemployed and vacancy inflows to the set of main explanatory variables of the matching function. In this case $X_{i,t} =$

[6] λ_t includes seasonal (quarterly) dummies and annual trend.

$[\ \ln U_{i,t}^S \quad \ln U_{i,t}^F \quad \ln V_{i,t}^S \quad \ln V_{i,t}^F]$, $\alpha_X = [\ \alpha_{SU} \quad \alpha_{SV} \quad \alpha_{FU} \quad \alpha_{FV}]'$ and the equation 3.7 turns to:

$$\ln M_{i,t} = \alpha_0 + X_{i,t}\alpha_X + \alpha_{SU}\ln(1+\gamma_{i,t}(\theta-1)) + Z_{i,t}\alpha_Z + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3.8}$$

The equation 3.8 (the augmented stock-flow matching function) will be estimated on Latvian data. The impact of unemployed training programme on the matching process can be evaluated by the use of the semi-elasticity of outflows with respect to the share of trained unemployed. This semi-elasticity, denoted by η is measured by:

$$\eta = \partial lnM/\partial\gamma = (\alpha_{SU}(\theta-1))/(1+\gamma(\theta-1)) \tag{3.9}$$

Positive and statistically significant RHS of equation 3.9 would suggest that training facilitates the matching process and increases outflows from unemployment.

The estimation of the augmented matching function on regional administrative data has already been employed in European context. Burda and Lubyova [1995], Svejnar et al. [1995], Boeri and Burda [1996] work on the data from 76 Czech and 38 Slovak districts, (Lehmann [1995], Gora et al. [1996]), Puhani [1999] use regional data from 49 Polish voidodships, but Dmitrijeva and Hazans [2007] from 33 Latvian districts, Steiner and al. [1998] and Hagen [2003] use data on 35 Labour Offices in East Germany, but Hujer et al. [2002], Hujer and Zeiss [2003] on 141 regions of West Germany. The differences across these studies mostly regard the variables used to express the extents of active labour market policy (expenditure and expenditure per capita, participants, inflows and outflows of participants, share of participants in unemployment pool, ect.), the specification of the matching function (simple, stock-flow or spatially augmented), the estimation strategies (pooled regression, fixed or random effect models, dynamic panel models, ect).

3.5 Data and Variables

Data used in our analysis of macroeconomic efficient of unemployed training originates from the regional data base of the State Employment Agency of Latvia[7]. It covers 33 Latvian administrative regions (NUTS 4) for a period from January 1999 to July 2006, on a monthly basis.

3.5.1 Main components of the matching function

The variables standing for the main components of the matching function - the stock of unemployed U^S, the flow of unemployed U^F, the vacancy stocks V^S , the vacancy flows V^F , the outflows from registered unemployment to employment M - as well as an additional macroeconomic context indicators - growth in regional secondary employment - originate from the same data set and have the same properties, that the data used for the empirical analysis of the matching function in chapter 2. The reader can therefore refer to the appropriate sections of chapter 2 for description of variables and sources (table 2.8), descriptive statistics (tables 2.7 and 2.6) and the discussion on the main patters of these variables (section 2.3).

Let us recall briefly that unemployment data only refer to registered job seekers, while vacancy data cover only job announcements placed through SEAL, *i.e.* available in the first place to registered unemployed. The dependent variable (outflow to employment) also concerns the outflow from the pool of registered unemployed. The coherence between the matching pools (unemployed, vacancies) and the output (matches or hires) is therefore respected. In addition, the participation in ALMP programme evaluated herein (occupational training) is also conditional on the registration with the State Employment Agency.

With respect to qualification structure, both registered unemployed and vacancies posted through SEAL mainly regard the pool of manual and low-qualification jobs

[7] I would like to thank Grieta Tentere and Ilze Berzina from the Latvian State Employment Agency for cooperation in provision of necessary data.

(see table 3.1 below).

Table 3.1: **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

Source: State Employment Agency of Latvia. Notes: (a) *"Manual"*: ISCO categories 5-9. *"Non-manual"*: ISCO categories 1-4. (b) *"Manual"* for vacancies also includes military professions, but for unemployed - military professions and those without any declared occupation; (c) For year 2003 data covers only the first 6 months.

At the same time manual jobs include, among others, service workers and shop and market workers, craft and related trades workers, plant and machine operators and assemblers. All these jobs require a certificate in state language. Many of these jobs nowadays require also computer skills. A significant part of occupational training promotes, in addition to occupation specific skills, the related skills in state of foreign language or computer literacy and thus regard directly manual workers [8].

As mentioned above, to evaluate the effects of training programmes on aggregate efficiency of the labour market, the matching function must be augmented with the share of trained unemployed. We use therefore a corresponding **policy variable** $\gamma_{i,t}$. The construction and properties of this variable are presented in what follows.

3.5.2 Policy variable

The policy variable $\gamma_{i,t}$ - a share of trained individuals among the total number of unemployed (at the beginning of each month) - is not directly available from SEAL aggregate data. We therefore face several options concerning the use of this variable: *(i)* we can obtain its correct value from other sources (individual data, if available) or/and *(ii)* we can construct its proxy from available aggregate data.

[8]Moreover, Hazans (2005, section 3D) shows that in Latvia, among all job-seekers, propensity to use services of the State Employment Agency is decreasing in educational attainment.

Correct value of the variable γ from individual data. The information allowing to calculate the share of trained unemployed in the unemployment pool is rarely delivered by the aggregate data. Meanwhile it can easily be calculated from the database containing individual records on unemployed and ALMP programme participants. Such database was only recently (2006) constructed for Latvia[9], it covers the time period from January 2003 to August 2006, but the main aggregates (number of unemployed, inflows and outflows from the pool) extracted from this dataset take reasonable values starting from January 2004 only. We therefore extract the values of the number of trained unemployed in each region and at the beginning of each month and run the estimations with the correct version of the variable $\gamma_{i,t}$ for the time period after the EU accession (starting from April 2004).

Construction of a proxy variable PTU. Aggregate data enables us to observe the following variables: for month t and region i, $CT_{i,t}$ is the number of persons completing training programs, while $TE_{i,t}$ is the number of trained individuals that have transited to jobs [10] 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 [11], we have used the difference between the number of persons completing training programmes and the number of trained unemployed who have outflowed to employment over a long enough period (a year) as a proxy for the number of trained unemployed.

[9]The construction of such data set was realized by the author in the framework of research project on "Reasons and duration of unemployment and social exclusion in Latvia" initiated by the Ministry of Welfare of Latvia and founded by ESF (European Social Fund). This individual data set is also used for microeconomic evaluation of unemployed training, carried in Chapter 3 of this thesis.

[10]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.

[11]At least not for the total estimation period 1:1999 -6:2007 and not until beginning of 2007, as explained above

Let $CCT_{i,t}$ be a cumulated (over all past periods) sum of unemployed who have completed a training programme 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.

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 labour market states (non-activity, participation in other programs).

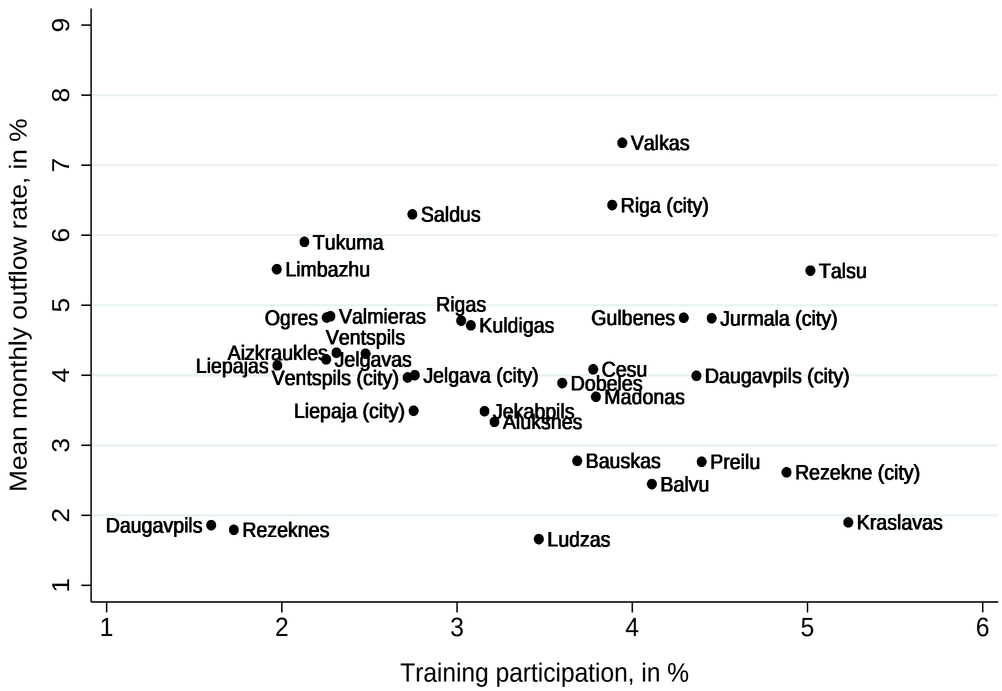
To control for this issue we adopt the following strategy: we use the approximated share of trained unemployed (PTU) to estimate the augmented matching function in a time period from 1999 to 2006 (overall and separated by the the EU accession date), but use the correct value of the the share of trained unemployed extracted from the individual dataset (variable γ) to perform the robustness check for the latest estimation period - after May 1st 2004.

The descriptive statistics on constructed proxy $PTU_{i,t}$ and its elements, as well as for the correct variable $\gamma_{i,t}$ are given in the table 3.3 in appendix.

Actually, the share of trained unemployed in the total number of unemployed does not exceed 10 percents, i.e. $\gamma_{i,t}$ is significantly lower than indicated by the proxy variable $PTU_{i,t}$, we use for macroeconomic evaluation. However the regional and time variations in this variable are correctly reflected by the aggregate data and thus the results based on a corrected value of the variable $\gamma_{i,t}$ are very similar to the ones obtained when using its proxy (differences are only marginal).

Figure 3.3 reflects a potential relationship between regional monthly outflow-to-job rates and the share of trained unemployed in the pool (variables are averaged over time). Several groups of districts can be distinguished in this respect:

Figure 3.3: Outflow rate and participation in training by region



Source: Author's calculations based on the data from State Employment Agency of Latvia. Note: Mean values for period 5:2004-7:2006.

- Valkas and Talsu regions, as well as the capital city Riga, display both the highest outflow rates (above 5 percent), and the highest involvement of unemployed in training programmes (the share of trained unemployed lies between 3.5 and 5 percent in these areas).

- By contrast, in the districts located in the depressed Eastern part of Latvia (Daugavpils and Rezeknes) the rates of exit to employment are very weak (between 1 and 2 percent) and, at the same time, the participation of unemployed in re-qualification and skills-upgrading programmes is also relatively low (below 2 percent).

- In districts of Preilu, Kraslavas and in the city of Rezekne, training programmes seem to be substantially promoted (participation rates above 4 percent), but the performance in term of exit rates is relatively weak (between 2 and 3 percent).

- In the regions of Saldus, Tukuma and Limbazhu the involvement of unemployed in training is weak (between 2 and 3 percent), while the observed exit rates are higher than country-average.

- In all other regions of Latvia, the monthly rates of transition to employment are between 3 and 5 percent, while the participation in training is between 2 and 5 percent.

While it is difficult to draw any conclusions on the relationship between regional transition to employment rates and the degree of unemployed involvement into training from the general picture, it seems that this relationship is sligtly positive among the most defavorised, in terms of unemployment, Latvian districts (Balvu, Daugavpils, Kraslavas, Ludzas, Preilu, Rezeknes, where the unemployment rates are high compared to national average). This suggests that unemployed training might, at least in part, contribute to increase the outflow to jobs in some of Latvian districts. These conclusions are of course preliminary - a more rigorous analysis is performed in the next section.

3.6 Estimation procedure and related issues

The data structure being similar to the one used in chapter 2, the same treatment issues apply. Spatial disaggregation and frequency of the data are high, which mitigates potential aggregation biases. Estimation are performed using Park-Kmenta (GLS) and Beck and Katz (PCSE) procedures to bring necessary corrections to non-sphericity problems typically arising in Cross Section Time Series (CSTS) data. We use regional and time fixed effects to correct for heterogeneity in observation units and to minimize the potential biais from the build-in endogeity in the matching function (details in chapter 2, section 2.4).

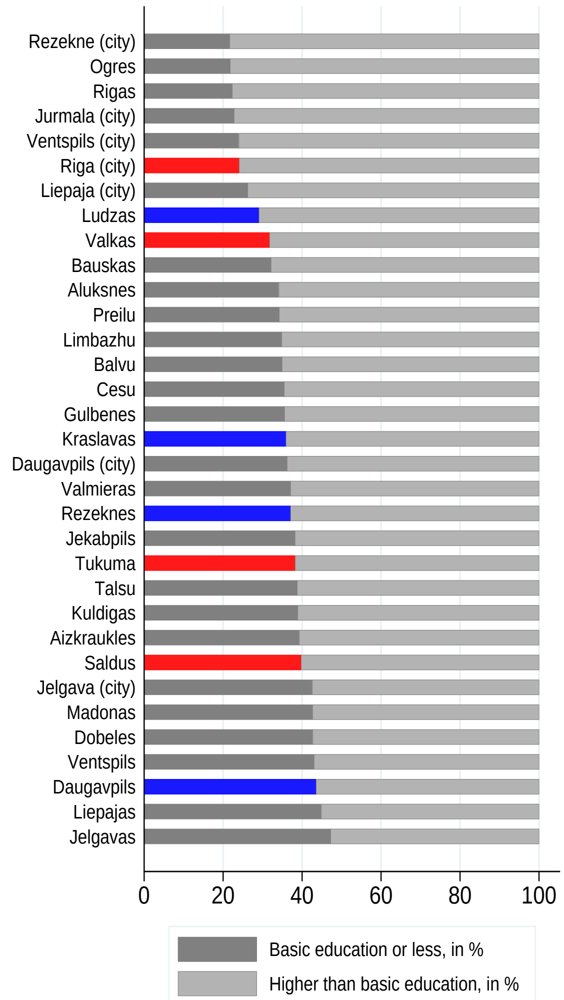
Let us turn to the estimation issues related to policy evaluation through the augmented matching function.

In general, the majority of studies that perform policy evaluations use expenditure on ALMP or number of current participants in ALMP (as policy variables). These studies are often concerned by the problem of endogeneity. The ALMP variable is likely to be endogenous since local labour market offices may raise their expenditures on these programmes if labour 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 programme last about 3-4 months. Thus if the authorities react to worsening in current labour market situation and increase expenditures on ALMP programmes (and number of participants) at period t, these new participants will only appear in our variable $\gamma_{i,t+4}$ or $PTU_{i,t+4}$ (*i.e.* in four months). Thus there is no link between current decrease of hires and increase in our policy variable.

Another issue, which is often of concern in evaluation studies, mostly at the microeconomic level, is the possibility of selection bias (see Heckman et al. [1999]). In fact, administrators at employment offices may have incentives to select more able unemployed into training programmes and in this case the evaluated impact of retraining is overestimated since it captures (i) the causal (positive) effect of training and (ii) ability based selection (also positive) effect since outflow rate of unemployed with higher ability is higher. We will control for this issue when performing the microeconomic evaluation of unemployed training in chapter 4.

When performing policy evaluation with aggregate data (which is the case here) the selection issue can be addressed only partially. On one hand, it can be useful to use the information on regional distributions of unemployed in terms of education. We do not possess such data on monthly basis for a time period long enough to perform the corrected estimation, but can derive some qualitative conclusions from the data available for February 2006. The structure of the pool of unemployed in terms of education is not homogeneous across Latvian regions (the share of unemployed with basic education or lover education level varies from 22 percent in the city of Rezekne to 47 percent in Jelgavas region). Meanwhile the distribution of regions in terms of educational level of unemployed does not reflect the regional distribution nor in terms of outflows to jobs (see figure 3.4 below) nor in terms of matching efficiency (see estimation results in section 3.7) .

Figure 3.4: Unemployed in Latvian regions by education level



Source: Author's calculations based on the data from State Employment Agency of Latvia. Note: Data refers to February 2006.

On the other hand, when observation units are regions rather than individuals, and region fixed effects are present (which is our case), the selection issue is less of a problem.

One cannot only attribute positive effect of training on regional outflows to selection of better individuals into training programs. In addition, most training involves promotion of occupation specific (equipment related) or general (e.g. state or foreign language, computer) skills. It is unlikely that without these skills the same persons would be equally able to find jobs. We therefore believe that our aggregate results are not compromised by possible selection bias.

Another econometric issue appearing in the current study, is the non-linearity of equation 3.8 in the unknown parameter θ (relative search efficiency of trained unemployed). We have chosen the following method for liberalization: we estimate each model (see specifications below) for different values of θ, going from 0 to 10 with a step of 0.01, and we keep the value θ^* of θ, which maximizes the likelihood function[12]. Depending on specification and estimation method θ^* varies between 1.4 and 2.45 (when estimating with the proxy of the share of trained unemployed) or between 2.7 and 3.4 (when estimating with correct version of this variable). Mean value of θ^* is 2.1, implying that trained unemployed are on average 2.1 times more efficient in their search than untrained ones. As a next step we estimate the equation 3.8 replacing $(\ln U_{i,t} + \ln(1+\gamma_{i,t}(\theta-1))$ by $G = (\ln U_{i,t} + \ln(1+\gamma_{i,t}(\theta^*-1)))$, where θ^* is the likelihood maximizing value of θ for a given model.

In order to rule out the possibility that any region-specific unobserved component in the variable $\gamma_{i,t}$ may not be removed when including the linear fixed effects μ_i, we assume that θ (the relative search effectiveness of trained unemployed) is homogenous across regions. The contents and duration of courses under the occupational training programme being similar across regions, this assumption seems reasonable. When θ is assumed homogenous across regions the regional heterogeneity in $\gamma_{i,t}$ is removed by mean deviation transformation and the regional difference in outcomes of training can be attributed to better information, better performance of SEA staff when making job and training offers or other unobserved factors.

[12]The graphs displaying log likelihood as a function of θ can be found in the appendix.

Specifications: augmented stock-flow matching function:

Let us now turn to the detailed description of estimated specifications. Those are similar to the ones used for the estimations of the matching function for Latvia in chapter 2.

- **Specification [I]**: The baseline specification, which includes main explanatory variables (stocks and flows of unemployed and vacancies) and the additional labour demand indicator (growth in secondary employment), policy variable, region dummies (reference region - Riga city), time dummies (quarters, omitted first quarter) and time trend (year).

- **Specification [II]**: To make sure the results are not affected by influential observations related to capital city Riga (where unemployed stock values are a lot higher than elsewhere), we run previous specification ([I]) but exclude Riga city from the sample (in this case Riga district is used as reference).

  Further, we make use of time dimension of the data in order to learn whether the changes in employment legislation have affected matching efficiency in Latvia. In 1999-2006 several major changes, which could have influenced labour supply (or search effort of unemployed) and labour demand, have occurred. These regard the level of unemployment benefit and the amount of legal minimum wage.

- **Specification [III]**: The average level of unemployment benefit has dropped by 15 percents in August 2000 (when benefit amount calculation rules became harsher) and has raised by 15 percents in February 2003 (when the ceiling on benefit amount was removed). The specification [III] shows the effect of changes in unemployment benefit amount. It adds to the baseline specification [I] two step dummy variables: one for the period after 1st August 2000 and another for the period after 1st February 2003.

- **Specification [IV]**: Shows the effect of changes in minimum wage amount in Latvia. This amount was raised by 20 percent in July 2001 and by 17 percents in January 2003, by 14 percent in January 2004, by 13 percent in January 2006. We add to the specification [I] step dummy variables for the above changes: first for the period after 1st July 2001, second for the period after 1st January 2003, third for the period after 1st January 2004 and then the fourth for the period after 1st January 2006.

The policy-augmented stock flow matching function is specifications [I] - [IV] is estimated on Latvian data by GLS and PCSE methods, for three time periods - total time period 1:1999 to 7:2006, time period before the EU accession 1:1999 to 4:2004, time period after the EU enlargement 5:2004 - 7:2006. For the last time period after EU accession the estimations are performed with both approximated and correct share of trained unemployed. This gives the total of 32 regressions, the results being reported in tables 3.4 - 3.7 in the appendix.

3.7 Estimation results

We can now turn to the discussion of estimation results. All results being displayed in the appendix, we present here a synthetic table 3.2, collecting the results of estimation of specification [I] over different time periods.

Matching process

Regarding to the main components of the matching function, the results are in line with the ones obtained in chapter 2 when estimating a non-augmented matching function.

Generally, constant returns to scale can not be rejected when estimating the matching function for total time period (1:1999 to 7:2006), but are rather increasing when time periods are split into before-after EU accession. The absence of region and time specific effects is always rejected. The matching process in Latvia follows a stock-flow pattern; stock of unemployed and the inflow of new vacancies being the main variables determining the outflows from unemployment to employment. The labour demand dominates labour supply in match creation, but the role of labour supply is increasing over time.

The negative relationship between the generosity of labour market institutions and the performance of the economy in terms of matching is also confirmed. The elasticity

Table 3.2: **Estimation results: augmented stock-flow matching function**

Variables, parameters: *Dep.var: ln outflows*	Total GLS [I]	Before EU GLS [I]	After EU GLS [I]	After EU (c) GLS [I]
ln unemployed (stock) :	**0.856***** [0.075]	**1.068***** [0.081]	**1.526***** [0.263]	**1.041***** [0.185]
ln unemployed (flow):	**0.050*** [0.028]	**0.041** [0.032]	**0.054** [0.053]	**0.046** [0.053]
ln vacancies (stock):	**0.027***** [0.007]	**0** [0.008]	**0.034***** [0.011]	**0.034***** [0.011]
ln vacancies (flow):	**0.204***** [0.011]	**0.206***** [0.013]	**0.200***** [0.020]	**0.195***** [0.020]
Indicator for local labour demand	**0.742***** [0.065]	**0.815***** [0.067]	**-0.105** [0.294]	**-0.191** [0.297]
Time trend (annual)	**0.001** [0.003]	**-0.009**** [0.004]	**0.093***** [0.021]	**0.113***** [0.023]
Constant	**-5.1** [6.611]	**11.6** [8.930]	**-197.2***** [43.520]	**-232.8***** [48.261]
Regional dummies (test)	753***	724***	677***	632***
Quarterly dummies (test)	62***	59***	40***	40***
Relative search effectiveness of trained unemployed: $\theta*$	2.02	1.81	2.45	3.32
Semi-elasticity of new matches with respect to the proportion of trained unemployed : η evaluated at mean value of γ	0.72**	0.75***	1.56***	2.24***
Returns to Scale	1.14	1.32	1.81	1.32
Constant returns to scale, test	3.0*	14***	9***	2.45
Observations	2737	1953	784	784
Regions	33	33	33	33
Heteroscedasticity, test	1031***	836***	490***	425***
Autocorrelation, test	20.4***	14.5***	7.8***	7.5***

Notes: (c) indicates that the estimations were performed with correct value of variable γ - the share of trained unemployed in the pool of unemployed workers. All other details can be found in explanatory notes to tables 3.4 - 3.7 in the appendix.

of outflows with respect to unemployed pool increases over time and is above one for both before and after EU accession time periods[13], while the elasticity with respect to vacancy inflow is around 0.20.

Effects of unemployed training

Turning to the policy evaluation issues, our results display positive and statistically significant impact of the share of trained unemployed on outflows to employment. These results are robust with respect to chosen specification and do not differ significantly with the respect to estimation time period or the variable chosen to reflect the share of trained unemployed (approximated or correct value, see section 3.6 for more details).

[13] Galuscak and Munich [2005] also find the elasticity of outflows to be higher then one. In our estimations of a standard (non-augmented) matching function (results are not reported, but available on request) this elasticity is about 0.9. In case of augmented matching function the elasticity is higher since it applies not only to the stock of unemployed ($lnU_{i,t}$) but to the term $G = lnU_{i,t} + ln(1+\gamma_{i,t}(\theta^* - 1)$, which, conditional on normalization of search effectiveness of non-trained unemployed ψ_{NT} to 1, represents the search effective stock of unemployed. It seems reasonable to find in this case the higher elasticity of outflows from unemployment.

The effect of unemployed training on aggregate outflows from unemployment is evaluated using the estimated semi-elasticity of outflows with respect to the share of trained unemployed. This semi-elasticity is obtained from equation 3.9, using the estimation results and the period's average value for the proxy of the share of trained unemployed (0.21 in the time period from 1:1999 to 7:2006, 0.18 from 1:1999 to 4:2004 and 0.29 from 5:2004 to 7:2006) or the correct value of the share of trained unemployed (0.034 in the time period from 5:2004 to 7:2006). The results of estimation with the correct variable γ display even higher efficiency of unemployed training programs: the semi-elasticity of matches with respect to the share of trained unemployed varies, in the period 5:2004 -7:2006, from 1.92 to 2.40 conditional on specification (for comparison it varies from 1.11 to 1.64, when estimating with the proxy of the variable γ, table 3.6).

Let us interpret the results using the semi-elasticity, obtained from the estimations with correct value of the share of trained unemployed. Those will refer to the time period after May 1st 2004. In this case the semi - elasticity, evaluated at $\gamma = 0.034$, equals 2.24 (table 3.7, 2nd column, specification [I]).

The variable γ being defined as the proportion of trained unemployed in the total number of unemployed, the semi-elasticity can be interpreted as follows: when the share of trained unemployed in the beginning of the month increases by one unity - which in our case is one percentage point, meaning an increase from 3.4 to 4.4 percents or by 851 extra trained persons, see table 2.6, column 8) - the number of matches, created within the following month, increases by 2.24 percent or by 85 units (3554*0.024). Thus one new match may be created by additionally training $851/85 = 10$ unemployed. According to the data from SEAL, in the period from 2004 to 2006, the average per head cost of unemployed training was around 679 Lats[14]. In the same period of time (2004-2006) the average GDP per employed was 8803 Lats annually or 733 Lats monthly. Therefore the expenses of training 10 additional unemployed, would be covered if the additionally matched unemployed keep the job for at least 9 months (6790/733). Thus the expenses on training can easily be covered at the macroeconomic level.

[14] 1 Latvian Lat makes approximately 1.49 Euros.

Our results support a substantial role of training programmes in fighting unemployment while the available macroeconomic studies on other transition economies do not seem to have reached the consensus on this issue[15]. Positive effects of different (including non-training) ALMP programmes are found by Burda and Lubyova [1995], Svejnar et al. [1995], Boeri and Burda [1996] in Czech Republic and Burda and Lubyova [1995] in Slovakia. A positive impact of training is pointed out by Steiner and al. [1998] in Eastern Germany, by Puhani [1999] in Poland and by Dmitrijeva and Hazans [2007] in Latvia. Meanwhile, other studies conducted on Poland (Lehmann [1995], Gora et al. [1996]), East or West Germany (Hagen [2003], Hujer et al. [2002], Hujer and Zeiss [2003]) do not find any significant impact of unemployed training programs.

It should be noted, however, that all above listed studies operate with the traditional matching function (not stock-flow) and most of them choose the expenditure on ALMP as explanatory variable when evaluating the efficiency of policy programmes. 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 labour demand.

Regional heterogeneity

Both the efficiency of the matching process and the efficiency of unemployed training varies across Latvian districts. Figure 3.5 displays the efficiency of matching (both with and without controlling for the effect of training programs) in various Latvian districts and in comparison with capital city Riga.

Both before and after Latvia's accession to the EU, the lowest matching efficiency has been observed in Daugavpils, Rezeknes and Ludzas districts and in the cities of Rezekne and Liepaja. The highest efficiency characterized Valkas, Saldus, Limbazhu and Ventspils districts.

[15] See Puhani [1999] for a more detailed survey on the results of macroeconomic policy evaluations in transition countries. 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 et al. [2004] for OECD, transition and development countries, Leetmaa and Vork [2003] for Estonia, Kluve et al. [1999] for Poland).

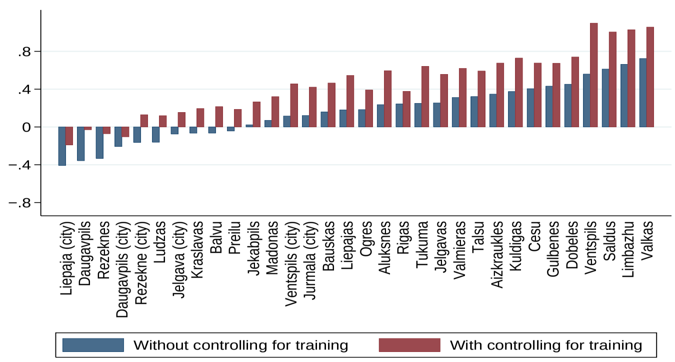
In the time period before 1st May 2004, the matching performance in those regions was significantly different (worst for the former group and better for the latter) than in the capital city Riga. Other districts displayed the results, which are similar to the one for Riga city. After 1st May 2004, this was the case of all districts, except Valkas.

Regional differences in matching can be explained by several factors: heterogeneity in unemployment involvement in training, varying efficiency of the programs, or, also, differences in skills and efficiency of staff in different SEA regional units. Some of this heterogeneity can be removed when controlling for unemployed participation in training programme in the estimated model (augmented matching function).

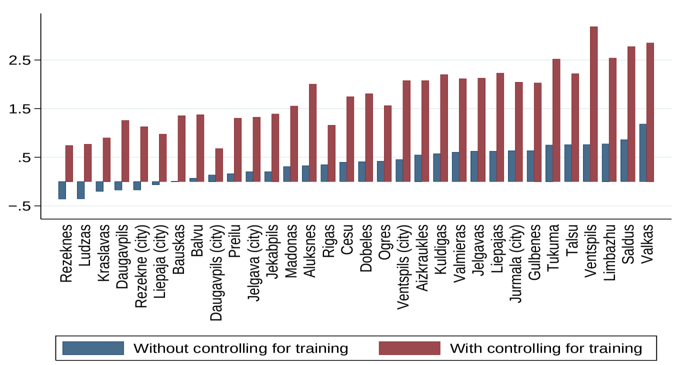
The results of estimation of the augmented matching function reveal that the gap in matching efficiency between Riga city and other districts is higher when the taking into account the magnitude of unemployed involvement in training. In this case, none of the districts perform significantly worst than Riga city. In turn, the range of districts which perform significantly better have increased: 20 districts out of 32 in the time period prior to EU enlargement and all regions, except Ludzas, after the EU enlargement. This suggests that in some districts - Tukuma, Ogres, Valmieras, Liepajas, Jelgavas, where the involvement in occupational training is the lowest, but performance indicators increase significantly when taking the participation in ALMP into account- the overall matching efficiency can be improved by increasing the involvement of unemployed in training programmes.

Figure 3.5: Matching efficiency across Latvian regions (comparing to Riga city)

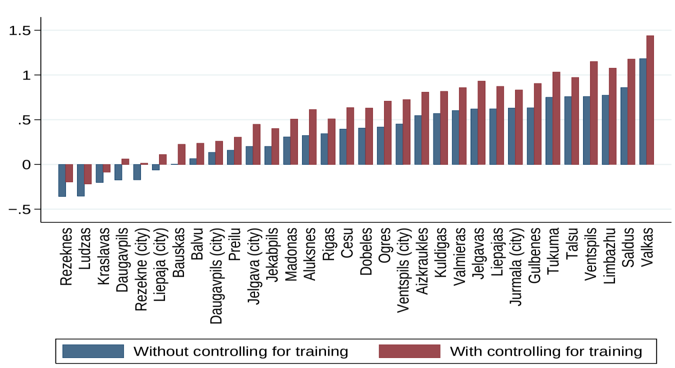
Time period 1:1999 - 4:2004



Time period 5:2004 - 7:2006



Time period 5:2004 - 7:2006, correct γ



Source: Author's calculations based on the data from State Employment Agency of Latvia.

3.8 Conclusions and policy perspective

The objective of this chapter was to investigate the aggregate effects of active labour market policy. We consider the potential of unemployed training (a measure aiming to reduce skill and qualification mismatch between labour supply and labour demand) in increasing outflows from unemployment to jobs.

To quantify these effects, we estimate an augmented matching function on monthly cross section data from Latvia and used the share of trained unemployed to measure the extent of policy intervention in each of Latvian districts.

The main results are the following:

First, we confirm our previous findings on a stock-flow patterns in the matching process in Latvia and on the dominance of labour demand in the creation of new matches.

Second, we find that the effect of unemployed occupational training on aggregate outflow from unemployment, evaluated through the estimated semi-elasticity of outflows with respect to the share of trained unemployed, is positive and statistically significant. Unemployed participation in training increases thus the number of transitions from unemployment to jobs.

Third, the calculations based on estimation results reveal that the monthly number of new matches (hires) realized in the labour market can be increased by one unity by additionally training 10 unemployed. A simple cost-benefit comparison based on the data on average training costs, one hand, and the data on average productivity of employed in terms of GDP per head, on the other hand, reveals that training programmes can be easily be covered on the aggregate level if the average job tenure in the country reaches 9 months.

Several conclusions with regard to active labour market policy programmes can be derived based on these results. The important role played by the new job vacancies in the outflows from unemployment, suggests intensive use of programmes susceptible to promote the creation of new jobs (subsidized jobs, credits to self-employed etc.). At the same time and despite the driving role of labour demand, training has an important effect on unemployment reduction. Given financial feasibility of this programme at the aggregate level and given the potentiality of important social effects (reducing discouragement and social exclusion) the further promotion of training programmes is strongly suggested.

3.9 Appendices

Table 3.3: **Descriptive statistics, aggregated data**

Variable	Mean	Variation	S.d.	Min	Max	Obs.		Mean*
	Latvia 1:1999 - 07:2006							
Outflows from training	20	overall	37	0	729	Nit	3003	664
		between	28	3	168	Ni	33	
		within	25	-140	581	Nt	91	
Outflows of trained	12	overall	21	0	209	Nit	3003	411
		between	19	2	113	Ni	33	
		within	9	-77	108	Nt	91	
Trained unemployed (proxy PTU), in%	21	overall	12	1	79	Nit	3003	21
		between	8	9	42	Ni	33	
		within	8	-14	66	Nt	91	
	Latvia 1:1999 - 04:2004							
Outflows from training	21	overall	40	0	729	Nit	2112	686
		between	29	3	178	Ni	33	
		within	28	-149	572	Nt	64	
Outflows of trained	13	overall	22	0	209	Nit	2112	426
		between	20	2	122	Ni	33	
		within	10	-85	100	Nt	64	
Trained unemployed (proxy PTU), in%	18	overall	9	1	52	Nit	2112	18
		between	7	6	35	Ni	33	
		within	6	-10	35	Nt	64	
	Latvia 5:2004 - 07:2006							
Outflows from training	19	overall	29	0	242	Nit	891	607
		between	24	3	145	Ni	33	
		within	17	-111	116	Nt	27	
Outflows of trained	11	overall	17	0	148	Nit	891	379
		between	15	2	93	Ni	33	
		within	7	-51	67	Nt	27	
Trained unemployed (proxy PTU), in%	29	overall	13	11	79	Nit	891	30
		between	12	14	59	Ni	33	
		within	5	16	53	Nt	27	
Trained unemployed (correct gamma), in %	3.4	overall	1.9	0.2	11.3	Nit	891	3.5
		between	1.1	1.7	5.6	Ni	33	
		within	1.6	-0.3	9.5	Nt	27	

Notes: (1) Outflows from training stand for the number of unemployed which have completed training program during the considered month. (2) Outflows of trained stand for the number of unemployed which have previously completed training program (unconditionally of the date of completion) and have found jobs during the considered month. (3) Trained unemployed stand for the number of individuals, that have previously completed training program (unconditionally of the date of completion) and are at the end the considered month still unemployed. (4) Statistics are calculated on regional panel data on monthly frequency. (5) $Mean*$ stands for the mean of the variable, when data are aggregated over all regions. (6)N_{it} - total observation number; N_i - number of regions; N_t - number of time periods (months). (7) 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 3.4: **Latvia - Estimation results: augmented stock-stock matching function (time period 01:1999 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]
ln Unemployed (stock):	**0.856*** **	**0.867*** **	**0.828*** **	**0.829*** **	**0.857*** **	**0.861*** **	**0.842*** **	**0.853*** **
	[0.075]	[0.076]	[0.073]	[0.070]	[0.107]	[0.107]	[0.101]	[0.097]
ln Unemployed (inflow):	**0.050***	**0.036**	**0.051***	**0.064** **	**0.007**	**0.002**	**0.007**	**0.023**
	[0.028]	[0.029]	[0.029]	[0.029]	[0.043]	[0.043]	[0.042]	[0.042]
ln Vacancies (stock)	**0.027*** **	**0.028*** **	**0.025*** **	**0.016** **	**0.024*** **	**0.024*** **	**0.021** **	**0.011**
	[0.007]	[0.007]	[0.007]	[0.007]	[0.009]	[0.009]	[0.009]	[0.008]
ln Vacancies (inflow)	**0.204*** **	**0.202*** **	**0.203*** **	**0.200*** **	**0.188*** **	**0.188*** **	**0.189*** **	**0.185*** **
	[0.011]	[0.011]	[0.011]	[0.011]	[0.015]	[0.015]	[0.015]	[0.014]
Local labour demand indicator	**0.742*** **	**0.742*** **	**0.741*** **	**0.756*** **	**0.731*** **	**0.730*** **	**0.727*** **	**0.744*** **
	[0.065]	[0.066]	[0.066]	[0.065]	[0.118]	[0.118]	[0.117]	[0.115]
Time trend (year)	**0.001**	**0.003**	**0.004**	**0.003**	**0.009**	**0.009**	**0.013**	**0.01**
	[0.003]	[0.003]	[0.003]	[0.004]	[0.008]	[0.008]	[0.008]	[0.009]
Constant	**-5.048**	**-9.161**	**-12.396***	**-10.247**	**-20.808**	**-21.899**	**-28.422***	**-23.839**
	[6.611]	[6.791]	[7.018]	[7.691]	[15.879]	[15.883]	[16.226]	[17.852]
UBA1 (after 01/08/2000)			**0.019**				**0.019**	
			[0.020]				[0.052]	
UBA2 (after 01/02/2003)			**-0.077*** **				**-0.092***	
			[0.019]				[0.050]	
MWA1 (after 01/07/2001)				**-0.002**				**-0.012**
				[0.020]				[0.050]
MWA2 (after 01/01/2003)				**-0.095*** **				**-0.107** **
				[0.021]				[0.052]
MWA3 (after 01/01/2004)				**-0.021**				**-0.03**
				[0.022]				[0.054]
MWA4 (after 01/01/2006)				**0.125*** **				**0.138***
				[0.028]				[0.072]
Regional dummies (test)	753***	629***	779***	811***	1256***	867***	1329***	1422***
Quarterly dummies (test)	62***	68***	66***	71***	13**	13***	14***	16***
Relative search effectiveness of trained unemployed: $\theta*$	2.02	1.93	1.91	1.73	1.73	1.72	1.64	1.52
Semi-elasticity of new matches with respect to proportion of trained unemployed: η evaluated at γ=0.21:	0.72***	0.67***	0.63***	0.52***	0.54***	0.54***	0.47***	0.40***
Returns to scale	1.14	1.13	1.11	1.11	1.08	1.08	1.06	1.07
Constant returns to scale (test)	3.0*	2.7*	1.89	2.08	0.43	0.43	0.29	0.47
Observations	2737	2647	2737	2737	2737	2647	2737	2737
Regions	33	32	33	33	33	32	33	33
Coef. of. det R2					0.88	0.88	0.89	0.89
Heteroscedasticity, test	1031***	745***	989***	989***				
Autocorrelation, test	20.39***	19.82***	19.77***	19.25***				

Table 3.5: **Latvia - Estimation results: augmented stock-flow matching function (time period 01:1999 - 04:2004)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [III]	GLS [IV]	PCSE [I]	PCSE [II]	PCSE [III]	PCSE [IV]
ln unemployed (stock) :	**1.068*****	**1.093*****	**1.078*****	**1.033*****	**1.070*****	**1.080*****	**1.091*****	**1.033*****
	[0.081]	[0.082]	[0.081]	[0.080]	[0.122]	[0.121]	[0.116]	[0.116]
ln unemployed (flow):	**0.041**	**0.028**	**0.043**	**0.044**	**0.001**	**-0.003**	**0.002**	**0.001**
	[0.032]	[0.033]	[0.033]	[0.033]	[0.046]	[0.046]	[0.046]	[0.046]
ln vacancies (stock):	**0**	**0.001**	**0.001**	**0**	**-0.007**	**-0.007**	**-0.006**	**-0.008**
	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]	[0.009]	[0.009]
ln vacancies (flow):	**0.206*****	**0.202*****	**0.206*****	**0.207*****	**0.182*****	**0.181*****	**0.183*****	**0.183*****
	[0.013]	[0.013]	[0.013]	[0.013]	[0.017]	[0.017]	[0.017]	[0.017]
Indicator for local labour demand	**0.815*****	**0.816*****	**0.811*****	**0.827*****	**0.794*****	**0.795*****	**0.786*****	**0.798*****
	[0.067]	[0.067]	[0.067]	[0.066]	[0.115]	[0.115]	[0.114]	[0.114]
Time trend (annual)	**-0.009****	**-0.006**	**0.002**	**0.002**	**-0.003**	**-0.002**	**0.009**	**0.004**
	[0.004]	[0.004]	[0.005]	[0.006]	[0.010]	[0.010]	[0.011]	[0.014]
Constant	**11.57**	**6.348**	**-10.55**	**-9.823**	**0.562**	**-0.635**	**-23.25**	**-12.15**
	[8.930]	[9.163]	[10.239]	[12.561]	[20.211]	[20.164]	[22.378]	[27.663]
UBA 1 (after 01/08/2000)			**0.026**				**0.035**	
			[0.018]				[0.043]	
UBA 2 (after 01/02/2003)			**-0.054*****				**-0.062**	
			[0.019]				[0.047]	
MWA1 (after 01/07/2001)				**0.013**				**0.008**
				[0.018]				[0.044]
MWA2 (after 01/01/2003)				**-0.075*****				**-0.068**
				[0.023]				[0.054]
MWA3 (after 01/01/2004)				**0.002**				**0.034**
				[0.033]				[0.077]
Regional dummies (test)	724***	605***	750***	739***	1397***	966***	1470***	1482***
Quarterly dummies (test)	59***	67***	66***	54***	15***	16***	17***	14***
Relative search effectiveness of trained unemployed: $\theta *$	1.81	1.68	1.64	1.63	1.54	1.51	1.41	1.42
Semi-elasticity of new matches with respect to the proportion of trained unemployed :η evaluated at γ=0.18	0.75***	0.66***	0.62***	0.58***	0.53***	0.5***	0.42***	0.4***
Returns to Scale	1.32	1.32	1.33	1.28	1.25	1.25	1.27	1.21
Constant returns to scale, test	14***	14***	14***	11***	3.5***	3.6*	5***	2.7*
Observations	1953	1889	1953	1953	1953	1889	1953	1953
Regions	33	32	33	33	33	32	33	33
Coef.of det.R2					0.91	0.91	0.91	0.91
Heteroscedasticity, test	836***	803***	830***	857***				
Autocorrelation, test	14.5***	13.9***	14.2***	14.1***				

Table 3.6: **Latvia - Estimation results: augmented stock-flow matching function (time period 05:2004 - 07:2006)**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [IV]	PCSE [I]	PCSE [II]	PCSE [IV]
ln Unemployed (stock):	**1.526*** **	**1.605*** **	**1.482*** **	**1.450*** **	**1.472*** **	**1.416*** **
	[0.263]	[0.269]	[0.249]	[0.351]	[0.352]	[0.345]
ln Unemployed (inflow):	**0.054**	**0.047**	**0.049**	**0.005**	**0.002**	**0.002**
	[0.053]	[0.054]	[0.054]	[0.092]	[0.092]	[0.091]
ln Vacancies (stock)	**0.034*** **	**0.032*** **	**0.032*** **	**0.032** **	**0.031** **	**0.031** **
	[0.011]	[0.012]	[0.012]	[0.014]	[0.014]	[0.014]
ln Vacancies (inflow)	**0.200*** **	**0.203*** **	**0.199*** **	**0.194*** **	**0.195*** **	**0.194*** **
	[0.020]	[0.020]	[0.020]	[0.027]	[0.027]	[0.027]
Local labour demand indicator	**-0.105**	**-0.117**	**-0.134**	**0.194**	**0.194**	**0.162**
	[0.294]	[0.295]	[0.293]	[0.403]	[0.403]	[0.397]
Time trend (year)	**0.093*** **	**0.104*** **	**0.077*** **	**0.107** **	**0.112** **	**0.092**
	[0.021]	[0.022]	[0.026]	[0.046]	[0.046]	[0.063]
Constant	**-197.2*** **	**-218.6*** **	**-165.1*** **	**-224.4** **	**-234.3** **	**-193.6**
	[43.520]	[45.011]	[53.313]	[93.522]	[94.009]	[126.937]
MWA4 (after 01/01/2006)			**0.073** **			**0.064**
			[0.036]			[0.106]
Regional dummies (test)	677***	592***	673***	14334***	6064***	12911***
Quarterly dummies (test)	40***	45***	44***	7*	7*	8*
Relative search effectiveness of trained unemployed: $\theta*$	2.45	2.45	2.09	2.3	2.29	2.02
Semi-elasticity of new matches with respect to proportion of trained unemployed: η evaluated at γ=0.29	1.56***	1.64***	1.23***	1.37***	1.38***	1.111***
Returns to scale	1.81	1.89	1.76	1.68	1.7	1.64
Constant returns to scale, test	9***	10***	8***	3.4***	3.6***	3.1***
Observations	784	758	784	784	758	784
Regions	33	32	33	33		
Coef. of det. R2				0.94	0.94	0.94
Heteroscedasticity, test	490***	479***	502***			
Autocorrelation, test	7.8***	7.5***	7.8***			

Table 3.7: **Latvia - Estimation results: augmented stock-flow matching function (time period 05:2004 - 07:2006). Robustness check with corrected value of PTU variable**

Dep. variable: ln Matches (outflows from registered unemployment to employment)	GLS [I]	GLS [II]	GLS [IV]	PCSE [I]	PCSE [II]	PCSE [IV]
ln unemployed (stock) :	**1.041*****	**1.099*****	**1.128*****	**1.120*****	**1.142*****	**1.160*****
	[0.185]	[0.190]	[0.192]	[0.262]	[0.263]	[0.273]
ln unemployed (flow):	**0.046**	**0.04**	**0.044**	**0.005**	**0.002**	**0.002**
	[0.053]	[0.054]	[0.054]	[0.092]	[0.092]	[0.091]
ln vacancies (stock):	**0.034*****	**0.033*****	**0.032*****	**0.032****	**0.031****	**0.031****
	[0.011]	[0.012]	[0.012]	[0.014]	[0.014]	[0.014]
ln vacancies (flow):	**0.195*****	**0.198*****	**0.194*****	**0.191*****	**0.192*****	**0.191*****
	[0.020]	[0.020]	[0.020]	[0.027]	[0.027]	[0.027]
Indicator for local labour demand	**-0.191**	**-0.209**	**-0.222**	**0.142**	**0.14**	**0.112**
	[0.297]	[0.299]	[0.295]	[0.409]	[0.409]	[0.402]
Time trend (annual)	**0.113*****	**0.124*****	**0.091*****	**0.126*****	**0.131*****	**0.104**
	[0.023]	[0.024]	[0.027]	[0.048]	[0.048]	[0.064]
Constant	**-232.777*****	**-254.081*****	**-188.114*****	**-259.156*****	**-268.556*****	**-215.120***
	[48.261]	[49.589]	[55.460]	[97.484]	[97.733]	[127.847]
UBA 1 (after 01/08/2000)						
UBA 2 (after 01/02/2003)						
MWA1 (after 01/07/2001)						
MWA2 (after 01/01/2003)						
MWA3 (after 01/01/2004)						
MWA4 (after01/01/2006)			**0.083****			**0.073**
			[0.037]			[0.107]
Regional dummies (test)	632***	578***	637***	40272***	6735***	13455***
Quarterly dummies (test)	40***	45***	44***	7.2*	7.6*	8**
Relative search effectiveness of trained unemployed: $\theta*$	3.32	3.36	2.81	3.17	3.19	2.78
Semi-elasticity of new matches with respect to the proportion of trained unemployed: η evaluated at $\gamma = 0.034$	2.24***	2.40***	1.92***	2.26***	2.33***	1.95***
Returns to Scale	1.32	1.37	1.40	1.35	1.37	1.38
Constant returns to scale, test	2.45	3.2*	3.6*	1.52	0.67	1.7
Observations	784	758	784	784	758	784
Regions	33	32	33	33		
Coefficient of determination R2				0.95	0.95	0.94
Heteroscedasticity, test	425***	415.9***	488.1***			
Autocorrelation, test	7.5***	7.3***	7.6***			

Explanatory notes for tables 3.4 -3.7:

(1) GLS: Model estimated by Generalized Least Squares method. PCSE: Model estimated by Panel Corrected Standard Errors method.
(2) [I] - [IV]: specifications (see section 3.6 for details); All models include regional and time (quarterly) dummies and time (annual) trend. Local labor demand indicator: growth in local (within region) secondary employment. (3) UBA 1 - UBA 2 are time dummies for changes in unemployment benefit amount (UBA): UB1 1=1 starting from 1/08/2000 when UBA dropped from 50 to 43 Ls, UBA 2=1 starting from 01/02/2003 when UBA raised from 43 to 50Ls.
(4) MWA 1 - MWA 4 are time dummies for changes in minimum wage amount: MWA 1=1 starting from 1/07/2001, when minimum wage raised from 50 to 60 Ls, MWA 2=1 starting from 01/01/2003 when MWA raised from 60 to 70 Ls, MWA 3=1 starting from 01/01/2004 when MWA raised from 70 to 80 Ls, MWA 4=1 starting from 01/01/2006 when MWA raised from 80 to 90 Ls.
(5) Constant returns to scale (CRS), test: test for constant returns to scale in estimated matching function. Ho: α_{SU} + α_{FU}+ α_{SV} + α_{FV}=1 in stock-flow specification.
(6) θ^* is the value of parameter θ (relative search effectiveness of trained unemployed), used in estimations (the likelihood maximizing value θ for each model).
(7) The semi-elasticity of outflows with respect to the share of trained unemployed η is calculated from equation 3.8 using estimated coefficients. η is evaluated at period's respective mean value of the share of trained unemployed (proxy or correct value). Proxy: for the period 1:1999 -07:2006, γ=0.21; for the period 1:1999 -04:2004, γ=0.18; for the period 5:2004 -07:2006, γ=0.29. Corrected value: for the period 5:2004 -07:2006, γ=0.034.
(8) Heteroscedasticity, test: modified Wald test for group wise heteroscedasticity (Greene 2000, 598).
(9) Autocorrelation, test - Baltagi test for autocorrelation.
(10) Standard errors in parentheses: for PCSE models standard errors corrected for heteroscedasticity,cross sectional correlation and panel specific AR1 are reported.
(11) ***, **, * - estimates significantly different from zero at 1,5,10 percent level respectively.

Chapter 4

Microeconomic effects of labour market policy

4.1 Introduction

The analysis of the matching process between job seekers and job vacancies, carried in chapters 2 and 3, allows performing the diagnostics of labour market functioning and measuring how the active labour market policies affect the efficiency of the matching process at the aggregate level. Meanwhile it does not allow a more careful evaluation of the effects of the programmes on job seeker individual employability. Consequently, the microeconomic evaluation of ALMP programs is performed in this chapter.

We apply the "propensity score matching" (PSM) methodology developed by Rosenbaum and Rubin [1983], and Heckman et al. [1999]. This evaluation methodology consists in contrasting two groups of individuals, treated and non-treated by programs, with otherwise similar characteristics, for example in terms of gender, education, age. Then the difference in their labour market outcome in terms of re-employment and future earnings is considered.

This approach is recognized as one of the most efficient in microeconomic evaluation of active labour market policy programs and is extensively applied to policy intervention analysis in European countries. Hamalainen and Ollikainen [2004] for Finland, Brodaty et al. [2002] for France, Caliendo et al. [2005a], Caliendo et al. [2005b], Lechner [1999b] for Germany, Loretzen and Dahl [2005] or Raaum et al. [2003] for Norway, Fredriksson and Johansson [2003] for Sweden are several among multiple studies[1].

Nevertheless, with the exception of the work of Leetmaa and Vork [2003] on Estonian data, and Kluve et al. [2002] on data from Poland, this approach is rarely applied to the analysis of transition or accession countries, mainly due the lack of the adequate data. For Latvia, this will be the first microeconomic evaluation of policy intervention.

Primary data files provided by the State Employment Agency of Latvia (SEAL) are used to construct the individual database of unemployed and programme participants (381,844 job seekers in total), registered by SEAL as unemployed in the period between January 2003 and August 2006. Available data allows evaluating the following ALMP programmes: (*i*) unemployed occupational training (vocational training, requalification and rising of qualifications); (*ii*) modular training in state language for non - Latvians; (*iii*) modular training in other skills (foreign language, computer literacy, project management and business operation, driving). We measure the impact of participation in each of those programmes on the unemployed chances to be employed within 6, 9, 12, 18 and 24 months after the date of registration. We assess temporal evolution in programme efficiency by separating the unemployed pool in three groups according to the year of their registration with SEAL (2003, 2004 or 2005 - 2006).

Moreover, large number of observations allows to examine heterogeneity in programme effect across different socio-demographic (gender, age, education) and regional groups. We also test the sensitivity of our results to a so called "hidden" or "covert" bias, related to the potential effect of unobservable variables (motivation, for example) on unemployed participation in evaluated programmes and his/her outcome in the labour market.

The reminder of this chapter is organized as follows. Section 4.2 gives more details on the evaluated measures and completes the descriptives on participation in the ALMP

[1] See Kluve [2007]for a detailed review

programmes in Latvia (given in chapter 3) with the information derived from individual data. The evaluation methodology is presented in section 4.3. Section 4.4 describes the construction of working dataset, introduces the main definitions retained to form treatment and control groups and describes estimation strategy. Evaluation results are displayed and discussed in section 4.5, while section 4.6 concludes and derives policy suggestions.

4.2 Evaluation context

The aim of this chapter is to evaluate the efficiency of unemployed training programmes, proposed by the State Employment Agency of Latvia, on individual employability of participants. Our focus is on the programmes oriented towards increasing the knowledge and skills of unemployed *via* training: occupational training programme (OT) and two types of modular training: language training (MLT) and modular training in other skills (MOT). The individual data used in this chapter (see details in section 4.4) gives the possibility to derive additional information on programme participation and to assess the socio-demographic profile of the participants.

In total over 12 percent of Latvian unemployed, registered with the SEAL between January 2003 and August 2006, completed one of three training programs, mentioned above.

About half of participants (5.4 percent of Latvian unemployed) were involved in **occupational training** (OT)[2]. This programme is implemented in Latvia since the beginning of the 90's and is the most important in terms of allocated funds. The design of the programme allows either obtaining a new profession (vocational training and re-qualification involves 75 percent of participants in occupational training) or upgrading skills in a current occupation (raising of qualifications involves 25 percent of participants). The average duration of the programme is between 4 and 6 months and educational programs are selected by SEAL according to the demand in the labor

[2]The programme evaluated from macroeconomic perspective in chapter 3 of this thesis.

market (inquired through employer's surveys).

Since 2003 the SEAL also organizes modular training: a short-term (50 to 150 hours) training oriented towards the improvement of various basic and comprehensive skills necessary for successful integration in the labour market. Modular training is implemented in the framework of a larger "Measures to Increase Competitiveness" programme (MIC), which also includes professional orientation sessions and consultations on job search methods (short programmes undergone by the majority of job seekers). The aggregate data used in the previous chapters does not allow to distinguish between various sub-types of MIC, making impossible the macroeconomic evaluation of this measure. Individual data, by contrast, gives such possibility and enables us to include modular training in the set of evaluated training programmes. Between January 2003 and August 2006 over 6 percent of all registered unemployed participated in modular training. State Employment agency proposes two types of modular training: language training (MLT) and modular training in other skills (MOT).

Language training is an educational course in state language (Latvian), which is proposed to the unemployed for whom Latvian language is not native. For the record, those compose almost 50 percent of all registered unemployed, but more than half of them do not possed a certificate of proficiency in Latvian language or have the certificate of low level of proficiency. Such certificate is delivered by respective authorities after an examination. For school leavers the examination is provided in the framework of graduation tests, while for older individuals examination sessions are organized in major cities by the CCDE (Center for Curriculum Development and Examinations, operating under the Ministry of Education of Latvia). For the majority of professional jobs, jobs in public sector and jobs in services, the certificate of proficiency (or a certificate of proficiency of a certain level) is a necessary requirement for employment (also at legal level). Therefore the absence of such certificate (or certification of lowest proficiency level) often forms an obstacle to employment: concerned unemployed make therefore a target group for language training programme.

Modular training in other skills (MOT) covers training in foreign language (English, German); computer literacy or improving of computer skills; training in project management, accounting, record keeping, marketing or business operation; receipt of driving licence and qualification (various categories plus tractor driving).

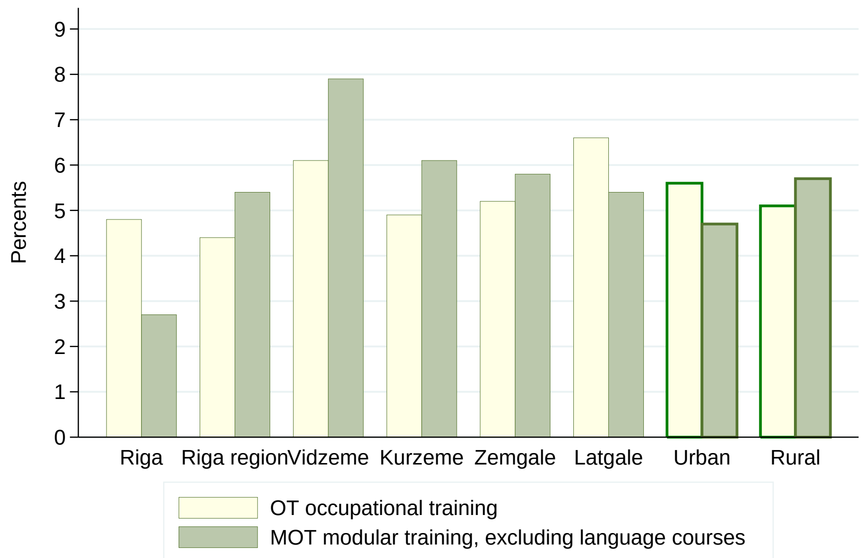
Among all unemployed involved in modular training between years 2003 and 2006, 18 percent completed Latvian language training, 4 percent were involved in business related training (project management, accounting, record keeping), whereas the remaining participants were involved in foreign language training, computer skill related training or driving related training (about 25 percent of participants in each). For 2 percent of unemployed involved in modular training programme language training was combined with other types of modular training, whereas 14 percent of participants have also completed occupational training.

Generally speaking, the highest involvement of unemployed in various training programmes is observed in Vizdeme and Latgale regions, but the lowest - in Riga region (the region surrounding capital city Riga). The participation of unemployed in training programmes is quite similar across urban and rural areas (see figure 4.1). Meanwhile, the unemployed living outside major cities or regional centers are more involved in modular training and less in occupational training.

The participation in training programmes is higher among female unemployed, comparing to males (see table 4.1). In the time period between 2003 and 2006, over 7 percent of females were involved in occupational training and almost 8 percent in various modular training programmes (MLT and MOT). By contrast, only 6 percent of males have undergone either occupational or modular training.

With respect to the age of the unemployed, the participation of unemployed above 45 years of age in training programmes is the lowest for both occupational and modular training. Only 2.1 percent of unemployed in pre-retirement age (over 55) have undergone occupational training and only 3 percent were involved in language or other types of modular training. The participation rates were relatively homogenous within the

Figure 4.1: Unemployed participation in ALMP, by place of residence



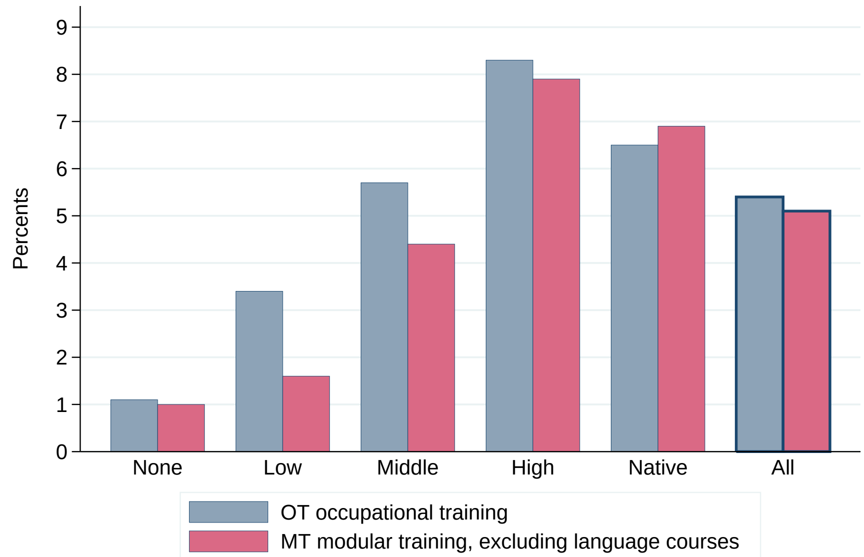
Source: Individual data set constructed from the records of SEAL. Note: Participation is defined in percent of the total number of unemployed in respective region or area.

following age groups - below 25 years, 25 to 34 years, 35 to 44 years: 6 percent for occupational training and 7 percent for various types of modular training in each of these groups.

The participation in training seems to increase with the level of educational attainment: the unemployed with basic education or lower education level display the weakest participation rates, but those with secondary education or above are the most involved in occupational and modular training.

The situation with the proficiency in state (Latvian) language is alarming. About 13 percent of unemployed, registered between the beginning of 2005 and August of 2006, did not possess a certificate of proficiency in Latvian language and 12 more percent had a certificate of low level of proficiency. Recent analysis of unemployment risks and duration by Hazans et al. [2007] shows that those are the groups of unemployed, which, other things equal, have the lowest job finding probabilities, comparing to native

Figure 4.2: Unemployed participation in ALMP, by level of proficiency in Latvian language



Source: Individual data set constructed from the records of SEAL. Notes: Proficiency levels: None - No Latvian language proficiency certificate; Low - Certified low level of proficiency in Latvian; Middle - Certified low level of proficiency in Latvian; High - Certified high level of proficiency in Latvian; Native - Native speaker or graduated from the institution where the courses were held in Latvian; All - All proficiency groups together.

speakers or those with high level of proficiency. The involvement of such unemployed in language training is naturally high (3 percent versus 1 percent on average across all unemployed), but their participation in other training programmes is very low (see figure 4.2). This is mostly due to the fact that occupational and other skill related training courses are provided in Latvian language and the majority of non-Latvians are not able (or are not sure about their ability) to undergo an educational programme in a non-native language.

In what follows, we will evaluate the efficiency of above mentioned programmes (occupational training, modular training in state language and modular training in other skills) in promoting employment among the participants and will assess the heterogeneity of the effects across various socio - demographic groups.

4.3 Evaluation methodology: Propensity score matching

4.3.1 Theoretical issues

The microeconomic evaluation of active labour market policy programmes with non-experimental data is realized within the potential outcome framework of Roy-Rubin model (Roy [1951], Rubin [1974]). The main building blocks of the model are individuals, treatment and potential outcomes.

We consider the participation in one particular programme versus non involvement: each unemployed i from the population of size N faces two exhaustive and exclusive states of nature - participation and non participation. We denote by T_i the variable expressing unemployed participation status: $T_i = 1$ for the unemployed who complete the programme (in the evaluation literature those are often referred to as *treated*) and $T_i = 0$ for those who did not participate in the programme (*untreated* unemployed). Let Y_i be the variable that reflects the unemployed i outcome (result, response) in the labour market. For example, the outcome can be unemployment length or unemployed labour market status at a certain moment of time (say 9 months after registration) or also, his monetary outcome in terms of wage in future job.

It is assumed that participation in the ALMP programme (variable T_i) affects unemployed outcome in the labour market (variable Y_i). This assumption is further verified empirically. The variable $Y_i(T_i)$ reflects the potential labour market outcome, given the participation status of the unemployed: $Y_i(1)$ is the potential outcome if the unemployed completes the evaluated programme and $Y_i(0)$ the potential outcome in the opposite case. The causal effect of the treatment can be defined for each unemployed i as the difference of these two potential outcomes:

$$C_i = Y_i(1) - Y_i(0) \tag{4.1}$$

The fundamental evaluation problem is that individual can only be in one treatment state at a time (either participate in the programme or not). In other words, it is not possible to simultaneously observe $T_i = 1$ and $T_i = 0$, as well as $Y_i(1)$ and $Y_i(0)$. The observed outcome can be written as follows:

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0) \tag{4.2}$$

For treated unemployed ($T_i = 1$) only a realization of $Y_i(1)$ is observable (the variable $(1 - T_i)$ in the equation 4.2 will take the null value), while for untreated unemployed one can only observe the realization of $Y_i(0)$. The unobserved outcome is termed a *counterfactual* outcome[3].

Due to this observation (missing data) problem, neither the individual causal effect of the treatment, nor its distribution over the population of unemployed can be identified. It is common therefore to focus on some features of the impact distribution, such as its mean. The focus is shifted from the evaluation of individual effects to the assessment of population average effects.

The average effect of the programme on the total population of unemployed - ATE for *Average Treatment Effect* - is defined as:

$$C = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)] \tag{4.3}$$

The average effect of the programme on those who have not participated in it - ATN for *Average Treatment effect on Non-treated* - can be expressed as:

$$C_0 = E[Y(1) - Y(0)|_{T=0}] = E[Y(1)|_{T=0}] - E[Y(0)|_{T=0}] \tag{4.4}$$

Nevertheless, for policy evaluation it is more interesting to focus on ATT (*Average Treatment effect on Treated*) - the effect on those who actually have benefited from the treatment. It can be written as follows:

$$C_1 = E[Y(1) - Y(0)|_{T=1}] = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] \tag{4.5}$$

[3]The notion of potential outcome supposes that the effect of the treatment on each individual is not affected by the participation decision on any other individuals, *i.e.* the pair of potential outcomes $(Y_i(1), Y_i(0))$ for individual i is independent of the treatment of other individuals. This assumption (Stable Unit Treatment assumption from Rubin [1980]) guarantees that the average treatment effect can be estimated independently of the size and composition of treated population.

The first component of equation 4.5 is observable and thus can be evaluated from the data: this is the average outcome of the unemployed belonging to the group of programme participants, denoted "T group". By contrast, the second term of the equation, expressing the potential outcome of treated unemployed in the absence of the programme can not be directly observed: it should be estimated. Theoretically, one could use the data on the labour market outcome in the group of those unemployed who did not participate in the programme, denoted "C" group, as counterfactual information. In this case, the following assumption should be made:

$$E[Y(0)|_{T=1}] = E[Y(0)|_{T=0}] = E[Y(0)] \tag{4.6}$$

This assumption supposes that in the absence of the programme both treated and untreated individuals would witness the same labour market outcome. In other words, we suppose that "T" and "C" group individuals are identical in terms of all possible characteristics, other than treatment. All individuals have therefore the same chances to participate in the programme, which means that treatment is assigned on a random basis.

If the assumption 4.6 is verified, then the Average Treatment effect on Treated C_1 can be evaluated by comparing the empirical mean of outcome variable Y_i between two groups of unemployed (treated and untreated).

$$\Delta = E[Y(1)|_{T=1}] - E[Y(0)|_{T=0}] = C_1 \tag{4.7}$$

The difference of empirical means Δ is often termed as "naive" estimator, since it does not take into account such important aspects as selection or self-selection into treatment. In reality the assumption 4.6 rarely holds since treated and untreated individuals are not identical. The heterogeneity comes from various socio-demographic or other factors, observable or potentially unobservable. Those factors may affect both the probability that a given unemployed participates in the programme and his/her outcome at the labour market. For example public temporary job programmes focus on those who have the lowest chances to find jobs by themselves due to insufficient or inadequate education, qualification or due to the lack of other skills. On the other hand the *"cream skimming"* behavior is also common: for achieving better performance results, the staff of the State Employment Agency may tend to select the most motivated and skilled individuals into training programmes. Displaying high learning ability and good chances to complete the programme, those individuals have indeed the highest chances to be employed, even without training. Finally, the subjective anticipation on programme benefits may affect unemployed own motivation and willingness to participate.

When any of the above is the case, one speaks about the *selection bias*, which compromises the assumption on the equity of potential outcomes of treated and untreated individuals in the absence of the programme (4.6) and introduce bias in "naive" estimator Δ:

$$\Delta = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] + E[Y(0)|_{T=1}] - E[Y(0)|_{T=0}] = C_1 + B_{TT} \qquad (4.8)$$

The selection bias can be measured by $B_{TT} = E[Y(0)|_{T=1}] - E[Y(0)|_{T=0}]$.

Thus, when "T" and "C" unemployed groups (treated, control) are not homogeneous with respect to a set of observable individual characteristics X, the difference in labour market outcomes between these two groups can not be attributed only to the effect of the treatment (ALMP programme). This problem can however be solved by comparing the individuals with the same (or similar) characteristics (gender, age, education, for instance). Searching for similar individuals (twins) across "T" and "C" groups is called "matching" or "pairing".

When treated and untreated unemployed are similar in terms of observable individual characteristics X, then those characteristics can not affect the unemployed chances to be treated and thus do not affect the variable T. It can thus be assumed that, conditional on a set of characteristics X the outcomes (Y(1), Y(0)) are independent of programme participation:

$$(Y(1), Y(0)) \amalg T|X \qquad (4.9)$$

Being in the heart of evaluation studies, the assumption 4.9 is known under various names: CIA for Conditional Independence Assumption (Lechner [1999a]), ITA for Ignorable Treatment Assumption (Rosenbaum and Rubin [1983]), or also unconfoundness assumption.

Using CIA, it now can be assumed that "T" and "C" group unemployed would have same labour market outcomes in the absence of the program:

$$E[Y(0)|_{T=1,X}] = E[Y(0)|_{T=0,X}] \tag{4.10}$$

When conditioning on a set of individual characteristics X, the average programme effect on participants C_1(ATT) can be written as follows:

$$C_1 = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] = E_X(E[Y(1)|_{T=1,X}] - E[Y(0)|_{T=1,X}]|_{T=1}) \tag{4.11}$$

And using CIA:

$$C_1 = E_X(E[Y(1)|_{T=1,X}] - E[Y(0)|_{T=0,X}]|_{T=1}) = E_X(E[Y|_{T=1,X}] - E[Y|_{T=0,X}]|_{T=1}) \tag{4.12}$$

The effect C_1 can thus be evaluated by analyzing similar (twin) individuals belonging to "T" and "C" groups and comparing their respective labour market outcomes.

Practice, however, turns to be more complicated than theory: the greater is the number of characteristics included in X - the higher the difficulty to find twins across "T" and "C" groups. The dimension of conditioning may be reduced if instead of the set of variables X one uses a variable which summarizes the effect of X on T. Rosenbaum and Rubin [1983] suggest using the probability of treatment (probability to participate in the programme), conditional on individual characteristics X.

$$\pi(X) = Pr(T = 1|X) = Pr(T|X) \tag{4.13}$$

The probability $\pi(X)$ is often referred to as the *propensity score*.

The use of such balancing score does not compromise the CIA assumption (see Rosenbaum and Rubin [1983] or Dehejia and Wahba [2002]).

$$(Y(1), Y(0)) \amalg |X \Longrightarrow Y(1), Y(0)) \amalg T|\pi(X) \tag{4.14}$$

Using the propensity score, the effect C_1(ATT) can be written as:

$$C_1 = E_{\pi(X)}(E[Y(1)|_{T=1,\pi(X)}] - E[Y(0)|_{T=0,\pi(X)}]|_{T=1}) \tag{4.15}$$

Therefore, the effect of the treatment can be evaluated by using the propensity score to identify "twins" among treated and untreated individuals and by comparing the mean outcomes between "T" and "C" groups in matched sub-samples. However, in order to ensure the comparability between treated and untreated individuals, there must be a sufficient overlap between the propensity scores in two groups of unemployed:

$$0 < \pi(X) < 1 \tag{4.16}$$

This overlap condition is also knows as common support condition (we will return to this issue in what follows).

4.3.2 Practical implementation

In practice the microeconomic evaluation of ALMP programs by *"propensity score matching"* can be realized in two steps.

- **First**, one determines the propensity scores by estimating for each individual (observation) the probability to be treated, conditional on a set of observable characteristics X. It is usually done by using probit or logit models.

- **Second**, using estimated propensity score, one determines the average treatment effect, by performing the following steps:

  – Matching: for each treated unemployed (programme participant), one identifies "twins" - the unemployed from the control group with the same propensity score.

– Estimation of the effect: the effect of the programme (difference between the average outcome of programme participants and their "twins" from the group of control) is estimated for each value of the propensity score.

– Estimation of average treatment effect: the average of the effects, conditioned on the values of propensity scores, is calculated.

Several decisions are made during the implementation: choosing matching algorithm, imposing the common support condition, deciding on the repeated use of the same observations. Various controls should be performed after implementation: assessing matching quality or testing the sensitivity of the results to a so called "hidden" or "covert" bias. We briefly discuss these issues in what follows.

Common support and trimming. In order to realize precise matching "T" and "C" group individuals should have comparable propensity scores. Therefore, after estimating the propensity scores, it is useful to identify the propensity score intervals for each of "T" and "C" groups, to define an interval common for both groups (common support) and to use for matching only the individuals who display the propensity scores belonging to this common interval. Usually the propensity score, which is the probability to participate in the program, is higher in "T" group. The common interval will therefore lay between the minimum value of the propensity score in "T" group to its maximal value in "C" group.

It can occur that even inside the common support interval for some "T" group individuals there is no corresponding "C" group individuals with the same or close value of the propensity score. Therefore, one can analyze the density of propensity score distribution and withdraw from the sample the observations associated with the lowest density of the propensity score. This procedure is called *trimming*. It is common to withdraw 2-5 percent of "T" group individuals.

Matching algorithms. While matching is realized using the mono-dimensional variable $\pi(X)$, it may still be difficult to find for a treated individual a "twin" from the control group with exactly the same value of the propensity score. Several matching algorithms can be used in order to address this problem: stratification on propensity score, nearest neighbor matching, caliper/radius or Kernel matching.

Nearest neighbor is the most straightforward and commonly used method. It proposes for a given "T" group individual to consider as twins those "C" group individuals that have the closest propensity scores. It is possible when realizing matching that some of control group individuals have already been used as "twins". If such individuals are withdrawn from the control group after being used, the control group becomes smaller and it might become more difficult to find matches for the following "T" group individuals. In this case the order in which the individuals are picked for pairing, influences the possibility to find an appropriate match. The researcher should therefore ensure the random ordering of individuals in the sample or (as most commonly used) to allow replacement (*i.e.* repeatedly use the same control observations if necessary). Such decision involves, however, a trade-off between bias and variance (Smith and Todd [2005]): when replacement is allowed the probability of finding the most appropriate "twin" increases, reducing bias between the "T" and "C" groups and improving matching quality, but meanwhile the number of different controls used to construct a comparison group shrinks, hence increasing the variance of the matching estimator.

Nearest neighbor matching does not necessarily mean that there may be only one neighbor for every treated individual. One can use oversampling and identify several closest neighbors for each "T" group individual. In this case the variance-bias tradeoff involves lower variance (more counterfactuals in control group) but higher bias and lower quality of matching. In addition, as remarked by Caliendo and Kopeinig [2005], when using oversampling, one also has to decide on the number of allowed matching partners and on the way of weighting them, when constructing counterfactual information.

Caliper and Radius matching methods consider as twins those "C" group individuals which display the closest propensity scores and are also located within a given distance (caliper) from the propensity score of the considered individual "T". This restricted version of nearest neighbor method, proposed by Cochran and Rubin [1973], is helpful in the situations when the researcher is concerned by matching quality and has reasons to suppose that the nearest neighbor can still be located far away. Another version of caliper matching is radius matching, suggested by Dehejia and Wahba [2002]. They propose to use as counterfactuals, not one but all untreated individuals located within a given radius from the treated individual. As oversampling, described above, it gives reduced variance of estimates but at the same time the risk of bad matches is also reduced by imposing the maximum distance between treated individuals and their "neighbors".

Stratification or interval matching method proposes to realize matching between "T" and "C" group individuals based on the intervals of propensity score values (Rosenbaum and Rubin [1984]). Therefore the common support of the propensity score is separated into a set of intervals (stratas). Then, within each interval, the mean difference in outcomes between treatment and control group is calculated. A weighted average of the interval impact estimates (weighted according to the share of treated population in each interval) is further used to construct overall average impact estimate. The choice of interval length or, equivalently, the number of intervals, is crucial when implementing this method. Following Cochran and Chambers [1965] and further Imbens [2004] for propensity score matching, using five sub-classes is often enough to remove most of the bias associated with all covariates. Meanwhile it is useful to check, first, whether the propensity score is balanced within each stratum (Aakvik [2001]), and second, in case propensity score is balanced, whether the covariates are balanced (Dehejia and Wahba [1999]).

Kernel method is one of the most recently developed matching estimators. It constructs a match for every "T" group individual as a weighted average of all "C" group individuals. Weights are defined according to the distance, in terms of propensity scores and Kernel functions, between each individual from the control group and the "T" group individual for which the match is constructed. The use of more information to construct counterfactuals obviously reduces variance of the estimates, while the fact that all (both "good" and "bad") matches are used to construct counterfactual information, increases bias. As Caliendo and Kopeinig [2005] note, the proper imposition of common support condition is of major importance when implementing Kernel matching. The choice of the Kernel function and the bandwidth is subjective to the researches. However, one should take into account that the choice of the bandwidth parameter involves a tradeoff between a small variance and unbiased estimate of density function (see Caliendo and Kopeinig [2005] for a review).

Matching quality. When matching is completed one can address its quality. Let us recall that the conditioning is realized on the propensity score, and not directly on a set of covariates X. Therefore it is useful to verify the ability of the matching procedure to balance the relevant covariates across treatment and comparison groups. This can be done by estimating the standardized bias before and after matching. Following Rosenbaum and Rubin [1985] and Sianesi [2002], for each covariate in X the standardized bias is defined as the ratio (in percent) of the difference of the sample means in the treated and comparison sub-samples and the square root of the average of the sample variances in both groups. Thus bias before and after matching are defined as:

$$B_{Before}(X) = 100\frac{\overline{X}_1 - \overline{X}_0}{\sqrt{(V_1(X) + V_0(X))/2}}$$

$$B_{After}(X) = 100\frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{(V_1(X) + V_0(X))/2}}$$

The bias before matching is calculated on full treated and control group sub-samples (variables $\overline{X}_1$ and $\overline{X}_0$ denoting respective sample means), while bias after matching is calculated on matched sub-samples of treated and their respective twins (sample means denoted by $\overline{X}_{1M}$ and $\overline{X}_{0M}$).

For a set of covariates, median absolute standardized bias before and after matching may be compared. The total reduction of bias after matching is only possible in case of exact matching, but for propensity score matching the matching quality is considered as sufficient in most empirical studies when a standardized bias is below 3 or 5 percent. In case where some covariate, say variable X_B, is responsible for most of the bias between

"T" and "C" groups, one could think of implementing a combined matching algorithm: exact matching on variable X_B and propensity score matching on the rest of covariates. Technically, this turns to realize a propensity score matching on sub samples, separated by the values of the variable X_B. In addition such separation also allows assessing effect heterogeneity within respective groups.

Matching quality can also be analyzed by re-estimating the propensity scores on the matched sample (as proposed by Sianesi [2002]) and comparing pseudo R2 and the results of the tests for the joint significance of the regressors in the estimated model before and after matching. Obviously, if the quality of matching (twin search) is high, none of the regressors explains the probability of treatment after matching, implying R2 (pseudo) close to zero and P-value of the test for joint significance of the regressors close to one.

Covert bias. The evaluation method described above is based on the unconfoundedness assumption, which states that, conditional on observable characteristics contained in X, treatment is assigned at random. However, a presence of an unobservable variable which simultaneously affects assignment into treatment and the potential outcome makes room for a "hidden bias". Clearly with non-experimental data it is impossible to quantify the magnitude of selection bias induced by such unobserved variable. In turn, it is possible to measure, using sensitivity analysis, the robustness of evaluation results with respect to deviations from the unconfoundedness assumption. Following Rosenbaum [2002] one can determine how strongly should the unobserved variable affect the selection in order to alter the significance of estimated treatment effect. We briefly expose the approach, while a more detailed exposition can be found in Rosenbaum [2002], Aakvik [2001] and Becker and Caliendo [2007]. Assume that the participation probability of the individual i depends on both a set of observed characteristics X_i and the unobservable variable u_i. Then $\pi_i = \pi(X_i, u_i) = Pr(T = 1|X_i, u_i) = F(\beta X_i + \gamma u_i)$, where β reflects the impact of observable characteristics on selection into programme, whereas γ measures the effect of unobservable variable u_i on selection or participation decision. If there is no hidden bias, $\gamma = 0$ and the participation is determined solely by observable characteristics X_i. In contrast, if the study is not free of hidden bias, two individuals similar in terms of observable characteristics X will have different chances to participate in the programme. For example, if the function F is the logistic distribution, the odd ratio of two individuals i and j is given by: $(\frac{\pi_i}{1-\pi_i})/(\frac{\pi_j}{1-\pi_j}) = \frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)} = \frac{e^{\beta X_i+\gamma u_i}}{e^{\beta X_j+\gamma u_j}}$ and, if i and j are similar in terms of observable characteristics X and only differ in terms of unobserved variable u: $(e^{\beta X_i+\gamma u_i})/(e^{\beta X_j+\gamma u_j}) = e^{\gamma(u_i-u_j)}$.

Thus the difference in the odds of i and j in receiving the treatment depends on their unobserved heterogeneity $(u_i - u_j)$, and on the magnitude of the impact that the unobserved variable has on selection (if $\gamma = 0$ odds are the same). Following Aakvik [2001], who proposes to simplify the analysis by treating the unobserved variable as a dummy variable, taking either the null value (if there is no bias) or the unit value (in the opposite case), the variable e^γ, which we denote as Γ, can be seen as a measure of departure from the situation free of bias. As shown by Rosenbaum [2002], the odd ratio that either one of the individuals i or j will receive treatment has the following bounds:

$$\frac{1}{\Gamma} \leq \frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)} \leq \Gamma$$

Both individuals have the same probability to participate in the programme if $\Gamma = e^\gamma = 1$. Otherwise, if $\Gamma = 2$ for example, two individuals which are apparently similar in terms of X could differ in their odds of receiving the treatment by factor of 2. Increasing Γ and examining the implication for the significance of estimated treatment effects would give the insight on the robustness of the evaluation results with respect to potential "hidden bias". Obviously, if only a slight departure from a bias free situation (Γ close to unity) is sufficient to turn the treatment effects into insignificant, the results should be interpreted with caution[4].

[4]This situation does not witness on the presence of a hidden bias or on the fact that the results are in fact insignificant. It just alarms the researcher that the robustness of treatment effects to possible bias is low.

4.4 Dataset, definitions

4.4.1 Dataset construction

Microeconomic evaluation may only be realized using the individual unemployed data: a dataset containing the information on socio-demographic attributes of the unemployed as well as observation-specific information on labour market history and participation in active labour market policy programmes. Since such data set was until recently non-existent for Latvia, we use primary (untreated) data files provided by the State Employment Agency of Latvia to construct the individual database of unemployed and programme participants [5].

The resulting data set gives information on 381 844 job seekers (including programme participants), registered as unemployed in the time period between January 2003 and August 2006. Apart from delivering the information on a large set of individual characteristics of the unemployed - gender, age, ethnicity, place of residence by municipality, major and complementary education, occupation before registration with SEAL, work experience in major or other occupations - it also gives the information on labour market history (unemployment length, direction of outflow from unemployment), allows to identify the history of participation in any of existing ALMP programmes and even enables distinguishing among several programme sub-types.

For evaluation purposes we need to define the treatment and comparison groups. We separately evaluate each of three unemployed training programmes, *i.e.* occupational training (OT), modular training in state language (MLT) and modular training in other skills (MOT). For each of these programmes, the **treatment group** is composed of

[5] The construction of individual database of unemployed and programme participants from primary records of SEAL was only recently (beginning of 2007) completed, with the participation of the author, in the framework of research project on "*Reasons and duration of unemployment and social exclusion in Latvia*" initiated by the Ministry of Welfare of Latvia and founded by ESF (European Social Fund). The contents and structure of primary data files, as well as the information of the procedure of building a unified data set and examination of its adequacy with respect to aggregate data can be the reports to this project or on request from the authors. but those are available on request. All primary data files as well as the resulting data set are the property of the SEAL. Any requests concerning the use of these data should be addressed directly to this organization.

unemployed completed the programme[6]. Due to insufficient number of observations we do not evaluate any combination of the above programs and, in order to avoid evaluating mixed effects, withdraw from the sample the individuals which have completed more than one of the three evaluated programs or more than one of proposed ALMP programmes in general.

The **comparison group** would consist of individuals who did not participate in either one of evaluated programs. We also withdraw from the control group those who participated in subsidized job creation programme or in public temporary work programme (not evaluated here but having potentially important effects on individual employability). At the same time, we allow in both treatment and control groups the participation in the following programmes: information and professional orientation sessions, consultations on job search methods, interview and CV writing, consultation of jurist or psychologist. These programs are very short (several hours), they are undergone by the majority of the unemployed and therefore should not alter the evaluation results.

Another important step is the definition of the **outcome variable**. Since we analyze the employment effects of the programmes we retain as the outcome variable a binary variable capturing the outflow to regular employment at different time horizons (6, 9, 12, 18, 24 months after registration). For example the outcome variable at 6 month horizon takes the unit value for individuals being employed within full 6 months since registration with the SEAL (in other words with unemployment duration below 7 months and outflow direction to employment) and zero otherwise. We will refer to time horizon for outcome variable as THO.

As mentioned above, we limit the treatment group to those unemployed who have completed the evaluated programme, thus excluding from the sample the individuals who at the time of evaluation are still engaged in programmes. However this exclusion

[6] We thus exclude from the sample the individuals who started the programme but for various reasons did not complete it. While it can be argued that those can still benefit from the effect of the program, we are unable to distinguish the reason of interruption (and those reasons can be very different) and choose to avoid another source of unobserved heterogeneity between treatment and control groups. In addition it should be noted that a major part of unemployed (over 80 percent) completes training.

is not total, but is conditional on time horizon chosen for the outcome variable. For example, for time horizon of 6 months, the unemployed still undergoing programmes at the end of the 6th month of unemployment will be withdrawn from the sample. Instead they will be included in the sample for programme evaluation at a longer time horizon, say 9 months, when the programme will most probably be completed.

The estimation sample is also reduced by the presence of the **censure** at the 31 August 2006. In general about 25 percent of the sample are censured. We therefore exclude those from the analysis, but, again, conditional on the time horizon chosen for the outcome variable. For the evaluation horizon of 6 months, we would withdraw all those registered in unemployment after 28 February 2006; for the evaluation horizon of 9 months - those registered after 31 December 2005, and so on. This may seem an important reduction, but in the same time the unemployed withdrawn due to censure are quite alike to all other unemployed in the group; therefore such measure should not alter our results.

The above limitations leave us with a reduced, but sufficiently large sample. For the evaluation of occupational training we dispose a control group of 250,792 individuals and a treatment group of 9 773 unemployed (at THO of 12 months). In order to access temporal developments in programme efficiency, but also with the aim to reduce calculation time, the sample is further split in three sub-samples according to the year of unemployed registration with SEAL: 2003 (81 903 controls and 2 947 participants), 2004 (85 668 controls and 2 759 treated) or 2005 - 2006 (83 221 controls and 4 040 participants).

The evaluation of modular training in state language is only performed for the period 2005-2006. Training in state language is implemented in the framework of modular training since 2003 (before it was implemented in other setting), but in the first two years of implementation the number of treated unemployed was insufficient for evaluation. In addition, modular training in state language is a targeted programme focused on the unemployed with insufficient knowledge of Latvian language. We therefore exclude from the sample native Latvians or those who have graduated from the educational institution with education provided in Latvian (we suppose those are fluent). This leaves us with the sample of 40588 controls and 1311 participants.

As to the evaluation of modular training in other skills, it can be evaluated starting from 2004. We separate the total number of unemployed in two sub-samples according to the year of unemployed registration with SEAL: 2004 (85668 controls and 2130 treated) or 2005-2006 (83221 controls and 5202 participants).

4.4.2 Characteristics of treatment and comparison groups

The descriptive statistics on the estimation sample separated by participation status is given in tables 4.2 -4.3 in the appendix. The application of the matching estimator, used in our analysis, is especially appealing when the groups of treated and untreated individuals are not homogenous in terms of socio-demographic characteristics. Otherwise a sample mean difference ("naive" estimator) would be sufficient to evaluate the treatment effect of the programme. The analysis of the descriptive statistics on the sample of programme participants and non participants reflect that the heterogeneity between the two groups is important, suggesting the presence of selection into programmes.

The highest deviation between programme participants and non-participants is in terms of gender. For all evaluated measures, the sample of untreated individuals is well balanced (almost half-half), whereas the sample of programme participants consists in majority of females (over 60 percent).

Another source of deviation is ethnicity: Latvians represent about 50 percent of all untreated unemployed, while among programme participants[7] from 65 to 70 percent. As suggested above, low participation of non-Latvians may be related to the fact that most training programmes are provided in Latvian language, which is non-native (and

[7]We mean here occupational training and those types of modular training that are not related to state language, since language training is targeted on non-Latvians.

often unspoken) for such unemployed.

In terms of age, the share of prime age individuals (24 to 44 years old) is almost identical among trained and untrained unemployed (about 50 percent). At the same time, programme participants are on average younger than their untrained peers: among treated one can find a higher proportion of unemployed below 24 years old (except for those in modular training) and smaller proportion of senior unemployed.

In terms of education the imbalance mostly concerns the unemployed with the education below basic: representing about 7-10 percent of the control group, those rarely participate in training. This may be due to the low learning ability or to the lack of interest towards learning in this group. It can also reflect the subjective selection criteria of SEAL staff. The proportion of the individuals with higher education is systematically higher among programme participants, and this is especially true for modular training. This is most probably related to the contents of the programme: it proposes, among other, training in business organization, project management, book keeping or computer literacy - skills that make a good complement to higher education.

With regard to the profession, the unemployed with elementary occupation or without any occupation[8] are under-represented among programme participants, while service workers, shop and market sales workers are over-represented. Meanwhile the share of unemployed without work experience is higher among programme participants, comparing to non-participants.

When considering occupational training, the share of unemployed residing in urban areas is comparable across the groups of treated and untreated individuals, while urban residents are clearly more represented among participants in language training and less among the participants in other skill related modular training (especially in 2005-2006).

In terms of regions, most imbalance between the groups of treated and untreated unemployed arises with respect to Riga city - the share of unemployed residing in this area is much lower among programme participants.

[8] See below the definition of main variables.

4.4.3 Matching variables

After defining the estimation samples, we estimate the propensity scores. The following variables are used to define socio-demographic characteristics of the unemployed: gender, age, ethnicity, education, work experience, place of residence, inflow months.

With regard to the age, unemployed are divided in 5 age groups: below 25, 25-34, 35-44, 45-54, over 55.

Ethnicity is defined according to the major groups of Latvian population: Latvian, Russian or other (Ukrainian, Byelorussian, Lithuanian, Estonian, among others). When evaluating modular training in state language (which is focused on non-Latvians) the level of proficiency in Latvian language is used instead of ethnicity. The level of proficiency is defined according to the certificate of proficiency (none, low, middle, high), delivered by respective authorities after an examination.

The education of the unemployed is defined according to 7 levels: less than basic, basic general, basic vocational, secondary general, professional after secondary, higher.

The profession is defined as the occupation at previous job (for those who have worked prior to registration with SEAL) or profession by education (certified by the diploma or graduation certificate, but not necessarily supported by work experience). We also define a complementary variable reflecting work experience; we consider as experienced those unemployed, who have worked prior to registration with SEAL and those who were able to indicate a profession (not necessarily certified) in which they have ever worked. All other unemployed are considered as those without work experience.

Place of residence is defined by aggregating the municipality of residence of the unemployed by districts (for occupational training) or regions (for modular training). Different levels of aggregation are due to very uneven distribution of observations in some sub-samples. Aggregation in districts results in 33 units[9] (7 cities and 26 districts),

[9] NUTS 4 level division.

while aggregation in regions results in 6 units[10] (Riga city separated from surrounding Riga region and 4 other regions of Latvia - Kurzeme, Latgale, Zemgale, Vidzeme). We also introduce a complementary variable displaying wherever the area of residence of the individual is urban (cities and district centers) or rural (all other areas). This allows to control for the differences between two types or areas in terms of programme accessibility and quality as well as in terms of economic activity in the region.

We also use the month of registration with SEAL for the estimation of propensity scores and realizing matching. This allows to introduce a control for seasonality and the effects of other macroeconomic factors.

4.4.4 Estimation strategy

The number of observations in the control group being high, we perform matching using nearest neighbor method, with replacement but without oversampling (one-to-one matching). In order to insure sufficient quality of pairing, we impose a maximal distance (caliper) of 1 percent between treated individuals and their "twins". We impose the common support condition and withdraw from the sample such treated individuals, who's propensity scores are in low density zones (2 percent). We also run a variety of quality and sensitivity tests in order to assess the robustness of the results. The standard errors are calculated using the analytical expression for the variance of the nearest neighbor estimator[11].

As mentioned above, the sample is split in 3 sub-samples, according to the year of unemployed registration with SEAL: 2003, 2004 or 2005-2006. All three sub-samples are used for the evaluation of occupational training programme; for modular training

[10] Roughly corresponding to NUTS 3 level division.

[11] The analytical expression for the nearest neighbor matching estimator (generalized to radius matching) is $ATT = C_1 = \frac{1}{N^T}\sum_{i\in T} Y_i^T - \frac{1}{N^T}\sum_{j\in C} w_j Y_j^C$ and its analytical variance is $Var(C_1) = \frac{1}{N^T}\sum_{i\in T} Var(Y_i^T) + \frac{1}{(N^T)^2}\sum_{j\in C}(w_j^2) Var(Y_j^C)$ with N^T a number of treated individuals in matches sample, Y^T and Y^C the outcomes of treated and control individuals, respectively (see Becker and Ichino [2002]).
The bootstrap on standard errors was neither feasible (due to high calculation time implied by a large sample) nor recommended (Abadie and Imbens [2006] show that the bootstrap fails to work for nearest neighbor matching estimator.

in state language we use 2005-2006 sub-sample and for evaluating modular training in other skills we use 2004 and 2005-2006 sub-samples.

As it can be derived from the comparison of treatment and control groups above, those are rather heterogeneous in terms of gender, age, ethnicity, education, region of residence. Matching estimators based on exact pairing are efficient in reducing such heterogeneity, whereas when pairing (matching) is based on propensity scores, the bias from observable heterogeneity is not always completely eliminated. In order to address this issue, we additionally perform the group specific analysis within the most heterogenous groups (it can also be seen as exact matching on certain of characteristics, combined with propensity score matching on all remaining variables). In addition, such procedure of separate within group analysis allows comparing the estimated treatment effects across various socio-demographic groups of unemployed and thus assessing effect heterogeneity.

For the evaluation of occupational training, the analysis has been separately performed on 20 sub-samples defined according to the following characteristics: gender (2 groups), age (3 groups: below 25, 25 to 44, over 44), ethnicity (3 groups: Latvians, Russians, unemployed of other ethnicity), region of residence (6 groups: Riga city, Riga region, Kurzeme, Latgale, Zemgale, Vidzeme), education (4 groups: basic or less, secondary general, secondary vocational or professional after secondary, higher) and work experience (2 groups).

For the evaluation of modular training in state language, the analysis has been separately performed on 13 sub - samples, defined according to gender (2 groups), level of proficiency in Latvian language (3 groups: low, middle level of proficiency or without certificate), education (4 groups, as above), work experience (2 groups) and area of residence (2 groups: urban, rural).

For the evaluation of modular training in other skills the analysis has been separately performed on 20 sub - samples, defined similarly to those for occupational training.

In order to insure the appropriate observation number for inter-group analysis, the respective sub samples were not separated by the year of unemployed registration with SEAL. We pool all unemployed registered in the period between January 2003 and August 2006, while the year and the month of their registration is, as previously, used for estimation of propensity scores and pairing.

4.5 Empirical results

Let us now turn to the empirical results of evaluation. We first review the estimation of propensity scores, giving information on factors that influence the participation in training programmes. Further, we discuss the estimated treatment effects (overall and within various socio-demographic groups) and assess matching quality and the sensitivity of the results to potential covert bias.

4.5.1 Selection into programmes

The propensity scores for all models were estimated using probit models, where the dependent variable is a binary variable for participation status and explanatory variables are socio-demographic characteristics of the unemployed, as defined above. The results are displayed in table 4.4 in the appendix.

Generally speaking, women have higher probability to participate in both occupational and modular training. The unemployed of 45 years of age and older have low chances to be selected into one of these programmes, while the youngest unemployed (below 25 years old) have the highest chances to participate in occupational training. Compared to Latvians, unemployed with other ethnicity have lower probability to participate in occupational training and in those types of modular training which are not oriented towards improving the proficiency in Latvian language.

The involvement in training is increasing with the level of educational attainment: those with the education level below basic have the lowest probability to participate, while the unemployed with higher education are the ones most likely to participate. Generally, this would witness the selection of the most "able to learn" individuals into programs. However taking into account that the majority of Latvian unemployed obtained their education before 1992, in the framework of old industry oriented system, it may also be argued that even the most educated individuals may need to change or to upgrade their qualifications, and thus benefit from training programmes.

Senior officials, managers, technicians, associate and other professionals as well as clerks, service, shop and market sales workers have the highest probability to participate in all skill related training (occupational training and modular training, except language courses), whereas craft and related trades workers have relatively high chances to be involved in occupational training. Those without any occupation, surprisingly have the lowest chances to participate in occupational training, but high probability to undergo modular training (both language and skill related). When comparing those who have never worked to those who have already participated in the labour market, unemployed with work experience are less involved in occupational training and more in skill related modular training (modular training, excluding language). The unemployed from rural areas have weaker access to programs, their probability to participate is significantly lower comparing with those residing in the cities and district centers.

Within different socio - demographic groups the results are qualitatively the same. Women and young unemployed (below 25) enjoy higher chances to be involved in occupational training, whereas the probability to undergo a training programme is always the lowest among the unemployed older than 45 years (except for those with higher education), among the non-Latvians and those with the lowest education level (below basic), those residing in rural areas (except for Riga region inhabitants). The involvement in training is increasing in education level, except for the young unemployed, the residents of Latgale region and those without work experience. Within these groups unemployed with basic or secondary general education have high chances to participate in training relative to the unemployed with secondary vocational education. Higher education increases the probability to participate in training for males, for the unemployed over 45 years of age, for non-Latvians, for unemployed with work experience and for Riga and Latgale region residents. In contrast, for the youngest unemployed, it decreases the involvement probability.

4.5.2 Treatment effects

Let us now turn to the results of programme evaluation, being displayed in tables 4.5 - 4.10 in the appendix.

Generally, the matching quality is sufficiently high for the results to be interpreted with confidence. Figures 4.8 and 4.9, displaying the distribution of propensity scores across treatment and comparison groups, suggest that the overlap between two groups is sufficient to ensure a large common support and appropriate quality of matching. The result tables (4.5 to 4.7), displaying along with treatment effect the tests for covariate balancing, suggest that matching procedure was successful in reducing the imbalances between treatment and control groups: median bias after matching does not exceed 3 percent. Moreover, re-estimating the propensity scores on the matched data, confirms that none of observable socio-demographic covariates explains participation status after matching, also suggesting that the selection bias has been successfully removed by pairing procedure.

Figure 4.3 below compares the average employment outcomes - a shift from unemployment to employment within 6, 9, 12, 18 and 24 months since registration with SEAL - of trained (treated) and untrained (controls) individuals[12]. The results are displayed separately for each of training programmes (OT, MLT MOT) and are sorted by the year of inflow into unemployment programs (2003, 2004 or 2005-2006).

The results suggest that occupational training (OT) is helpful in adjusting unemployed skills to the requirements of the employers and increases job finding rate among the participants. On average the job finding rate of those who have completed the programme is 1.4 -1.5 times higher than for those unemployed who did not participate in

[12] Hereinafter we will alter the terms employment index, job finding index or rate when referring to the mean employment outcomes in the treatment and control groups.

the programme.

The employment indexes are increasing over time among both trained and untrained unemployed, but faster for programme participants[13]. This suggests that also the average effect of the programme (the difference between the outcomes of trained and untrained), which characterizes the effectiveness of occupational training, also increases over time.

Interesting conclusions may be drawn when comparing the evaluation results, performed by different methods: "naive" estimator, parametric and non-parametric matching estimator (see table 4.10). As above mentioned, "naive" estimator is a simple difference of means between the groups of treated and untreated individuals. Nonparametric matching estimator is the group mean difference between treated and untreated in the matched sample (ATT). It allows to take into account the observed heterogeneity between programme participants and nonparticipants, without assuming a particular form of relationship between treatment and outcome variables. The parametric estimator, in turn, would assume the linear relationship between these two variables. We use for parametric analysis a simple probit model, with binary dependent variable corresponding to an outcome variable used in nonparametric evaluation (employment index at time horizon of 6, 9, 12, 18 or 24 months) and a set of covariates including a dummy variable T reflecting participation status of the unemployed and the socio-demographic characteristics used in propensity score estimation and pairing[14]. In this case, the estimated coefficient of the treatment variable T, allows to derive an approximation of the treatment effect, which can be compared to the results of nonparametric evaluation.

The results displayed in table 4.10 indicate that there is a strong selection into occupational training: the "naive" estimator gives higher differences than matching estimator, showing that the treated have on average better performance than non treated

[13] Compare for example, the job finding outcomes for the unemployed registered in 2003 and those inflowed in 2005-2006: the group mean of the outcome variable at THO of 9 months has increased by 12 percentage points (from 33 to 45 percent) for treated unemployed and by 7 percentage points (from 24 to 31 percent) for untreated.

[14] "Naive" estimator can also be seen as parametric estimator without controlling for the socio-demographic characteristics.

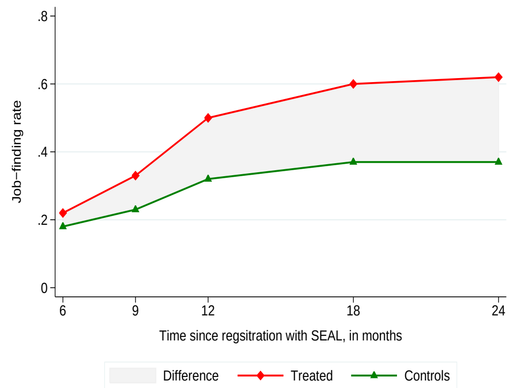
or equivalently, that the most successful individuals are participating in programmes. Meanwhile, the selection can mainly be explained by observable variables: sensitivity of the results to hidden bias is low.

The results suggest that for occupational training in general, only a very important departure from a bias-free situation would alter the significance of the treatment effects. For example at THO of 12 months the treatment effects would turn into insignificant only if the odds in receiving treatment of two individuals, similar with respect to observable characteristics, differ by a factor exceeding 1.5. At higher time horizons, the critical value for this factor is far above 2. The results can therefore be considered as robust *vis-a-vis* to potential "hidden bias".

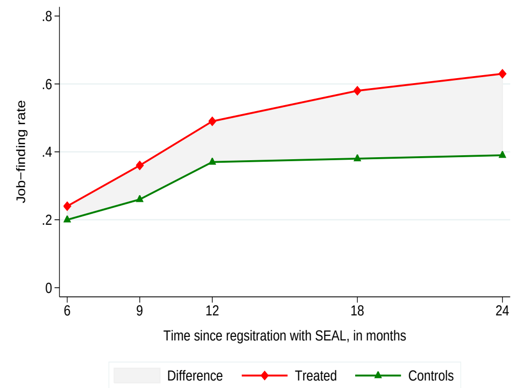
The results of parametric and non-parametric estimators are pretty close, which usually witnesses on the fact that the interaction between treatment and outcome variables may be explained by a linear model. However, when the regressors are all qualitative variables (which is our case) the linear function can be seen as an approximation of a non-linear function by interval, which explains the similarity between parametric and nonparametric results in our case. The figure 4.4 displays the average affect of OT programme (ATT) in different socio-demographic groups of unemployed. We compare the average effect of the programme on the job finding indexes at 12 month horizon (for other time horizons the results are qualitatively similar).

The effect of occupational training does not vary significantly with respect to the gender and is similar for Latvians and Russians, but is stronger for the unemployed with other ethnicity. With respect to the age, youngest unemployed (below 25 years of age) enjoy higher returns to training. The effect of occupational training decreases with the level of educational attainment and is higher for the unemployed without work experience. From regional perspective, the highest difference between treated and untreated individuals is observed in Kurzeme and Zemgale regions, but the lowest in Riga city.

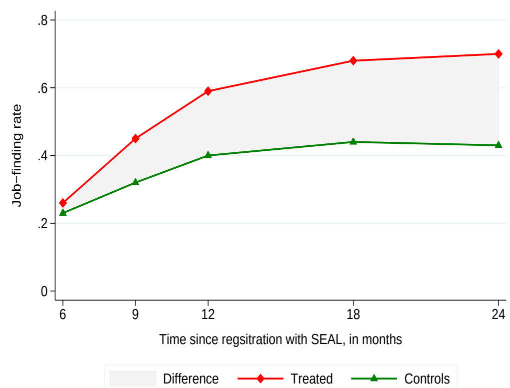
Figure 4.3: Policy evaluation results, by year of inflow into unemployment



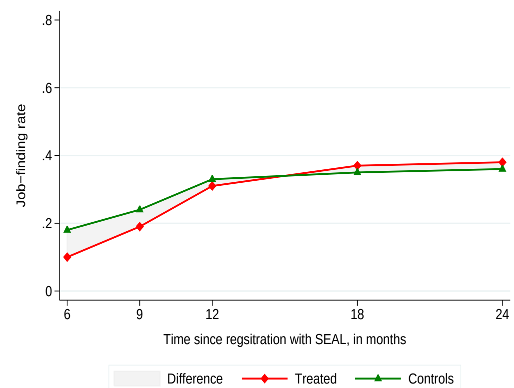
(a) OT, registration in 2003



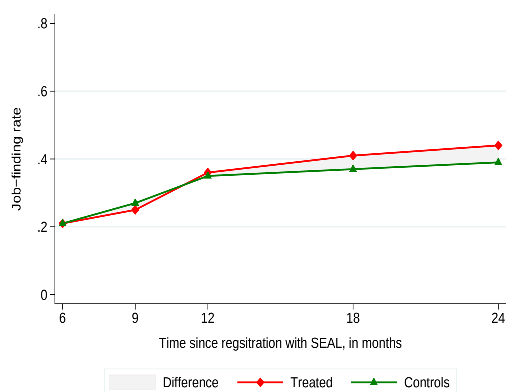
(b) OT, registration in 2004



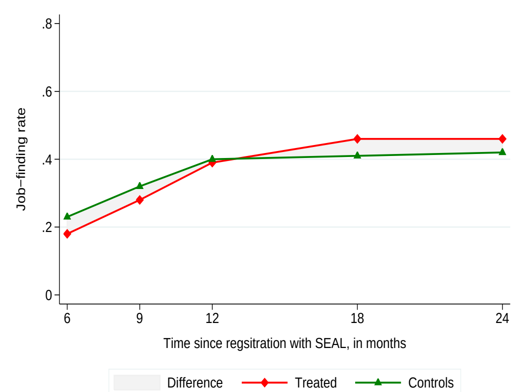
(c) OT, registration in 2005-2006



(d) MLT, registration in 2005-2006



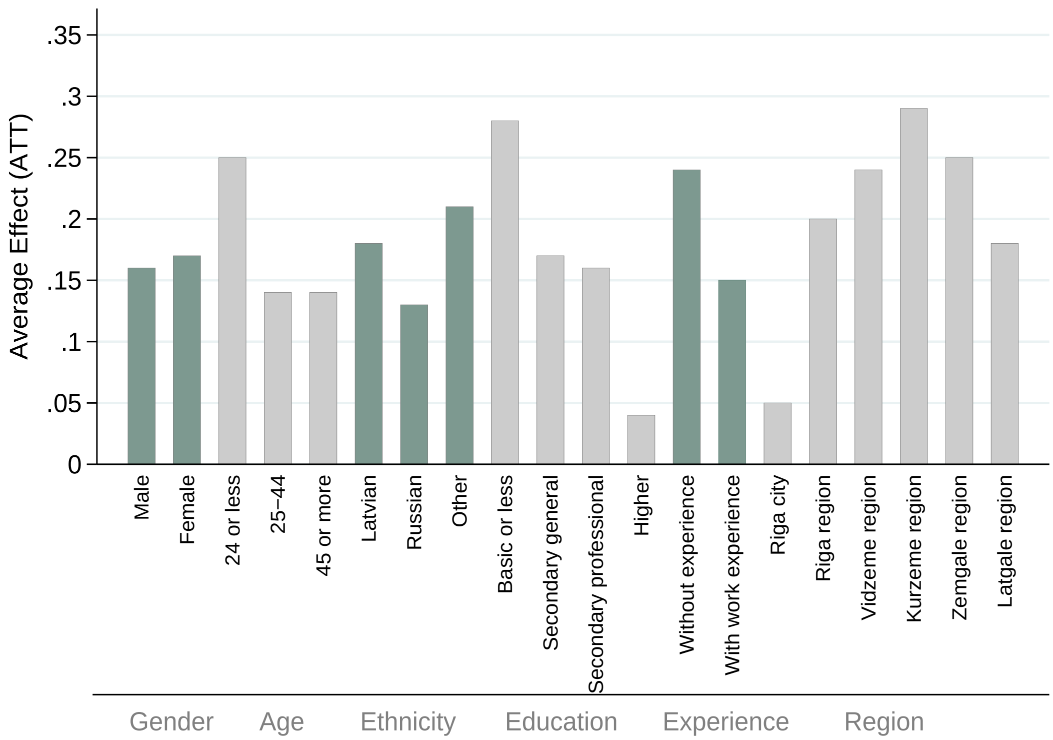
(e) MOT, registration in 2004



(f) MOT, registration in 2005-2006

Source: Author's calculations on SEAL individual data. Notes: Occupational training (OT), Modular language training (MLT), Other modular training (MOT).

Figure 4.4: Average effect of OT programme in different groups of unemployed



Source: Estimation results. Notes: The table displays the estimated ATT in different socio-demographic groups at 12 months time horizon.

As to the effects of modular training in state language, the results are puzzling. At short time horizons (6 and 9 months since registration), the untreated individuals have higher employment indexes than programme participants. This negative difference is statistically significant at short time horizon, but the effect turns to positive but insignificant at longer time horizons. The robustness to hidden bias[15] seems to be sufficiently high to rule out the possibility that the result is due to strong unobserved difference between programme participants and their untrained peers. We therefore conclude that the participation in modular language training along is not sufficient to significantly increase the employment opportunities of unemployed.

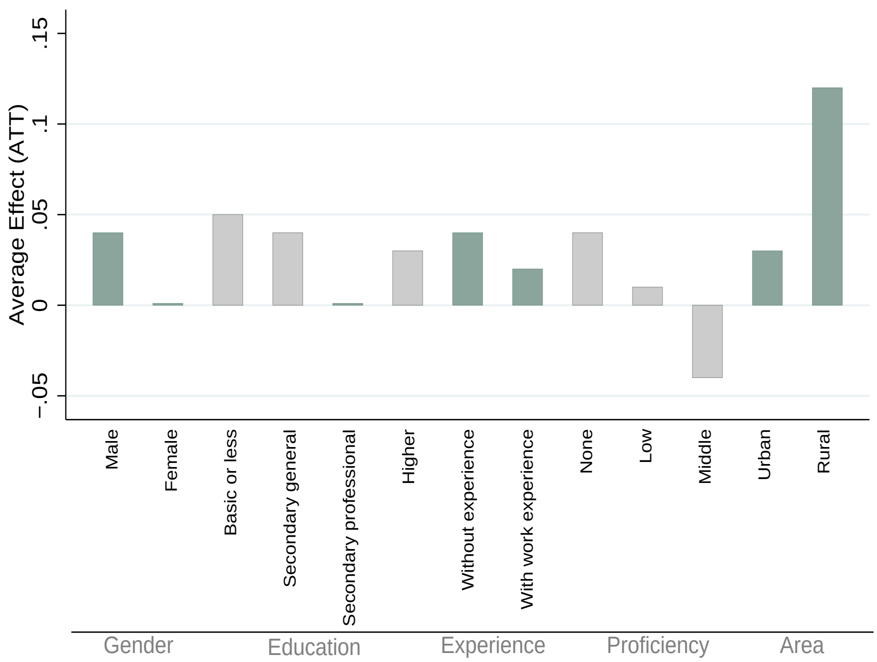
As for the other types of modular training (MLT), the difference between programme

[15]Sensitivity analysis is only performed for statistically significant effects.

participants and non participants is negative or insignificant at short time horizons, but becomes positive and significant in the long run (starting from the time horizon of 18 months). The impact of the programme is thus positive, but weak.

The figures 4.5 - 4.6 display the average affect of modular training (language training and other modular training) programmes in different socio-demographic groups of unemployed. The effect at 18 months horizon is displayed.

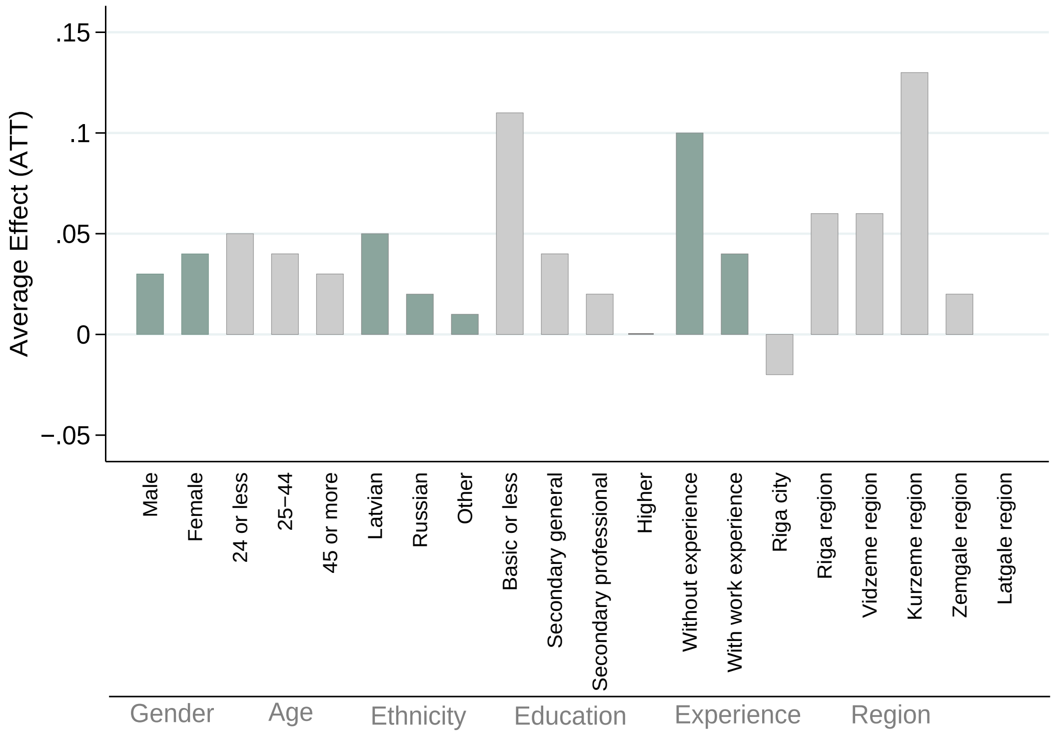
Figure 4.5: Average effect of MLT programme in different groups of unemployed



Source: Estimation results. Notes: The table displays the estimated ATT in different socio-demographic groups at 18 months time horizon.

With regard to modular training in state language, while the overall effect is very weak and in most cases not statistically significant, it seems to be higher among men and among unemployed without work experience, comparing to women and those with work experience, respectively. The unemployed without any certificate of proficiency in Latvian language, seem to benefit more from language training, although the effect is not statistically significant. The only group where language training significantly increases job finding rate among participants the group of rural area inhabitants.

Figure 4.6: Average effect of MOT programme in different groups of unemployed

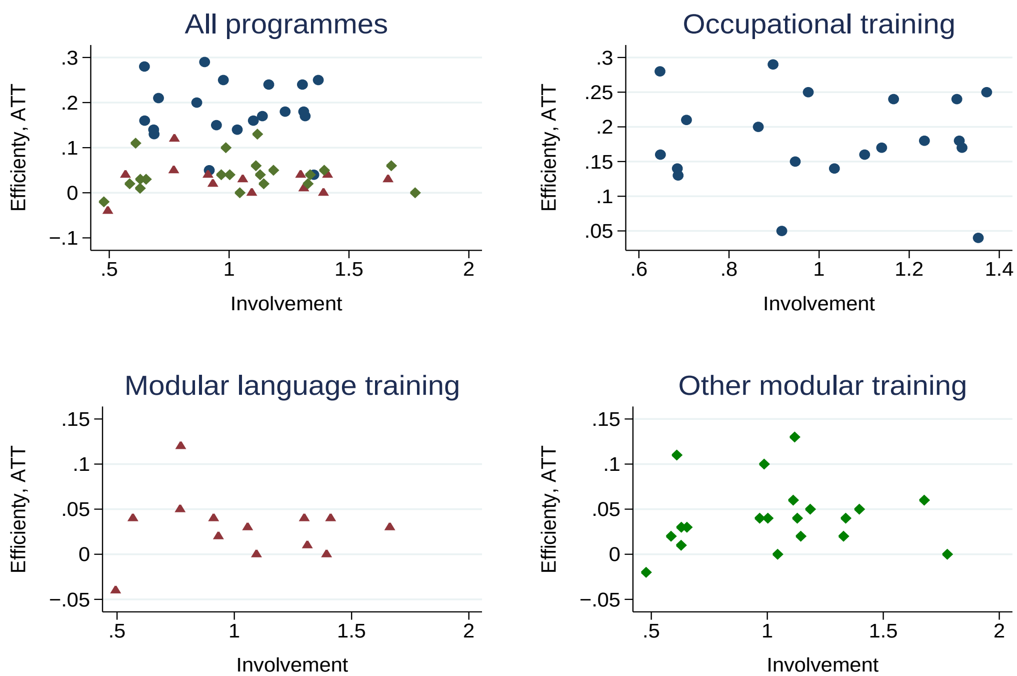


Source: Estimation results. Notes: The table displays the estimated ATT in different socio-demographic groups at 18 months time horizon.

With regard to other types of modular training (foreign language, computer literacy, etc.), the effect at 18 months THO is significant in both gender groups, but higher among women. The efficiency of the programme is decreasing with age and with the level of educational attainment and is higher among the unemployed without work experience, comparing to those who have previously worked. The returns to training are also higher among Latvians, while for the unemployed with any other ethnicity the difference between participants and nonparticipants is not statistically significant. When separating the unemployed according to the region of residence, the modular training has significant effect in Riga, Vidzeme and Kurzeme regions.

The above conclusions rise the following questions. To which extent are training programmes well targeted? Is there an empirical relationship between targeting of the programme and its efficiency? Figure 4.7 explores the interaction between two variables, based on the estimation results for various socio-demographic groups. The targeting of the programme can be analyzed by constructing the involvement or participation index L_i: for each socio-demographic group i the share of i group unemployed among programme participants is normalized by the share of the group in the total population ($L_i = \frac{T_i/T}{N_i/N}$). When L_i is below unity, it means that the group i is under-represented among programme participants (their share among participants is lower than on average among all unemployed). On the contrary, when L_i exceeds unity, the group i is a target group for the programme (the unemployed are over-represented among participants). In these terms, the occupational training programme is targeted on females, young unemployed, Latvians, unemployed with higher education but without work experience, those residing in Vidzeme or Latgale regions. The modular training in state language is targeted, evidently, on the unemployed without any knowledge of Latvian language or with low level of proficiency, but also on females, unemployed with higher education, and those without work experience. As for the other types of skill related training, the targeting is very much similar to the one for occupational training programme.

Figure 4.7: Participation and programme efficiency



Source: Estimation results. Notes: For occupational training the ATE at 12 month horizon is displayed, for modular training - at 18 months. The involvement is defined according to participation index $L_i = \frac{T_i/T}{N_i/N}$.

The efficiency of the programme in a given socio-demographic group can be analyzed by considering the difference in the labour market performance of programme participants and their "twins" from the control group. Neither the overall picture, nor the analysis by programme types is indicating on the positive relationship between targeting of the programme and its efficiency. Instead, data suggests that the best performing groups are not always the best represented.

4.6 Conclusions and policy suggestions

This chapter aims evaluating the employment effects of three training oriented ALMP programmes implemented by Latvian State Employment Agency: (OT) unemployed occupational training (vocational training, re-qualification and rising of qualifications); (MLT) modular training in state language for non - Latvians; (MOT) modular training in other skills (training in foreign language, computer literacy, project management and business operation, driving).

The microeconomic evaluation of unemployed training programmes is performed on an individual dataset constructed from primary data files provided by the SEAL. Matching estimator (propensity score matching) is used to measure the employment effects of the policy intervention.

The results support the positive effect of unemployed occupational training on the employment opportunities of participants. This finding joins the results of microeconometric evaluation of unemployed training in other European counties (using propensity score matching or other evaluation methods). Our evaluation is also in line with the results of the macroeconomic evaluation (performed in chapter 3), which shows that unemployed intensive involvement in occupational training allows to increase aggregate outflows from unemployment to employment.

As macroeconomic analysis, a microeconomic evaluation also highlights the fact that the efficiency of this programme increases over time.

A recent study on unemployed socio-psychological portrait (SEAL [2006]) shows that up to 60 percent of unemployed are ready to learn new professional skills. Meanwhile only 10 percent of them actually undergo SEAL occupational training. In addition, the same study indicates that many of registered unemployed do not have any certified profession or recent working experience (within the last 5 years). For these individuals occupational training can not be replaced (but can be complemented) by other competitiveness stimulating measures (related to the promotion of language, communication, computer and other skills).

Therefore, **further promotion of unemployed occupational training**, while increasing the flexibility of SEAL in adjusting the contents of training courses to current requirements of employers, can be recommended.

Separate within socio-demographic group analysis, performed in order to examine group-specific and regional effect heterogeneity of occupational training shows that the returns to training are homogenous with respect to the gender of the unemployed or their ethnicity (if comparing Latvians and Russians), but are heterogeneous in terms of their age (highest among the youngest unemployed), education or work experience (higher for less educated or experienced unemployed) or place of residence (highest in Kurzeme and Zemgale regions). It is difficult to establish an empirical relationship between the targeting of the programmes and its efficiency. While one of the best performing groups - youngsters - is also the most involved in the programme, other groups of unemployed displaying high returns to training - those with basic education or less and Kurzeme region residents - are not sufficiently represented among programme participants.

As to the evaluation of modular training, the results suggest low efficiency of training in state language and of modular training in other skills, comparing to the impact of occupational training. The language training programme (MLT) does not seem to increase significantly the employment opportunities of the participants, while other types of modular training have a positive, but weak effect, which only becomes statistically significant from 18 months time horizon.

The insignificant impact of language training may be explained by the fact that this training does not involve any certification procedure at the end. Meanwhile the certificate of proficiency is often required by the employers. Therefore the implementation of a **certification procedure after modular training in state language** should be considered.

In addition, a target group for this programme (unemployed without language proficiency certificate or those with the lowest level of proficiency) very weakly participates in other SEA training programs. Nevertheless low transitions to employment in general in this group suggest that the obstacles for succeeding in the labour market for such unemployed may not only be related to the lack of language skills, but also to inadequate level of education, qualifications or other basic and comprehensive skills. For such unemployed, and for the unemployed at high unemployment risk in general, **language training should be more often combined with occupational training** or modular training in computer skills, management, driving and so on.

The non-language modular training has a positive effect on re-employment of participants, but the effect is weak and only appears in the long term (after a year of unemployment). As for modular training in state language, other types of modular training do not deliver a certificate. The possession of the certificate is less of an issue when it is not related to the proficiency in state language, meanwhile the employers may still have doubts on the quality of the training provided by SEAL and the effective capacity of the participants to perform at the work place.

In such a case, it could be interesting **to introduce a combined training/practice at the work place programme**. This programme may consist of usual training programme which is followed by a work/internship period with an employer.

The main advantage of this kind of programme is to combine the provision of practice in the skills, acquired through training, and the reduction of a *"fear factor"* for both unemployed and the employers: employer can observe wherever the unemployed meets the requirements of the job, while worker can develop necessary social skills and self-confidence.

When combined training programme is designed as partially subsidized, employer enjoys benefits from employing the apprentice at reduced cost. In addition, combined training programme is closely monitored by SEAL: which therefore also acts as an insurer for both the employer and the worker.

Some steps in accessing the implementation of such combined training programs have already been made. In particular, the Law on the Support for Unemployed Persons and Persons Seeking Employment has recently been amended by Saema (March 29, 2007). The amendment concern the promotion of type of new active labour market policy programs: the employee-tryout at the work place, which enables the employer to verify in practice the unemployed correspondence to necessary requirements, the training at the work place and other combined training programs.

4.7 Appendixes

Table 4.1: **Unemployed participation in training oriented ALMP programmes**

	Occupational training	Modular training		
	Total (OT)	Total MT	Language (MLT)	Other (MOT)
Total	5.4	6.2	1.1	5.1
Gender				
Male	3.2	3.4	0.6	2.9
Female	7.1	8.4	1.5	6.9
Age				
24 or less	6.9	6.4	0.8	5.6
25 34	5.8	7.4	1.1	6.3
35 44	5.7	6.7	1.4	5.3
45 54	4.5	5.3	1.3	4
55 and more	2.1	3.3	0.9	2.5
Ethnicity				
Latvian	6.7	7	0.1	6.9
Russian	3.9	5.3	2.2	3.1
Other	4.2	5.6	2.2	3.5
Proficiency in Latvian language				
No proficiency certificate	1.1	4.1	3.1	1
Certified low level of proficiency	3.4	5.1	3.4	1.6
Certified middle level of proficiency	5.7	6	1.5	4.4
Certified high level of proficiency	8.3	8.4	0.4	7.9
Native speaker	6.5	6.9	0	6.9
Education				
Educational level less than basic	0.3	1.8	0.7	1.1
Basic education	4.7	4.5	0.8	3.7
Vocational education (without secondary)	3.3	3.4	0.7	2.8
General secondary education	6	6.4	1.1	5.3
Professional secondary education	5.9	7	1.3	5.8
Professional after general secondary	7.1	5.3	0.6	4.7
Higher education	7.2	10.4	1.7	8.8
Work experience				
No	6.5	6.9	1.5	5.3
Yes	5.2	6.1	1	5.1
Place of residence				
Urban (city or district center)	5.6	6.2	1.5	4.7
Rural	5.1	6.2	0.5	5.7
Regions				
Riga	4.8	4.2	1.4	2.7
Riga region	4.4	6.4	1.1	5.4
Vidzeme	6.1	8	0.2	7.9
Kurzeme	4.9	7	0.8	6.1
Zemgale	5.2	6.8	0.9	5.8
Latgale	6.6	7	1.6	5.4

Notes: (1) The table displays the share (in %) of programme participants (those who have completed training) in respective gender, age, ect. group (unemployed registered in 2003-2006). Occupational training (OT) includes training for the the groups at high risk of long-term unemployment. (2) Modular language training (MLT) includes training in Latvian language for non Latvians. (3) Other types of modular training (MOT) include training in foreign language (English, German), computer literacy, training in project management, accounting and sales, as well as training for driving licence of A or B category. (4) Native speakers include Latvians and those non-Latvians who have graduated from the institution where the courses were held in Latvian.

Table 4.2: **Occupational training. Descriptive statistics on estimation sample (employment within 12 months from registration)**

	Occupational training					
Year of registration	2003		2004		2005-2006	
	Controls	Treated	Controls	Treated	Controls	Treated
Total	81903	2947	85668	2759	83221	4040
in % of Total						
Gender						
Male	48	39	48	26	49	28
Female	52	61	52	74	51	72
Age						
24 or less	20	28	20	24	21	31
25-34	26	27	27	28	26	27
35-44	25	26	24	25	23	23
35-54	22	16	22	20	21	16
55 and more	8	3	9	4	9	3
Ethnicity						
Latvian	49	68	49	64	49	64
Russian	36	23	35	25	34	23
Other	15	9	16	11	17	13
Education						
Less than basic	10	1	7	0	9	0
Basic general	18	13	20	15	20	21
Basic vocational	3	2	2	1	2	1
Secondary general	25	30	27	30	27	31
Secondary vocational	36	40	36	41	33	35
Professional after secondary	0	0	0	0	0	0
Higher	8	13	9	12	9	11
Profession						
Military	0	1	0	0	0	0
Legislators, senior officials and managers	3	4	3	4	3	3
Professionals	4	6	4	5	4	5
Technicians and associate professionals	6	10	6	9	7	7
Clerks	5	8	5	10	6	9
Service workers and shop and market sales workers	18	23	17	24	17	22
Skilled agricultural and fishery workers	2	2	3	2	2	1
Craft and related trades workers	16	14	16	12	15	14
Plant and machine op.	13	9	13	8	12	8
Elementary occupations	23	16	23	16	22	18
Did not work or missing information	8	8	10	9	13	13
Work experience						
Without	12	17	14	16	18	23
With	88	83	86	84	82	77
Area						
Urban	63	63	62	67	64	62
Rural	37	37	38	33	36	38
Regions						
Riga city	29	26	29	32	31	25
Riga region	14	16	14	11	14	10
Vidzeme	10	11	10	11	10	12
Kurzeme	14	13	15	11	14	13
Zemgale	13	12	13	12	13	14
Latgale	20	22	19	23	18	25
Month of registration						
January	11	5	10	3	14	16
February	9	5	8	4	11	12
March	8	6	10	5	11	9
April	8	7	8	4	9	7
May	8	8	7	4	9	6
June	7	9	8	4	9	7
July	8	13	8	7	7	8
August	8	11	8	9	8	10
September	9	12	9	12	6	8
October	9	10	8	15	5	7
November	8	9	8	18	5	6
December	9	6	8	14	5	4

Notes: (1) Urban areas include cities and district centers.

Table 4.3: **Modular Training: Descriptive statistics on estimation sample (employment within 12 months from registration**

Registration in	Modular training: Other than language 2004 Controls	2004 Treated	2005 - 2006 Controls	2005 - 2006 Treated	Language 2005 - 2006 Controls	Language 2005 - 2006 Treated
Total	85668	2130	83221	5202	40588	1311
in % of Total						
Gender						
Male	48	27	49	31	48	27
Female	52	73	51	69	52	73
Age						
24 or less	20	19	21	27	18	17
25-34	27	33	26	32	25	24
35-44	24	24	23	23	24	29
35-54	22	18	21	14	23	23
55 and more	9	5	9	4	10	7
Ethnicity						
Latvian	49	69	49	70		
Russian	35	21	34	19		
Other	16	10	17	10		
Proficiency in Latvian						
No certificate of proficiency					31	45
Low level					26	36
Middle level					34	18
High level					9	1
Education						
Less than basic	7	1	9	2	11	7
Basic general	20	11	20	16	16	13
Basic vocational	2	1	2	1	2	2
Secondary general	27	26	27	26	28	26
Secondary vocational	36	41	33	39	34	38
Professional after secondary	0	0	0	0	0	0
Higher	9	19	9	15	8	14
Profession						
Military	0	0	0	0	0	0
Legislators, senior officials and managers	3	5	3	5	3	3
Professionals	4	8	4	6	3	6
Technicians and associate professionals	6	11	7	11	6	7
Clerks	5	9	6	8	5	6
Service workers and shop and market sales workers	17	26	17	25	17	13
Skilled agricultural and fishery workers	3	2	2	2	1	1
Craft and related trades workers	16	10	15	11	18	18
Plant and machine op. and assemblers	13	7	12	7	11	9
Elementary occupations	23	15	22	14	23	22
Did not work or missing information	10	7	13	11	13	14
Work experience						
Without	14	11	18	18	19	24
With	86	89	82	82	81	76
Area						
Urban	62	61	64	54	79	84
Rural	38	39	36	46	21	16
Regions						
Riga city	29	15	31	13	43	39
Riga region	14	14	14	16	10	15
Vidzeme	10	16	10	17	3	1
Kurzeme	15	18	14	15	8	10
Zemgale	13	18	13	18	9	10
Latgale	19	20	18	20	26	25
Month of registration						
January	10	4	14	12	14	15
February	8	4	11	10	12	14
March	10	5	11	10	11	14
April	8	5	9	8	10	10
May	7	6	9	8	9	9
June	8	7	9	9	8	7
July	8	9	7	9	7	7
August	8	9	8	11	8	10
September	9	11	6	9	7	7
October	8	12	5	5	5	4
November	8	14	5	5	5	3
December	8	15	5	3	4	2

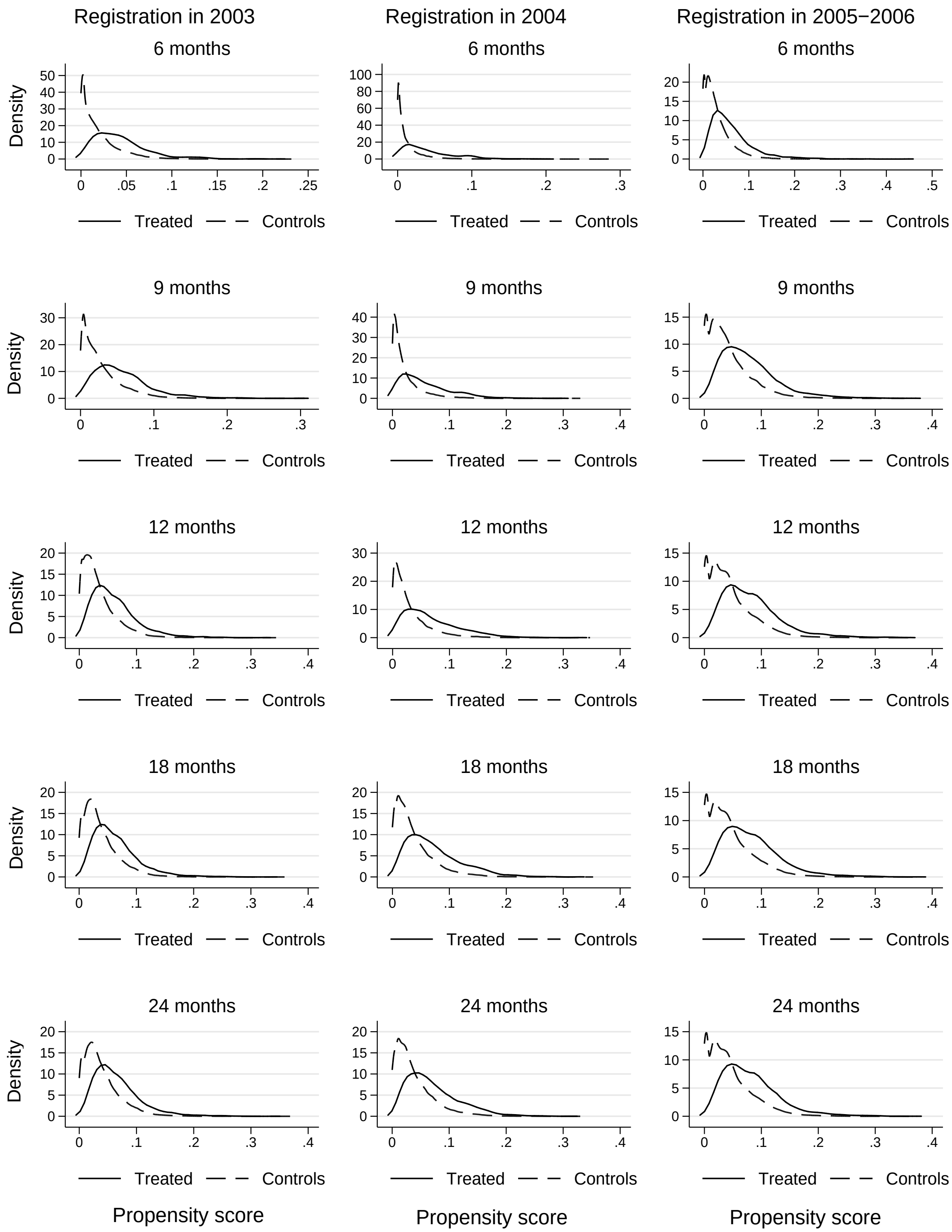
Notes: (1) Urban areas include cities and district centers. (2) When evaluating language courses, those fluent in Latvian or native speakers are excluded from the sample.

Table 4.4: **Estimation of propensity scores with probit models**

	Occupational training			Modular training		
				Language	Other	Other
Registered in	2003	2004	2005-2006	2005-2006	2004	2005-2006
Observations	84877	88427	86621	40963	87798	88329
Constant	**-1.727*** **	**-2.318*** **	**-1.654*** **	**-2.095*** **	**-2.595*** **	**-1.609*** **
	[0.074]	[0.082]	[0.066]	[0.094]	[0.080]	[0.051]
Gender (vs. Male)						
Female	**0.067*** **	**0.390*** **	**0.401*** **	**0.541*** **	**0.327*** **	**0.274*** **
	[0.019]	[0.021]	[0.018]	[0.030]	[0.023]	[0.016]
Age (vs. 25-34)						
Below 25	**0.135*** **	**0.104*** **	**0.149*** **	**0.013**	**-0.041**	**0.024**
	[0.026]	[0.027]	[0.022]	[0.043]	[0.030]	[0.020]
35-44	**0.03**	**0.017**	**-0.004**	**-0.02**	**-0.083*** **	**-0.123*** **
	[0.024]	[0.025]	[0.023]	[0.038]	[0.027]	[0.020]
45-54	**-0.095*** **	**-0.019**	**-0.125*** **	**-0.124*** **	**-0.125*** **	**-0.271*** **
	[0.027]	[0.027]	[0.024]	[0.039]	[0.029]	[0.022]
Over 55	**-0.352*** **	**-0.316*** **	**-0.405*** **	**-0.221*** **	**-0.277*** **	**-0.438*** **
	[0.048]	[0.045]	[0.040]	[0.055]	[0.046]	[0.035]
Education (vs. Secondary vocational)						
Less than basic	**-1.011*** **	**-1.621*** **	**-1.345*** **	**-0.367*** **	**-0.724*** **	**-0.555*** **
	[0.066]	[0.211]	[0.107]	[0.056]	[0.077]	[0.041]
Basic general	**-0.161*** **	**-0.135*** **	**0.032**	**-0.288*** **	**-0.280*** **	**-0.209*** **
	[0.029]	[0.029]	[0.024]	[0.047]	[0.034]	[0.024]
Basic vocational	**-0.165*** **	**-0.233*** **	**-0.172** **	**-0.219** **	**-0.236*** **	**-0.217*** **
	[0.060]	[0.078]	[0.068]	[0.105]	[0.088]	[0.062]
Secondary general	**0.051** **	**-0.039***	**0.057*** **	**-0.123*** **	**-0.070*** **	**-0.087*** **
	[0.022]	[0.023]	[0.020]	[0.036]	[0.025]	[0.019]
Professional after secondary	**0.016**	**-0.05**	**0.103**		**0.166**	**0.056**
	[0.150]	[0.245]	[0.206]		[0.234]	[0.193]
Higher	**0.079** **	**0.01**	**0.086*** **	**0.423*** **	**0.248*** **	**0.151*** **
	[0.033]	[0.034]	[0.031]	[0.051]	[0.034]	[0.027]
Ethnicity (vs. Latvian)						
Russian	**-0.383*** **	**-0.358*** **	**-0.340*** **		**-0.347*** **	**-0.334*** **
	[0.022]	[0.022]	[0.020]		[0.025]	[0.018]
Other	**-0.388*** **	**-0.341*** **	**-0.268*** **		**-0.299*** **	**-0.320*** **
	[0.030]	[0.030]	[0.025]		[0.033]	[0.023]
Proficiency in Latvian (vs. Middle)						
No certificate of proficiency				**0.736*** **		
				[0.039]		
Low level				**0.621*** **		
				[0.039]		
High level				**-0.705*** **		
				[0.092]		
Profession (vs. Elementary occupations)						
Military	**0.298** **	**0.102**	**0.099**	**0.087**	**0.275**	**0.22**
	[0.128]	[0.188]	[0.181]	[0.508]	[0.175]	[0.153]
Legislators, senior officials and managers	**0.167*** **	**0.242*** **	**0.089***	**0.216** **	**0.320*** **	**0.340*** **
	[0.049]	[0.052]	[0.048]	[0.086]	[0.053]	[0.041]
Professionals	**0.195*** **	**0.128** **	**0.007**	**0.267*** **	**0.296*** **	**0.253*** **
	[0.047]	[0.051]	[0.046]	[0.078]	[0.051]	[0.040]
Technicians and associate professionals	**0.226*** **	**0.218*** **	**-0.016**	**0.185*** **	**0.297*** **	**0.283*** **
	[0.038]	[0.040]	[0.036]	[0.063]	[0.042]	[0.032]
Clerks	**0.238*** **	**0.266*** **	**0.166*** **	**0.095**	**0.297*** **	**0.273*** **
	[0.039]	[0.039]	[0.034]	[0.063]	[0.043]	[0.033]
Service workers and shop and market sales workers	**0.152*** **	**0.161*** **	**0.045***	**-0.067**	**0.231*** **	**0.255*** **
	[0.029]	[0.030]	[0.026]	[0.047]	[0.033]	[0.024]
Skilled agricultural and fishery workers	**-0.027**	**0.014**	**-0.119***	**-0.15**	**-0.115**	**0.044**
	[0.066]	[0.067]	[0.067]	[0.134]	[0.077]	[0.057]
Craft and related trades workers	**0.069** **	**0.106*** **	**0.059** **	**0.057**	**0.048**	**0.063** **
	[0.031]	[0.033]	[0.029]	[0.043]	[0.038]	[0.028]
Plant and machine operators and assemblers	**0.001**	**0.063***	**-0.028**	**0.019**	**0.001**	**0.011**
	[0.035]	[0.037]	[0.032]	[0.051]	[0.042]	[0.030]
Without profession or missing inf.	**-0.064**	**0.04**	**-0.202*** **	**0.131***	**0.247*** **	**0.199*** **
	[0.051]	[0.053]	[0.041]	[0.071]	[0.063]	[0.040]
Work experience (vs. None)						
	-0.181* **	**-0.046**	**-0.217*** **	**0.054**	**0.185*** **	**0.052***
	[0.036]	[0.038]	[0.030]	[0.053]	[0.047]	[0.029]
Region (vs. Riga district)						
Riga (city)	**-0.079*** **	**0.131*** **	**0.084*** **	**-0.418*** **	**-0.360*** **	**-0.424*** **
	[0.030]	[0.034]	[0.030]	[0.046]	[0.038]	[0.027]
Vidzeme	**-0.065***	**0.115*** **	**0.257*** **	**-0.638*** **	**0.261*** **	**0.244*** **
	[0.034]	[0.038]	[0.033]	[0.110]	[0.037]	[0.026]
Kurzeme	**-0.093*** **	**0.003**	**0.132*** **	**-0.250*** **	**0.139*** **	**-0.003**
	[0.032]	[0.037]	[0.032]	[0.058]	[0.036]	[0.026]
Zemgale	**-0.033**	**0.125*** **	**0.227*** **	**-0.170*** **	**0.222*** **	**0.163*** **
	[0.033]	[0.036]	[0.031]	[0.056]	[0.036]	[0.025]
Latgale	**0.110*** **	**0.333*** **	**0.447*** **	**-0.219*** **	**0.176*** **	**0.130*** **
	[0.029]	[0.033]	[0.029]	[0.046]	[0.036]	[0.025]
Area (vs. Urban)						
Rural areas	**-0.162*** **	**-0.214*** **	**-0.100*** **	**-0.332*** **	**-0.180*** **	**-0.069*** **
	[0.030]	[0.032]	[0.027]	[0.039]	[0.023]	[0.017]

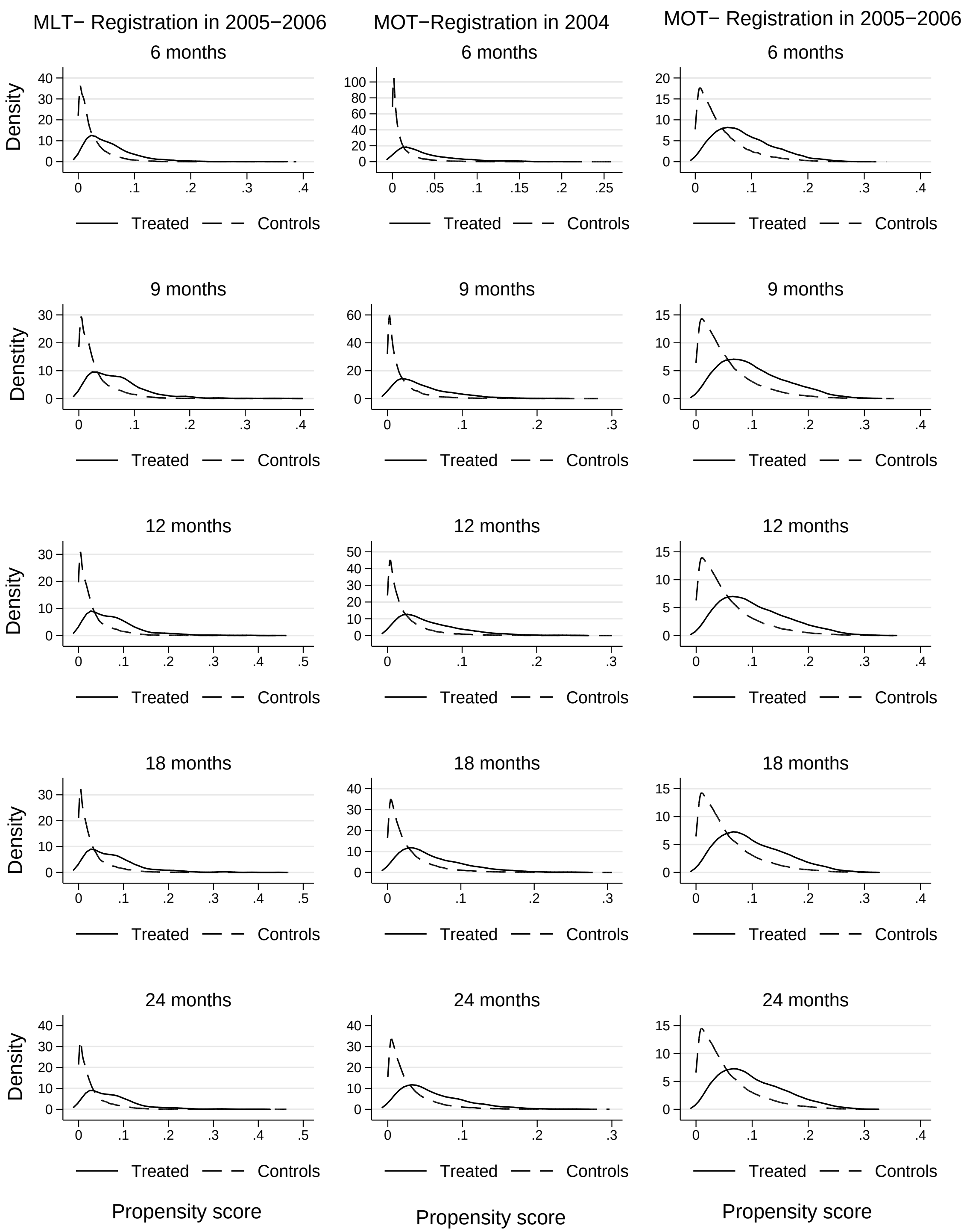
Notes: Table displays the results of probit model estimation, where the dependent variable is participation in the program. Sample used is the employed for the evaluation of programme effects on the re-employment within 12 months from the registration with SEAL (for other time horizons the results hold qualitatively). For evaluation of OT programme the propensity scores were calculated by separating place of residence in 33 districts (for presentation simplicity, we display here separation in 6 regions). The month of inflow into unemployment was included in all models when estimating propensity scores, but are not displayed here. (2) Urban areas include cities and district centers. (3) When evaluating language courses, those fluent in Latvian or native speakers are excluded from the sample.

Figure 4.8: Evaluation of occupations training (OT) programs
Distribution of propensity scores for treatment and control groups



Source: Evaluation results. Evaluation performed by PSM (Propensity Score Matching) for several groups of unemployed, according to the year of inflow into registered unemployment (2003, 2004 or 2005-2006) and for different outcome variables (employment within 6,9,12,18,24 months since registration).

Figure 4.9: Evaluation of modular training (MLT, MOT) programs
Distribution of propensity scores for treatment and control groups



Source: Evaluation results. Evaluation of MLT (language training) performed by PSM for unemployed registered in 2005-2006. Evaluation of MOT (other modular training) performed by PSM separately for unemployed registered in 2004 and for those registered in 2005-2006. Evaluation of MLT and MOT is effectuated for different outcome variables (employment within 6,9,12,18,24 months since registration).

Table 4.5: **Evaluation results: Occupational training (OT)**

Sample					Results					Covariate Balancing				Sensitivty to hidden bias	
Subsample	Year	THO	NOC Treated	NOC Controls	Treated	Controls	Differ.	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi 2$	Median Bias	Q-MH for $\Gamma = 1$	Crit. val. for Γ
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
BEFORE (Unmatched)	2003	6	1475	73276	0.22	0.16	0.06	0.01	6.35	0.107	1545	0.000	7.5		
AFTER (Matched, ATT)	2003	6	1446	73276	0.22	0.18	0.04	0.02	2.34	0.008	33	0.999	1.7	2.43	1.15 - 1.40
BEFORE (Unmatched)	2003	9	2447	81903	0.33	0.20	0.13	0.01	15.74	0.095	2098	0.000	6.5		
AFTER (Matched, ATT)	2003	9	2399	81903	0.33	0.23	0.10	0.01	7.16	0.007	48	0.970	1.5	7.33	1.60 - 1.75
BEFORE (Unmatched)	2003	12	2974	81903	0.50	0.26	0.24	0.01	28.7	0.080	2067	0.000	5.4		
AFTER (Matched, ATT)	2003	12	2915	81903	0.50	0.32	0.17	0.01	12.99	0.009	70	0.417	1.9	13.34	n.i
BEFORE (Unmatched)	2003	18	3259	81903	0.61	0.29	0.32	0.01	38.97	0.075	2074	0.000	5.3		
AFTER (Matched, ATT)	2003	18	3194	81903	0.60	0.37	0.24	0.01	18.58	0.006	56	0.846	1.1	19.01	n.i
BEFORE (Unmatched)	2003	24	3394	81903	0.62	0.30	0.32	0.01	40.45	0.075	2129	0.000	5.3		
AFTER (Matched, ATT)	2003	24	3327	81903	0.62	0.37	0.25	0.01	20.04	0.007	62	0.694	1.8	20.56	n.i
BEFORE (Unmatched)	2004	6	1059	79746	0.24	0.18	0.06	0.01	5.38	0.131	1478	0.000	6.7		
AFTER (Matched, ATT)	2004	6	1038	79746	0.24	0.20	0.04	0.02	2.26	0.014	40	0.996	2.1	1.93	1.10 - 1.40
BEFORE (Unmatched)	2004	9	2028	85668	0.36	0.23	0.13	0.01	13.24	0.118	2282	0.000	6.0		
AFTER (Matched, ATT)	2004	9	1988	85668	0.36	0.26	0.10	0.02	6.18	0.008	44	0.989	1.6	6.16	1.45 - 1.70
BEFORE (Unmatched)	2004	12	2759	85668	0.49	0.29	0.19	0.01	21.67	0.110	2700	0.000	5.8		
AFTER (Matched, ATT)	2004	12	2704	85668	0.49	0.37	0.12	0.01	8.18	0.008	61	0.713	1.5	9.12	n.i
BEFORE (Unmatched)	2004	18	3417	85668	0.59	0.32	0.27	0.01	32.93	0.095	2765	0.000	5.4		
AFTER (Matched, ATT)	2004	18	3351	85668	0.58	0.38	0.20	0.01	15.96	0.007	61	0.668	1.4	17.12	n.i
BEFORE (Unmatched)	2004	24	3465	85111	0.63	0.32	0.31	0.01	37.6	0.091	2656	0.000	5.3		
AFTER (Matched, ATT)	2004	24	3396	85111	0.63	0.39	0.24	0.01	18.99	0.006	54	0.887	0.8	19.80	n.i
BEFORE (Unmatched)	2005-2006	6	3093	94795	0.26	0.22	0.04	0.01	5.51	0.096	2626	0.000	5.3		
AFTER (Matched, ATT)	2005-2006	6	3032	94795	0.26	0.23	0.03	0.01	2.51	0.008	67	0.703	1.4	2.59	1.10 - 1.25
BEFORE (Unmatched)	2005-2006	9	3967	87040	0.45	0.29	0.16	0.01	21.28	0.094	3076	0.000	4.7		
AFTER (Matched, ATT)	2005-2006	9	3888	87040	0.45	0.32	0.13	0.01	11.56	0.007	75	0.423	1.3	12.00	1.70 - 1.90
BEFORE (Unmatched)	2005-2006	12	4040	82581	0.59	0.36	0.23	0.01	29.8	0.093	3031	0.000	4.3		
AFTER (Matched, ATT)	2005-2006	12	3960	82581	0.59	0.40	0.19	0.01	16.8	0.005	54	0.956	1.3	17.47	n.i
BEFORE (Unmatched)	2005-2006	18	3942	80173	0.68	0.38	0.30	0.01	37.92	0.095	3021	0.000	4.4		
AFTER (Matched, ATT)	2005-2006	18	3864	80173	0.68	0.44	0.25	0.01	21.41	0.006	66	0.723	1.3	21.74	n.i
BEFORE (Unmatched)	2005-2006	24	3860	79688	0.70	0.38	0.31	0.01	39.31	0.094	2936	0.000	4.1		
AFTER (Matched, ATT)	2005-2006	24	3783	79688	0.70	0.43	0.27	0.01	23.09	0.007	77	0.380	1.6	23.26	n.i

Note: see explanatory notes after table 4.7.

Table 4.6: **Evaluation results: Modular training (MLT and MOT)**

Subsample (1)	Year (2)	THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi 2$ (13)	Median Biais (14)	Q-MH for $\Gamma = 1$ (15)	Crit. val. for Γ (16)
Language training (MLT)															
BEFORE (Unmatched)	2005-2006	6	1176	45740	0.10	0.19	-0.09	0.01	-7.84	0.109	1194.4	0.000	7.2		
AFTER (Matched, ATT)	2005-2006	6	1153	45740	0.10	0.18	-0.08	0.01	-5.58	0.007	23.4	0.998	1.6	5.78	1.75 - 2.00
BEFORE (Unmatched)	2005-2006	9	1352	41827	0.19	0.25	-0.06	0.01	-5.34	0.114	1368.2	0.000	9.2		
AFTER (Matched, ATT)	2005-2006	9	1325	41827	0.19	0.24	-0.05	0.02	-3.11	0.008	27.8	0.985	2.6	3.00	1.20 - 1.50
BEFORE (Unmatched)	2005-2006	12	1311	39652	0.31	0.32	-0.02	0.01	-1.17	0.123	1429.8	0.000	9.0		
AFTER (Matched, ATT)	2005-2006	12	1285	39652	0.31	0.33	-0.02	0.02	-1.12	0.008	29.6	0.963	2.4	1.01	n.s.
BEFORE (Unmatched)	2005-2006	18	1240	38419	0.37	0.35	0.03	0.01	2.11	0.128	1412.8	0.000	9.1		
AFTER (Matched, ATT)	2005-2006	18	1216	38419	0.37	0.35	0.02	0.02	1.13	0.009	28.7	0.973	1.9	1.52	n.s.
BEFORE (Unmatched)	2005-2006	24	1212	38158	0.38	0.35	0.04	0.01	2.58	0.127	1377.1	0.000	8.8		
AFTER (Matched, ATT)	2005-2006	24	1188	38158	0.38	0.36	0.03	0.02	1.22	0.011	36.9	0.801	2.9	1.42	n.s.
Other types of modular training (MOT)															
BEFORE (Unmatched)	2004	6	1094	85668	0.21	0.18	0.03	0.01	2.74	0.135	1582.5	0.000	16.1		
AFTER (Matched, ATT)	2004	6	1073	85668	0.21	0.21	0.00	0.02	0.05	0.007	20.5	0.997	1.6	0.02	n.s
BEFORE (Unmatched)	2004	9	1707	85668	0.25	0.23	0.02	0.01	2.18	0.120	2011.9	0.000	15.1		
AFTER (Matched, ATT)	2004	9	1673	85668	0.25	0.27	-0.01	0.02	-0.91	0.005	23.9	0.985	1.4	0.81	n.s.
BEFORE (Unmatched)	2004	12	2130	85668	0.36	0.29	0.06	0.01	6.44	0.116	2331.1	0.000	12.1		
AFTER (Matched, ATT)	2004	12	2089	85668	0.36	0.35	0.01	0.02	0.62	0.006	34.7	0.745	1.4	0.67	n.s.
BEFORE (Unmatched)	2004	18	2531	85668	0.41	0.32	0.09	0.01	10.08	0.108	2476.9	0.000	11.5		
AFTER (Matched, ATT)	2004	18	2481	85668	0.41	0.37	0.05	0.01	3.12	0.004	26.3	0.964	1.6	3.39	1.15 - 1.25
BEFORE (Unmatched)	2004	24	2556	85111	0.44	0.32	0.11	0.01	12.04	0.105	2428.4	0.000	11.1		
AFTER (Matched, ATT)	2004	24	2505	85111	0.44	0.39	0.05	0.01	3.09	0.005	34.1	0.769	1.9	3.49	1.15 - 1.30
BEFORE (Unmatched)	2005-2006	6	4839	95341	0.18	0.22	-0.04	0.01	-6.81	0.098	3807.1	0.000	8.6		
AFTER (Matched, ATT)	2005-2006	6	4743	95341	0.18	0.23	-0.05	0.01	-6.15	0.003	42.1	0.712	1.0	6.02	1.30 - 1.45
BEFORE (Unmatched)	2005-2006	9	5333	87586	0.28	0.30	-0.01	0.01	-2.28	0.100	4091.7	0.000	9.2		
AFTER (Matched, ATT)	2005-2006	9	5227	87586	0.28	0.32	-0.04	0.01	-3.77	0.003	41.2	0.745	1.1	3.74	1.15 - 1.30
BEFORE (Unmatched)	2005-2006	12	5202	83127	0.39	0.36	0.03	0.01	4.87	0.101	3986.8	0.000	9.6		
AFTER (Matched, ATT)	2005-2006	12	5098	83127	0.39	0.40	0.00	0.01	-0.24	0.004	53.1	0.252	1.1	0.36	n.s.
BEFORE (Unmatched)	2005-2006	18	4918	80719	0.46	0.38	0.07	0.01	10.41	0.099	3732.1	0.000	8.2		
AFTER (Matched, ATT)	2005-2006	18	4820	80719	0.46	0.41	0.05	0.01	4.31	0.002	29.8	0.982	1.2	4.40	1.15 - 1.25
BEFORE (Unmatched)	2005-2006	24	4834	80234	0.47	0.39	0.08	0.01	11.16	0.100	3693.6	0.000	8.3		
AFTER (Matched, ATT)	2005-2006	24	4738	80234	0.46	0.42	0.04	0.01	4.01	0.004	50.6	0.373	1.4	4.13	1.15 - 1.25

Note: see explanatory notes after table 4.7.

Table 4.7: **Evaluation results within groups: Occupational training (OT)**

Sample				Results					Covariate Balancing			
Subsample (1)	THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi 2$ (13)	Median Biais (14)
Gender: Males												
BEFORE (Unmatched)	6	1842	117721	0.23	0.18	0.05	0.01	5.02	0.103	1954	0.000	5.6
AFTER (Matched, ATT)	6	1807	117721	0.23	0.21	0.02	0.01	1.72	0.012	61	0.996	1.6
BEFORE (Unmatched)	9	2645	121691	0.37	0.24	0.13	0.01	15.47	0.089	2286	0.000	5.8
AFTER (Matched, ATT)	9	2593	121691	0.37	0.28	0.09	0.01	6.81	0.010	70	0.978	1.7
BEFORE (Unmatched)	12	3000	119843	0.50	0.29	0.20	0.01	23.72	0.079	2242	0.000	5.0
AFTER (Matched, ATT)	12	2940	119843	0.49	0.33	0.16	0.01	12.3	0.008	66	0.992	1.2
BEFORE (Unmatched)	18	3200	118837	0.59	0.32	0.27	0.01	32.35	0.074	2179	0.000	4.7
AFTER (Matched, ATT)	18	3136	118837	0.59	0.35	0.23	0.01	18.47	0.007	57	0.999	1.2
BEFORE (Unmatched)	24	3220	118385	0.61	0.32	0.29	0.01	34.19	0.072	2135	0.000	4.6
AFTER (Matched, ATT)	24	3156	118385	0.61	0.35	0.26	0.01	20.85	0.009	78	0.899	1.5
Gender: Females												
BEFORE (Unmatched)	6	3785	136789	0.25	0.19	0.07	0.01	10.65	0.120	4184	0.000	6.2
AFTER (Matched, ATT)	6	3710	136789	0.25	0.22	0.03	0.01	2.94	0.008	81	0.867	1.4
BEFORE (Unmatched)	9	5797	132291	0.40	0.25	0.16	0.01	27.46	0.097	4686	0.000	5.2
AFTER (Matched, ATT)	9	5682	132291	0.40	0.29	0.11	0.01	11.85	0.006	91	0.612	1.0
BEFORE (Unmatched)	12	6773	129680	0.55	0.31	0.24	0.01	40.55	0.084	4524	0.000	4.4
AFTER (Matched, ATT)	12	6638	129680	0.55	0.38	0.17	0.01	18.66	0.006	120	0.060	1.0
BEFORE (Unmatched)	18	7418	128278	0.65	0.34	0.31	0.01	53.88	0.074	4245	0.000	3.9
AFTER (Matched, ATT)	18	7270	128278	0.65	0.40	0.24	0.01	28.35	0.005	110	0.180	1.1
BEFORE (Unmatched)	24	7499	127688	0.67	0.35	0.32	0.01	57.48	0.070	4085	0.000	3.7
AFTER (Matched, ATT)	24	7350	127688	0.67	0.41	0.26	0.01	31.06	0.006	126	0.026	0.9
Age: Below 25												
BEFORE (Unmatched)	6	1669	49238	0.26	0.17	0.09	0.01	8.98	0.134	1969	0.000	6.2
AFTER (Matched, ATT)	6	1636	49238	0.26	0.17	0.09	0.02	5.86	0.017	77	0.823	1.7
BEFORE (Unmatched)	9	2437	50927	0.42	0.21	0.21	0.01	24.27	0.121	2406	0.000	6.0
AFTER (Matched, ATT)	9	2389	50927	0.42	0.22	0.21	0.01	14.76	0.017	113	0.089	1.6
BEFORE (Unmatched)	12	2746	50295	0.52	0.25	0.27	0.01	31.03	0.110	2371	0.000	5.8
AFTER (Matched, ATT)	12	2692	50295	0.52	0.27	0.25	0.01	18.51	0.013	95	0.415	2.0
BEFORE (Unmatched)	18	2941	50038	0.59	0.26	0.32	0.01	38.6	0.101	2299	0.000	5.7
AFTER (Matched, ATT)	18	2883	50038	0.59	0.29	0.30	0.01	22.37	0.011	87	0.657	1.4
BEFORE (Unmatched)	24	2955	49970	0.60	0.27	0.34	0.01	40.2	0.100	2287	0.000	5.6
AFTER (Matched, ATT)	24	2896	49970	0.61	0.29	0.32	0.01	23.88	0.007	57	0.999	1.5
Age: From 25 to 44												
BEFORE (Unmatched)	6	2821	130239	0.24	0.20	0.05	0.01	6.26	0.114	3102	0.000	6.1
AFTER (Matched, ATT)	6	2765	130239	0.25	0.23	0.01	0.01	1.03	0.009	68	0.971	1.2
BEFORE (Unmatched)	9	4312	126392	0.39	0.26	0.13	0.01	19.21	0.092	3502	0.000	5.1
AFTER (Matched, ATT)	9	4226	126392	0.39	0.30	0.09	0.01	8.49	0.005	60	0.997	1.0
BEFORE (Unmatched)	12	5045	124205	0.54	0.33	0.22	0.01	31.87	0.082	3491	0.000	4.5
AFTER (Matched, ATT)	12	4945	124205	0.54	0.40	0.14	0.01	13.16	0.005	70	0.969	0.9
BEFORE (Unmatched)	18	5530	123088	0.64	0.35	0.29	0.01	44.53	0.074	3380	0.000	3.6
AFTER (Matched, ATT)	18	5420	123088	0.65	0.42	0.23	0.01	22.73	0.005	81	0.833	1.0
BEFORE (Unmatched)	24	5589	122646	0.67	0.36	0.31	0.01	47.9	0.072	3304	0.000	3.5
AFTER (Matched, ATT)	24	5478	122646	0.67	0.43	0.24	0.01	24	0.006	98	0.337	1.0
Age: 45 and above												
BEFORE (Unmatched)	6	1137	74195	0.23	0.17	0.06	0.01	5.71	0.120	1415	0.000	8.8
AFTER (Matched, ATT)	6	1115	74195	0.23	0.19	0.05	0.02	2.65	0.016	50	0.999	2.2
BEFORE (Unmatched)	9	1693	76300	0.36	0.23	0.13	0.01	12.48	0.116	1894	0.000	7.1
AFTER (Matched, ATT)	9	1661	76300	0.35	0.27	0.08	0.02	4.79	0.011	52	0.999	1.5
BEFORE (Unmatched)	12	1982	74660	0.53	0.30	0.23	0.01	21.82	0.109	2007	0.000	6.2
AFTER (Matched, ATT)	12	1944	74660	0.53	0.39	0.14	0.02	8.46	0.011	58	0.999	1.4
BEFORE (Unmatched)	18	2147	73626	0.64	0.33	0.31	0.01	29.59	0.107	2091	0.000	5.5
AFTER (Matched, ATT)	18	2105	73626	0.64	0.43	0.21	0.02	13.35	0.009	54	0.999	1.5
BEFORE (Unmatched)	24	2175	73094	0.67	0.34	0.33	0.01	31.7	0.104	2058	0.000	5.7
AFTER (Matched, ATT)	24	2132	73094	0.67	0.44	0.22	0.02	14.25	0.009	52	0.999	1.5

Evaluation results within groups: Occupational training (OT) - cont.

Sample				Results					Covariate Balancing			
Subsample (1)	THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi2$ (13)	Median Biais (14)
Ethnicity: Latvian												
BEFORE (Unmatched)	6	3632	128391	0.26	0.21	0.04	0.01	6.32	0.108	3595	0.000	7.5
AFTER (Matched, ATT)	6	3560	128391	0.26	0.23	0.03	0.01	2.93	0.008	76	0.926	1.3
BEFORE (Unmatched)	9	5478	124623	0.41	0.27	0.14	0.01	22.45	0.086	3927	0.000	5.9
AFTER (Matched, ATT)	9	5369	124623	0.41	0.30	0.11	0.01	11.36	0.005	80	0.867	0.9
BEFORE (Unmatched)	12	6366	122435	0.56	0.34	0.22	0.01	35.96	0.075	3810	0.000	5.0
AFTER (Matched, ATT)	12	6240	122435	0.56	0.38	0.18	0.01	19.24	0.004	77	0.921	0.9
BEFORE (Unmatched)	18	6894	121287	0.65	0.36	0.29	0.01	48.9	0.068	3649	0.000	4.7
AFTER (Matched, ATT)	18	6757	121287	0.65	0.40	0.25	0.01	28.1	0.004	81	0.841	0.9
BEFORE (Unmatched)	24	6945	120820	0.67	0.37	0.31	0.01	52.04	0.066	3558	0.000	4.7
AFTER (Matched, ATT)	24	6807	120820	0.67	0.41	0.26	0.01	29.58	0.005	87	0.721	1.0
Ethnicity: Russian												
BEFORE (Unmatched)	6	1352	86273	0.22	0.16	0.06	0.01	5.73	0.117	1640	0.000	6.6
AFTER (Matched, ATT)	6	1325	86273	0.21	0.19	0.03	0.02	1.62	0.014	50	0.999	2.0
BEFORE (Unmatched)	9	2009	89215	0.34	0.21	0.14	0.01	14.71	0.111	2133	0.000	5.6
AFTER (Matched, ATT)	9	1969	89215	0.35	0.25	0.10	0.02	6.46	0.012	67	0.986	1.7
BEFORE (Unmatched)	12	2333	87710	0.47	0.27	0.20	0.01	21.47	0.096	2082	0.000	4.9
AFTER (Matched, ATT)	12	2287	87710	0.48	0.35	0.13	0.02	8.28	0.012	75	0.915	1.7
BEFORE (Unmatched)	18	2563	86849	0.56	0.30	0.27	0.01	29.02	0.090	2088	0.000	4.8
AFTER (Matched, ATT)	18	2512	86849	0.57	0.37	0.20	0.01	13.81	0.008	57	0.999	1.7
BEFORE (Unmatched)	24	2598	86435	0.59	0.30	0.29	0.01	31.57	0.087	2053	0.000	4.8
AFTER (Matched, ATT)	24	2547	86435	0.59	0.38	0.22	0.01	15.07	0.011	76	0.895	1.6
Ethnicity: Other												
BEFORE (Unmatched)	6	643	39101	0.26	0.16	0.10	0.01	6.73	0.137	903	0.000	6.5
AFTER (Matched, ATT)	6	631	39101	0.26	0.18	0.08	0.02	3.2	0.033	57	0.994	2.6
BEFORE (Unmatched)	9	955	40101	0.38	0.21	0.17	0.01	12.28	0.126	1147	0.000	6.4
AFTER (Matched, ATT)	9	936	40101	0.38	0.25	0.13	0.02	5.77	0.021	54	1.000	2.6
BEFORE (Unmatched)	12	1074	39335	0.52	0.28	0.24	0.01	17.64	0.113	1122	0.000	5.5
AFTER (Matched, ATT)	12	1054	39335	0.52	0.31	0.21	0.02	9.57	0.026	77	0.906	2.8
BEFORE (Unmatched)	18	1161	38936	0.62	0.30	0.33	0.01	23.84	0.105	1100	0.000	5.5
AFTER (Matched, ATT)	18	1138	38936	0.63	0.37	0.26	0.02	12.4	0.022	68	0.983	2.1
BEFORE (Unmatched)	24	1176	38775	0.64	0.30	0.34	0.01	24.87	0.103	1092	0.000	5.3
AFTER (Matched, ATT)	24	1153	38775	0.64	0.35	0.29	0.02	14.28	0.015	48	0.999	1.9
Education: Basic or less												
BEFORE (Unmatched)	6	1150	69596	0.24	0.13	0.11	0.01	10.6	0.179	2109	0.000	7.0
AFTER (Matched, ATT)	6	1127	69596	0.24	0.16	0.08	0.02	4.79	0.016	50	0.999	2.2
BEFORE (Unmatched)	9	1644	75368	0.40	0.17	0.23	0.01	23.93	0.180	2863	0.000	6.7
AFTER (Matched, ATT)	9	1612	75368	0.40	0.19	0.21	0.02	12.86	0.014	64	0.989	1.6
BEFORE (Unmatched)	12	1857	74191	0.49	0.21	0.29	0.01	29.89	0.164	2868	0.000	6.9
AFTER (Matched, ATT)	12	1820	74191	0.50	0.22	0.28	0.02	17.49	0.012	59	0.997	1.7
BEFORE (Unmatched)	18	2020	73510	0.57	0.22	0.35	0.01	36.6	0.158	2944	0.000	6.4
AFTER (Matched, ATT)	18	1980	73510	0.58	0.25	0.33	0.02	21.27	0.011	61	0.996	1.4
BEFORE (Unmatched)	24	2030	73189	0.59	0.23	0.37	0.01	38.55	0.156	2920	0.000	6.3
AFTER (Matched, ATT)	24	1991	73189	0.60	0.23	0.37	0.02	24.42	0.011	63	0.992	1.5
Education: Secondary general												
BEFORE (Unmatched)	6	1677	67346	0.24	0.18	0.06	0.01	6.22	0.120	1892	0.000	6.9
AFTER (Matched, ATT)	6	1644	67346	0.25	0.21	0.04	0.02	2.43	0.011	50	0.999	1.6
BEFORE (Unmatched)	9	2556	67196	0.38	0.24	0.14	0.01	16.5	0.106	2314	0.000	6.1
AFTER (Matched, ATT)	9	2505	67196	0.39	0.29	0.10	0.01	7.05	0.009	64	0.984	1.2
BEFORE (Unmatched)	12	2964	66002	0.52	0.31	0.21	0.01	24.64	0.095	2311	0.000	4.5
AFTER (Matched, ATT)	12	2905	66002	0.52	0.36	0.17	0.01	12.41	0.008	61	0.993	1.4
BEFORE (Unmatched)	18	3209	65397	0.63	0.33	0.29	0.01	34.19	0.084	2184	0.000	4.8
AFTER (Matched, ATT)	18	3146	65397	0.63	0.39	0.24	0.01	17.92	0.008	66	0.974	1.3
BEFORE (Unmatched)	24	3239	65098	0.65	0.34	0.31	0.01	36.22	0.082	2135	0.000	4.5
AFTER (Matched, ATT)	24	3175	65098	0.65	0.40	0.25	0.01	19.68	0.006	49	0.999	1.0

Evaluation results within groups: Occupational training (OT) - cont.

Sample					Results					Covariate Balancing			
Subsample		THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi2$	Median Biais
(1)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Education: Secondary professional													
BEFORE	(Unmatched)	6	2118	89256	0.25	0.20	0.05	0.01	5.76	0.101	2041	0.000	6.2
AFTER	(Matched, ATT)	6	2076	89256	0.25	0.21	0.04	0.01	2.69	0.009	52	0.999	1.4
BEFORE	(Unmatched)	9	3239	89022	0.39	0.27	0.13	0.01	15.85	0.079	2226	0.000	5.8
AFTER	(Matched, ATT)	9	3175	89022	0.39	0.29	0.10	0.01	8.39	0.008	71	0.932	1.3
BEFORE	(Unmatched)	12	3787	87355	0.54	0.34	0.20	0.01	25.36	0.070	2217	0.000	4.0
AFTER	(Matched, ATT)	12	3712	87355	0.54	0.38	0.16	0.01	13.12	0.008	77	0.829	1.3
BEFORE	(Unmatched)	18	4112	86364	0.64	0.37	0.27	0.01	34.87	0.063	2118	0.000	3.8
AFTER	(Matched, ATT)	18	4030	86364	0.64	0.41	0.23	0.01	19.74	0.007	77	0.861	1.3
BEFORE	(Unmatched)	24	4155	85975	0.66	0.38	0.29	0.01	37.42	0.061	2059	0.000	3.8
AFTER	(Matched, ATT)	24	4072	85975	0.66	0.41	0.25	0.01	22.06	0.008	86	0.666	1.4
Education: Higher													
BEFORE	(Unmatched)	6	682	21501	0.25	0.29	-0.04	0.02	-2.16	0.079	484	0.000	5.6
AFTER	(Matched, ATT)	6	669	21501	0.24	0.28	-0.03	0.03	-1.36	0.026	48	0.999	2.9
BEFORE	(Unmatched)	9	1003	22005	0.41	0.38	0.03	0.02	1.88	0.070	577	0.000	4.7
AFTER	(Matched, ATT)	9	983	22005	0.40	0.40	0.00	0.02	0.18	0.018	50	0.999	2.0
BEFORE	(Unmatched)	12	1165	21653	0.59	0.48	0.12	0.02	7.67	0.059	542	0.000	4.7
AFTER	(Matched, ATT)	12	1142	21653	0.59	0.55	0.04	0.02	1.8	0.021	67	0.957	2.5
BEFORE	(Unmatched)	18	1277	21579	0.68	0.50	0.18	0.01	12.82	0.056	556	0.000	4.5
AFTER	(Matched, ATT)	18	1252	21579	0.68	0.53	0.15	0.02	7.29	0.018	62	0.986	2.1
BEFORE	(Unmatched)	24	1295	21535	0.71	0.50	0.20	0.01	14.29	0.055	545	0.000	4.8
AFTER	(Matched, ATT)	24	1270	21535	0.71	0.54	0.17	0.02	8.33	0.013	45	0.999	1.8
Work experience: Without													
BEFORE	(Unmatched)	6	1172	36682	0.22	0.11	0.12	0.01	12.78	0.186	1940	0.000	6.7
AFTER	(Matched, ATT)	6	1149	36682	0.22	0.15	0.08	0.02	4.45	0.023	73	0.902	2.2
BEFORE	(Unmatched)	9	1695	37103	0.38	0.13	0.25	0.01	29.75	0.184	2567	0.000	6.5
AFTER	(Matched, ATT)	9	1662	37103	0.38	0.18	0.20	0.02	11.97	0.021	97	0.390	2.2
BEFORE	(Unmatched)	12	1881	36408	0.46	0.15	0.31	0.01	35.85	0.170	2557	0.000	6.3
AFTER	(Matched, ATT)	12	1844	36408	0.46	0.22	0.24	0.02	14.52	0.017	85	0.766	1.8
BEFORE	(Unmatched)	18	1984	35910	0.53	0.16	0.37	0.01	42.9	0.159	2473	0.000	5.9
AFTER	(Matched, ATT)	18	1945	35910	0.53	0.23	0.30	0.02	18.95	0.018	98	0.375	2.2
BEFORE	(Unmatched)	24	1972	35688	0.55	0.16	0.39	0.01	44.62	0.159	2453	0.000	6.1
AFTER	(Matched, ATT)	24	1933	35688	0.55	0.24	0.31	0.02	19.1	0.021	112	0.085	2.0
Work experience: With													
BEFORE	(Unmatched)	6	4455	223905	0.25	0.20	0.05	0.01	8.77	0.110	4850	0.000	6.8
AFTER	(Matched, ATT)	6	4366	223905	0.25	0.24	0.02	0.01	1.68	0.006	74	0.958	1.0
BEFORE	(Unmatched)	9	6747	217261	0.40	0.26	0.14	0.01	24.76	0.091	5505	0.000	5.7
AFTER	(Matched, ATT)	9	6613	217261	0.40	0.30	0.10	0.01	11.48	0.004	79	0.898	0.9
BEFORE	(Unmatched)	12	7892	213497	0.55	0.33	0.22	0.01	40.51	0.082	5555	0.000	4.7
AFTER	(Matched, ATT)	12	7735	213497	0.55	0.40	0.15	0.01	18.19	0.004	92	0.629	0.9
BEFORE	(Unmatched)	18	8634	211587	0.65	0.36	0.29	0.01	55.53	0.076	5502	0.000	4.3
AFTER	(Matched, ATT)	18	8462	211587	0.65	0.42	0.23	0.01	29.1	0.004	88	0.710	0.9
BEFORE	(Unmatched)	24	8747	210767	0.67	0.36	0.31	0.01	59.26	0.074	5412	0.000	4.0
AFTER	(Matched, ATT)	24	8573	210767	0.67	0.43	0.25	0.01	31.66	0.004	101	0.360	0.9
Region: Riga city													
BEFORE	(Unmatched)	6	1530	74395	0.23	0.22	0.01	0.01	1.12	0.107	1602	0.000	8.0
AFTER	(Matched, ATT)	6	1500	74395	0.23	0.28	-0.06	0.02	-3.37	0.005	19	0.999	0.9
BEFORE	(Unmatched)	9	2262	74965	0.38	0.28	0.10	0.01	10.34	0.096	1970	0.000	7.0
AFTER	(Matched, ATT)	9	2217	74965	0.38	0.36	0.02	0.02	1.44	0.003	22	0.999	1.0
BEFORE	(Unmatched)	12	2659	73987	0.56	0.37	0.18	0.01	19.3	0.091	2094	0.000	5.4
AFTER	(Matched, ATT)	12	2606	73987	0.56	0.51	0.05	0.02	3.23	0.004	32	0.999	0.9
BEFORE	(Unmatched)	18	2857	73660	0.66	0.40	0.27	0.01	28.45	0.086	2088	0.000	4.6
AFTER	(Matched, ATT)	18	2800	73660	0.66	0.54	0.13	0.01	9.05	0.003	26	0.999	0.8
BEFORE	(Unmatched)	24	2879	73624	0.68	0.40	0.28	0.01	30.03	0.085	2076	0.000	4.7
AFTER	(Matched, ATT)	24	2822	73624	0.68	0.55	0.13	0.01	9.37	0.003	21	0.999	0.7

Evaluation results within groups: Occupational training (OT) - cont.

Sample					Results					Covariate Balancing			
Subsample		THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi2$	Median Biais
(1)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Region: Riga region													
BEFORE	(Unmatched)	6	632	33504	0.22	0.19	0.03	0.02	1.62	0.097	612	0.000	10.6
AFTER	(Matched, ATT)	6	620	33504	0.21	0.23	-0.02	0.02	-0.73	0.014	24	0.999	2.2
BEFORE	(Unmatched)	9	988	35385	0.38	0.25	0.12	0.01	8.84	0.097	882	0.000	8.3
AFTER	(Matched, ATT)	9	969	35385	0.38	0.27	0.11	0.02	4.99	0.016	43	0.992	2.2
BEFORE	(Unmatched)	12	1173	34688	0.56	0.32	0.24	0.01	17.15	0.087	897	0.000	7.3
AFTER	(Matched, ATT)	12	1150	34688	0.56	0.35	0.20	0.02	9.64	0.009	29	0.999	2.2
BEFORE	(Unmatched)	18	1270	34501	0.69	0.34	0.35	0.01	25.57	0.082	902	0.000	6.1
AFTER	(Matched, ATT)	18	1245	34501	0.68	0.36	0.33	0.02	16.6	0.009	30	0.999	1.2
BEFORE	(Unmatched)	24	1286	34452	0.71	0.34	0.36	0.01	26.89	0.080	891	0.000	5.2
AFTER	(Matched, ATT)	24	1261	34452	0.71	0.37	0.34	0.02	17.37	0.009	33	0.999	1.6
Region: Vidzeme													
BEFORE	(Unmatched)	6	651	22944	0.30	0.20	0.10	0.02	6.15	0.117	695	0.000	9.7
AFTER	(Matched, ATT)	6	638	22944	0.29	0.26	0.04	0.03	1.46	0.026	45	0.944	2.5
BEFORE	(Unmatched)	9	987	24462	0.45	0.27	0.19	0.01	12.9	0.096	800	0.000	8.5
AFTER	(Matched, ATT)	9	968	24462	0.45	0.31	0.14	0.02	6.16	0.018	49	0.953	2.2
BEFORE	(Unmatched)	12	1107	24014	0.60	0.32	0.27	0.01	18.93	0.083	756	0.000	8.1
AFTER	(Matched, ATT)	12	1085	24014	0.59	0.35	0.24	0.02	11.22	0.013	40	0.996	1.9
BEFORE	(Unmatched)	18	1204	23736	0.68	0.36	0.33	0.01	23.13	0.072	691	0.000	6.8
AFTER	(Matched, ATT)	18	1180	23736	0.68	0.40	0.28	0.02	13.78	0.013	43	0.991	2.0
BEFORE	(Unmatched)	24	1216	23638	0.70	0.36	0.34	0.01	24.13	0.068	658	0.000	6.3
AFTER	(Matched, ATT)	24	1192	23638	0.70	0.38	0.33	0.02	16.13	0.012	40	0.997	2.2
Region: Kurzeme													
BEFORE	(Unmatched)	6	653	31239	0.30	0.18	0.12	0.02	7.88	0.094	597	0.000	7.7
AFTER	(Matched, ATT)	6	640	31239	0.30	0.19	0.11	0.02	4.42	0.019	33	0.999	3.0
BEFORE	(Unmatched)	9	1061	36137	0.47	0.23	0.23	0.01	17.61	0.111	1073	0.000	7.7
AFTER	(Matched, ATT)	9	1040	36137	0.46	0.27	0.19	0.02	8.96	0.013	38	0.999	2.0
BEFORE	(Unmatched)	12	1249	35558	0.62	0.28	0.34	0.01	25.89	0.100	1087	0.000	7.0
AFTER	(Matched, ATT)	12	1225	35558	0.62	0.33	0.29	0.02	14.67	0.008	27	0.999	1.6
BEFORE	(Unmatched)	18	1387	35263	0.74	0.31	0.44	0.01	34.63	0.094	1110	0.000	6.2
AFTER	(Matched, ATT)	18	1360	35263	0.74	0.36	0.39	0.02	21.03	0.010	39	0.999	1.8
BEFORE	(Unmatched)	24	1410	35137	0.77	0.31	0.46	0.01	36.93	0.092	1099	0.000	6.1
AFTER	(Matched, ATT)	24	1382	35137	0.77	0.36	0.41	0.02	23.02	0.011	43	0.997	1.7
Region: Zemgale													
BEFORE	(Unmatched)	6	724	31810	0.27	0.16	0.11	0.01	7.72	0.140	969	0.000	8.7
AFTER	(Matched, ATT)	6	710	31810	0.27	0.17	0.10	0.02	4.46	0.017	33	0.999	2.2
BEFORE	(Unmatched)	9	1099	33626	0.41	0.21	0.20	0.01	15.66	0.134	1309	0.000	7.6
AFTER	(Matched, ATT)	9	1078	33626	0.41	0.21	0.21	0.02	10.21	0.009	28	0.999	1.9
BEFORE	(Unmatched)	12	1268	33090	0.50	0.25	0.25	0.01	19.94	0.116	1255	0.000	6.3
AFTER	(Matched, ATT)	12	1243	33090	0.50	0.24	0.25	0.02	13.15	0.010	34	0.999	1.9
BEFORE	(Unmatched)	18	1408	32827	0.56	0.27	0.30	0.01	24.63	0.107	1259	0.000	5.6
AFTER	(Matched, ATT)	18	1380	32827	0.56	0.29	0.28	0.02	14.63	0.014	52	0.951	2.1
BEFORE	(Unmatched)	24	1431	32745	0.58	0.27	0.31	0.01	25.56	0.105	1253	0.000	5.7
AFTER	(Matched, ATT)	24	1403	32745	0.57	0.27	0.31	0.02	16.52	0.012	46	0.986	1.5
Region: Latgale													
BEFORE	(Unmatched)	6	1437	47432	0.22	0.14	0.08	0.01	8.49	0.151	1956	0.000	10.1
AFTER	(Matched, ATT)	6	1409	47432	0.22	0.16	0.06	0.02	4.11	0.010	39	0.999	1.9
BEFORE	(Unmatched)	9	2045	48470	0.34	0.19	0.16	0.01	17.55	0.141	2411	0.000	8.9
AFTER	(Matched, ATT)	9	2005	48470	0.34	0.19	0.15	0.01	10.39	0.008	42	0.998	1.8
BEFORE	(Unmatched)	12	2317	47351	0.43	0.23	0.20	0.01	22.76	0.126	2362	0.000	7.5
AFTER	(Matched, ATT)	12	2271	47351	0.43	0.26	0.18	0.01	11.97	0.011	68	0.623	2.0
BEFORE	(Unmatched)	18	2492	46293	0.50	0.25	0.25	0.01	27.46	0.113	2219	0.000	7.4
AFTER	(Matched, ATT)	18	2444	46293	0.50	0.28	0.23	0.01	15.92	0.009	60	0.842	1.5
BEFORE	(Unmatched)	24	2497	45642	0.54	0.26	0.27	0.01	30.07	0.107	2111	0.000	6.9
AFTER	(Matched, ATT)	24	2448	45642	0.54	0.30	0.24	0.01	16.71	0.007	46	0.993	1.4

Table 4.8: **Evaluation results within groups: Modular training (MLT)**

Sample					Results					Covariate Balancing			
Subsample		THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi 2$	Median Biais
(1)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Gender: Male													
BEFORE	(Unmatched)	6	330	21569	0.14	0.19	-0.04	0.02	-2.05	0.134	112	0.000	7.6
AFTER	(Matched, ATT)	6	324	21569	0.15	0.19	-0.05	0.03	-1.62	0.089	16	0.992	3.0
BEFORE	(Unmatched)	9	369	19915	0.23	0.25	-0.02	0.02	-0.89	0.093	81	0.000	7.7
AFTER	(Matched, ATT)	9	362	19915	0.23	0.22	0.01	0.03	0.17	0.111	26	0.767	3.9
BEFORE	(Unmatched)	12	354	19058	0.32	0.31	0.02	0.02	0.68	0.098	79	0.000	8.7
AFTER	(Matched, ATT)	12	347	19058	0.32	0.31	0.01	0.04	0.4	0.115	24	0.861	3.4
BEFORE	(Unmatched)	18	335	18555	0.39	0.32	0.07	0.03	2.71	0.103	81	0.000	8.6
AFTER	(Matched, ATT)	18	329	18555	0.40	0.35	0.04	0.04	1.08	0.078	16	0.996	3.9
BEFORE	(Unmatched)	24	328	18445	0.40	0.33	0.08	0.03	2.92	0.095	71	0.000	8.9
AFTER	(Matched, ATT)	24	322	18445	0.40	0.34	0.06	0.04	1.59	0.154	29	0.688	2.2
Gender: Female													
BEFORE	(Unmatched)	6	846	24159	0.08	0.19	-0.11	0.01	-7.96	0.090	141	0.000	7.2
AFTER	(Matched, ATT)	6	830	24159	0.08	0.18	-0.10	0.02	-5.97	0.061	30	0.828	1.9
BEFORE	(Unmatched)	9	983	21901	0.18	0.26	-0.08	0.01	-5.93	0.077	136	0.000	8.5
AFTER	(Matched, ATT)	9	964	21901	0.18	0.25	-0.07	0.02	-3.57	0.035	20	0.995	2.4
BEFORE	(Unmatched)	12	957	20583	0.30	0.34	-0.04	0.02	-2.4	0.080	138	0.000	8.8
AFTER	(Matched, ATT)	12	938	20583	0.30	0.35	-0.05	0.02	-2.27	0.044	24	0.968	2.1
BEFORE	(Unmatched)	18	905	19854	0.37	0.37	0.00	0.02	0.1	0.087	143	0.000	8.8
AFTER	(Matched, ATT)	18	887	19854	0.36	0.37	0.00	0.02	-0.05	0.054	29	0.836	1.9
BEFORE	(Unmatched)	24	884	19703	0.38	0.37	0.01	0.02	0.51	0.088	141	0.000	8.7
AFTER	(Matched, ATT)	24	867	19703	0.37	0.38	-0.01	0.02	-0.37	0.060	31	0.780	2.2
Education: Basic or less													
BEFORE	(Unmatched)	6	252	12387	0.06	0.14	-0.08	0.02	-3.59	0.102	252	0.000	6.5
AFTER	(Matched, ATT)	6	247	12387	0.05	0.11	-0.05	0.03	-2.06	0.028	19	0.999	3.5
BEFORE	(Unmatched)	9	294	11482	0.15	0.18	-0.03	0.02	-1.49	0.098	270	0.000	9.7
AFTER	(Matched, ATT)	9	289	11482	0.14	0.12	0.02	0.03	0.81	0.023	18	0.999	3.3
BEFORE	(Unmatched)	12	282	11001	0.21	0.22	-0.01	0.02	-0.37	0.105	277	0.000	9.9
AFTER	(Matched, ATT)	12	277	11001	0.21	0.18	0.02	0.04	0.61	0.036	27	0.935	5.1
BEFORE	(Unmatched)	18	269	10720	0.25	0.23	0.01	0.03	0.53	0.113	285	0.000	9.2
AFTER	(Matched, ATT)	18	264	10720	0.25	0.20	0.05	0.04	1.21	0.034	25	0.976	5.0
BEFORE	(Unmatched)	24	262	10571	0.25	0.23	0.02	0.03	0.75	0.112	275	0.000	9.9
AFTER	(Matched, ATT)	24	257	10571	0.25	0.17	0.07	0.04	2.01	0.033	23	0.980	4.0
Education: Secondary general													
BEFORE	(Unmatched)	6	315	12780	0.11	0.18	-0.07	0.02	-3.18	0.059	176	0.000	7.7
AFTER	(Matched, ATT)	6	309	12780	0.11	0.18	-0.07	0.03	-2.37	0.015	13	0.999	3.4
BEFORE	(Unmatched)	9	356	11693	0.20	0.25	-0.05	0.02	-2.28	0.066	211	0.000	8.0
AFTER	(Matched, ATT)	9	349	11693	0.20	0.28	-0.08	0.03	-2.36	0.018	17	0.993	2.5
BEFORE	(Unmatched)	12	338	11060	0.33	0.32	0.00	0.03	0.08	0.072	220	0.000	9.4
AFTER	(Matched, ATT)	12	332	11060	0.33	0.35	-0.02	0.04	-0.63	0.017	15	0.998	2.5
BEFORE	(Unmatched)	18	321	10738	0.40	0.35	0.05	0.03	1.87	0.074	215	0.000	9.5
AFTER	(Matched, ATT)	18	315	10738	0.40	0.36	0.04	0.04	1.03	0.009	8	0.999	3.6
BEFORE	(Unmatched)	24	313	10655	0.41	0.35	0.06	0.03	2.23	0.071	203	0.000	8.6
AFTER	(Matched, ATT)	24	307	10655	0.41	0.35	0.07	0.04	1.59	0.013	11	0.999	3.1
Education: Secondary professional													
BEFORE	(Unmatched)	6	450	15951	0.11	0.21	-0.10	0.02	-5.15	0.053	217	0.000	5.4
AFTER	(Matched, ATT)	6	441	15951	0.11	0.22	-0.12	0.03	-4.47	0.019	23	0.943	2.6
BEFORE	(Unmatched)	9	521	14451	0.21	0.29	-0.08	0.02	-4.03	0.057	259	0.000	7.1
AFTER	(Matched, ATT)	9	511	14451	0.21	0.28	-0.07	0.03	-2.65	0.015	22	0.972	3.4
BEFORE	(Unmatched)	12	502	13586	0.34	0.37	-0.03	0.02	-1.47	0.061	263	0.000	8.7
AFTER	(Matched, ATT)	12	492	13586	0.34	0.40	-0.06	0.03	-1.83	0.007	9	0.999	2.1
BEFORE	(Unmatched)	18	471	13044	0.42	0.40	0.02	0.02	1.06	0.064	261	0.000	8.5
AFTER	(Matched, ATT)	18	462	13044	0.43	0.43	0.00	0.03	-0.06	0.014	17	0.996	2.5
BEFORE	(Unmatched)	24	462	12942	0.43	0.40	0.03	0.02	1.26	0.063	254	0.000	8.8
AFTER	(Matched, ATT)	24	453	12942	0.43	0.44	-0.01	0.03	-0.19	0.018	23	0.947	2.8

Evaluation results within groups: Modular training (MLT) - cont.

Sample					Results					Covariate Balancing			
Subsample		THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi 2$	Median Biais
(1)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Education: Higher													
BEFORE	(Unmatched)	6	158	3782	0.09	0.25	-0.15	0.03	-4.37	0.051	67	0.000	6.1
AFTER	(Matched, ATT)	6	155	3782	0.10	0.20	-0.10	0.04	-2.41	0.051	22	0.931	7.5
BEFORE	(Unmatched)	9	180	3445	0.20	0.36	-0.16	0.04	-4.35	0.057	81	0.000	7.0
AFTER	(Matched, ATT)	9	177	3445	0.20	0.31	-0.11	0.05	-2.23	0.028	14	0.998	4.6
BEFORE	(Unmatched)	12	188	3268	0.34	0.46	-0.12	0.04	-3.31	0.066	96	0.000	7.8
AFTER	(Matched, ATT)	12	185	3268	0.34	0.40	-0.06	0.05	-1.12	0.027	14	0.999	4.4
BEFORE	(Unmatched)	18	178	3192	0.39	0.49	-0.09	0.04	-2.43	0.063	88	0.000	7.4
AFTER	(Matched, ATT)	18	175	3192	0.39	0.37	0.03	0.06	0.52	0.054	26	0.802	5.3
BEFORE	(Unmatched)	24	174	3181	0.40	0.49	-0.09	0.04	-2.21	0.062	85	0.000	7.6
AFTER	(Matched, ATT)	24	171	3181	0.41	0.45	-0.04	0.06	-0.72	0.036	17	0.990	5.4
Work experience: Without													
BEFORE	(Unmatched)	6	283	7983	0.10	0.12	-0.02	0.02	-1.14	0.091	86	0.000	6.8
AFTER	(Matched, ATT)	6	278	7983	0.10	0.15	-0.05	0.03	-1.86	0.067	19	0.968	3.0
BEFORE	(Unmatched)	9	330	7505	0.16	0.14	0.02	0.02	0.93	0.097	105	0.000	8.2
AFTER	(Matched, ATT)	9	324	7505	0.15	0.14	0.01	0.03	0.22	0.057	20	0.972	2.5
BEFORE	(Unmatched)	12	313	7209	0.20	0.16	0.04	0.02	1.86	0.105	106	0.000	9.1
AFTER	(Matched, ATT)	12	307	7209	0.19	0.21	-0.01	0.03	-0.39	0.054	18	0.979	3.4
BEFORE	(Unmatched)	18	297	6988	0.23	0.17	0.07	0.02	2.92	0.115	110	0.000	10.0
AFTER	(Matched, ATT)	18	292	6988	0.23	0.18	0.04	0.04	1.17	0.034	11	0.999	4.8
BEFORE	(Unmatched)	24	291	6934	0.24	0.17	0.07	0.02	3.04	0.115	107	0.000	9.8
AFTER	(Matched, ATT)	24	286	6934	0.23	0.17	0.07	0.03	1.93	0.048	14	0.997	3.6
Work experience: With													
BEFORE	(Unmatched)	6	893	37459	0.10	0.20	-0.10	0.01	-7.75	0.126	191	0.000	6.5
AFTER	(Matched, ATT)	6	876	37459	0.10	0.19	-0.09	0.02	-5.2	0.066	26	0.917	2.3
BEFORE	(Unmatched)	9	1022	34052	0.20	0.28	-0.08	0.01	-5.62	0.111	181	0.000	6.7
AFTER	(Matched, ATT)	9	1002	34052	0.20	0.26	-0.06	0.02	-3.1	0.061	28	0.891	2.3
BEFORE	(Unmatched)	12	998	32180	0.34	0.36	-0.02	0.02	-1.25	0.117	187	0.000	7.0
AFTER	(Matched, ATT)	12	979	32180	0.34	0.38	-0.04	0.02	-1.61	0.048	21	0.993	2.1
BEFORE	(Unmatched)	18	943	31191	0.42	0.39	0.03	0.02	2	0.122	188	0.000	7.2
AFTER	(Matched, ATT)	18	925	31191	0.42	0.40	0.02	0.02	0.72	0.054	23	0.967	2.0
BEFORE	(Unmatched)	24	921	30988	0.43	0.39	0.04	0.02	2.49	0.122	185	0.000	7.5
AFTER	(Matched, ATT)	24	903	30988	0.43	0.42	0.01	0.02	0.36	0.068	27	0.824	2.6
Proficiency in Latvian: None or uncertified													
BEFORE	(Unmatched)	6	528	13824	0.08	0.13	-0.06	0.02	-3.93	0.097	140	0.000	6.1
AFTER	(Matched, ATT)	6	518	13824	0.08	0.13	-0.05	0.02	-2.73	0.038	16	0.999	2.8
BEFORE	(Unmatched)	9	603	12823	0.16	0.18	-0.01	0.02	-0.84	0.098	148	0.000	9.0
AFTER	(Matched, ATT)	9	591	12823	0.16	0.17	-0.01	0.02	-0.22	0.047	21	0.976	3.3
BEFORE	(Unmatched)	12	593	12235	0.26	0.22	0.04	0.02	2.31	0.109	156	0.000	9.0
AFTER	(Matched, ATT)	12	582	12235	0.26	0.24	0.02	0.03	0.66	0.045	20	0.985	2.9
BEFORE	(Unmatched)	18	570	11837	0.31	0.23	0.08	0.02	4.28	0.117	165	0.000	8.6
AFTER	(Matched, ATT)	18	559	11837	0.31	0.27	0.04	0.03	1.33	0.048	21	0.983	2.6
BEFORE	(Unmatched)	24	558	11731	0.32	0.23	0.08	0.02	4.56	0.116	160	0.000	8.6
AFTER	(Matched, ATT)	24	547	11731	0.31	0.28	0.03	0.03	1.14	0.053	23	0.960	2.8
Proficiency in Latvian: Low level													
BEFORE	(Unmatched)	6	427	11910	0.11	0.18	-0.07	0.02	-3.64	0.114	89	0.000	11.0
AFTER	(Matched, ATT)	6	419	11910	0.12	0.17	-0.05	0.03	-2.02	0.133	28	0.765	3.2
BEFORE	(Unmatched)	9	490	10854	0.22	0.25	-0.03	0.02	-1.69	0.119	110	0.000	11.7
AFTER	(Matched, ATT)	9	481	10854	0.22	0.25	-0.02	0.03	-0.86	0.073	20	0.960	2.4
BEFORE	(Unmatched)	12	469	10258	0.34	0.32	0.02	0.02	1.03	0.112	99	0.000	12.5
AFTER	(Matched, ATT)	12	460	10258	0.35	0.34	0.01	0.03	0.2	0.095	25	0.899	2.0
BEFORE	(Unmatched)	18	441	9896	0.42	0.35	0.07	0.02	3.18	0.116	97	0.000	12.6
AFTER	(Matched, ATT)	18	433	9896	0.42	0.41	0.01	0.04	0.32	0.092	21	0.903	2.5
BEFORE	(Unmatched)	24	431	9817	0.43	0.35	0.08	0.02	3.41	0.116	95	0.000	12.4
AFTER	(Matched, ATT)	24	423	9817	0.43	0.39	0.04	0.04	1.18	0.098	24	0.873	1.9

Evaluation results within groups: Modular training (MLT) - cont.

Sample				Results					Covariate Balancing			
Subsample	THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi2$	Median Biais
(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Proficiency in Latvian: Middle level												
BEFORE (Unmatched)	6	205	15236	0.11	0.21	-0.10	0.03	-3.54	0.262	42	0.020	8.3
AFTER (Matched, ATT)	6	201	15236	0.10	0.32	-0.22	0.04	-5.44	0.588	4	0.266	4.1
BEFORE (Unmatched)	9	240	14187	0.20	0.30	-0.10	0.03	-3.23	0.168	41	0.085	8.7
AFTER (Matched, ATT)	9	236	14187	0.20	0.37	-0.17	0.04	-3.89	0.478	15	0.364	3.1
BEFORE (Unmatched)	12	231	13329	0.37	0.39	-0.01	0.03	-0.46	0.156	39	0.118	10.2
AFTER (Matched, ATT)	12	227	13329	0.37	0.50	-0.13	0.05	-2.67	0.736	39	0.015	3.6
BEFORE (Unmatched)	18	212	12961	0.46	0.41	0.05	0.03	1.51	0.213	45	0.028	10.5
AFTER (Matched, ATT)	18	208	12961	0.47	0.51	-0.04	0.05	-0.86	0.583	19	0.306	4.1
BEFORE (Unmatched)	24	206	12900	0.48	0.41	0.06	0.03	1.82	0.217	44	0.035	11.2
AFTER (Matched, ATT)	24	202	12900	0.48	0.52	-0.04	0.05	-0.87	0.638	24	0.182	3.5
Area of residence: Urban												
BEFORE (Unmatched)	6	976	35505	0.10	0.19	-0.10	0.01	-7.78	0.112	221	0.000	7.2
AFTER (Matched, ATT)	6	957	35505	0.10	0.20	-0.10	0.02	-6.16	0.057	32	0.751	2.7
BEFORE (Unmatched)	9	1133	32690	0.19	0.26	-0.07	0.01	-5.53	0.102	220	0.000	8.4
AFTER (Matched, ATT)	9	1111	32690	0.19	0.24	-0.05	0.02	-2.74	0.038	24	0.970	2.5
BEFORE (Unmatched)	12	1104	31244	0.31	0.33	-0.02	0.01	-1.47	0.107	225	0.000	8.7
AFTER (Matched, ATT)	12	1082	31244	0.31	0.34	-0.03	0.02	-1.28	0.038	24	0.965	2.3
BEFORE (Unmatched)	18	1050	30567	0.38	0.35	0.02	0.02	1.65	0.113	231	0.000	8.5
AFTER (Matched, ATT)	18	1029	30567	0.38	0.35	0.03	0.02	1.23	0.042	25	0.931	2.2
BEFORE (Unmatched)	24	1027	30455	0.39	0.35	0.03	0.02	2.17	0.112	222	0.000	8.8
AFTER (Matched, ATT)	24	1007	30455	0.38	0.38	0.00	0.02	0.22	0.030	17	0.996	1.7
Area of residence: Rural												
BEFORE (Unmatched)	6	200	10057	0.11	0.16	-0.05	0.03	-2	0.109	52	0.014	8.7
AFTER (Matched, ATT)	6	196	10057	0.11	0.15	-0.05	0.03	-1.33	0.164	18	0.954	5.5
BEFORE (Unmatched)	9	219	8960	0.19	0.22	-0.03	0.03	-1.03	0.133	75	0.000	9.1
AFTER (Matched, ATT)	9	215	8960	0.18	0.15	0.03	0.04	0.74	0.064	10	0.999	4.7
BEFORE (Unmatched)	12	207	8232	0.28	0.28	0.00	0.03	-0.05	0.150	75	0.000	9.1
AFTER (Matched, ATT)	12	203	8232	0.27	0.25	0.02	0.04	0.55	0.171	23	0.679	4.1
BEFORE (Unmatched)	18	190	7677	0.35	0.31	0.04	0.03	1.12	0.162	75	0.000	10.2
AFTER (Matched, ATT)	18	187	7677	0.34	0.22	0.12	0.05	2.51	0.173	24	0.713	4.3
BEFORE (Unmatched)	24	185	7528	0.36	0.32	0.04	0.03	1.18	0.171	76	0.000	10.3
AFTER (Matched, ATT)	24	182	7528	0.36	0.29	0.07	0.05	1.3	0.107	11	0.966	4.7

Table 4.9: **Evaluation results within groups: Modular training (MOT)**

Sample				Results					Covariate Balancing			
Subsample (1)	THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi 2$ (13)	Median Biais (14)
Gender: Male												
BEFORE (Unmatched)	6	1858	86671	0.18	0.20	-0.02	0.01	-2.17	0.135	2442	0.000	11.5
AFTER (Matched, ATT)	6	1821	86671	0.18	0.22	-0.05	0.01	-3.34	0.007	37	0.983	1.6
BEFORE (Unmatched)	9	2180	83414	0.26	0.26	0.00	0.01	-0.22	0.124	2517	0.000	9.5
AFTER (Matched, ATT)	9	2137	83414	0.25	0.28	-0.03	0.01	-1.86	0.004	25	0.999	1.1
BEFORE (Unmatched)	12	2211	81566	0.37	0.31	0.05	0.01	5.27	0.117	2397	0.000	10.5
AFTER (Matched, ATT)	12	2167	81566	0.37	0.36	0.01	0.02	0.55	0.007	41	0.955	1.3
BEFORE (Unmatched)	18	2237	80560	0.41	0.33	0.08	0.01	7.8	0.103	2120	0.000	9.2
AFTER (Matched, ATT)	18	2193	80560	0.41	0.38	0.03	0.02	2.23	0.006	36	0.981	1.4
BEFORE (Unmatched)	24	2218	80108	0.42	0.34	0.09	0.01	8.42	0.101	2068	0.000	9.0
AFTER (Matched, ATT)	24	2174	80108	0.42	0.38	0.04	0.02	2.38	0.006	37	0.980	1.5
Gender: Female												
BEFORE (Unmatched)	6	4075	94095	0.19	0.20	-0.01	0.01	-2.06	0.133	4495	0.000	10.0
AFTER (Matched, ATT)	6	3994	94095	0.19	0.24	-0.05	0.01	-5.08	0.005	54	0.657	1.1
BEFORE (Unmatched)	9	4860	89597	0.28	0.27	0.01	0.01	2.13	0.121	4631	0.000	10.1
AFTER (Matched, ATT)	9	4763	89597	0.28	0.31	-0.03	0.01	-3.08	0.004	56	0.579	1.3
BEFORE (Unmatched)	12	5121	86986	0.39	0.34	0.05	0.01	7.82	0.111	4373	0.000	9.1
AFTER (Matched, ATT)	12	5019	86986	0.39	0.38	0.01	0.01	0.64	0.003	47	0.875	1.0
BEFORE (Unmatched)	18	5212	85584	0.45	0.36	0.09	0.01	13.42	0.101	4026	0.000	8.0
AFTER (Matched, ATT)	18	5108	85584	0.45	0.41	0.04	0.01	4.18	0.004	57	0.566	1.3
BEFORE (Unmatched)	24	5172	84994	0.47	0.37	0.10	0.01	14.84	0.099	3931	0.000	8.1
AFTER (Matched, ATT)	24	5069	84994	0.47	0.41	0.06	0.01	5.56	0.004	58	0.498	0.9
Age: Below 25												
BEFORE (Unmatched)	6	1551	36211	0.17	0.19	-0.02	0.01	-1.66	0.137	1775	0.000	11.6
AFTER (Matched, ATT)	6	1521	36211	0.17	0.19	-0.02	0.02	-1.08	0.007	30	0.996	1.9
BEFORE (Unmatched)	9	1762	35033	0.24	0.23	0.00	0.01	0.44	0.127	1793	0.000	10.4
AFTER (Matched, ATT)	9	1729	35033	0.24	0.25	-0.01	0.02	-0.9	0.007	35	0.985	1.7
BEFORE (Unmatched)	12	1805	34401	0.32	0.27	0.05	0.01	4.29	0.118	1692	0.000	9.4
AFTER (Matched, ATT)	12	1770	34401	0.32	0.27	0.05	0.02	2.77	0.008	39	0.950	2.1
BEFORE (Unmatched)	18	1830	34144	0.35	0.28	0.07	0.01	6.35	0.106	1535	0.000	8.8
AFTER (Matched, ATT)	18	1795	34144	0.35	0.30	0.05	0.02	3.07	0.006	28	0.999	1.3
BEFORE (Unmatched)	24	1824	34076	0.36	0.28	0.07	0.01	6.84	0.104	1506	0.000	8.9
AFTER (Matched, ATT)	24	1788	34076	0.36	0.31	0.04	0.02	2.47	0.008	38	0.960	1.8
Age: 25-44												
BEFORE (Unmatched)	6	3252	89068	0.20	0.21	-0.02	0.01	-2.15	0.141	3966	0.000	11.7
AFTER (Matched, ATT)	6	3187	89068	0.20	0.25	-0.05	0.01	-4.93	0.004	37	0.974	1.1
BEFORE (Unmatched)	9	3895	85221	0.29	0.28	0.01	0.01	1.5	0.131	4189	0.000	11.8
AFTER (Matched, ATT)	9	3818	85221	0.29	0.33	-0.04	0.01	-3.27	0.004	44	0.876	1.2
BEFORE (Unmatched)	12	4092	83034	0.41	0.35	0.06	0.01	7.44	0.122	4035	0.000	10.8
AFTER (Matched, ATT)	12	4012	83034	0.40	0.41	-0.01	0.01	-0.68	0.003	33	0.995	0.8
BEFORE (Unmatched)	18	4177	81917	0.47	0.37	0.10	0.01	13.18	0.112	3750	0.000	9.6
AFTER (Matched, ATT)	18	4094	81917	0.47	0.43	0.04	0.01	3.4	0.003	39	0.957	0.8
BEFORE (Unmatched)	24	4141	81475	0.49	0.38	0.11	0.01	14.42	0.111	3684	0.000	9.5
AFTER (Matched, ATT)	24	4059	81475	0.49	0.45	0.03	0.01	2.83	0.004	46	0.805	1.2
Age: 45 and above												
BEFORE (Unmatched)	6	1130	55318	0.17	0.19	-0.01	0.01	-1.22	0.158	1748	0.000	13.7
AFTER (Matched, ATT)	6	1108	55318	0.17	0.21	-0.04	0.02	-2.48	0.008	24	0.999	1.4
BEFORE (Unmatched)	9	1383	52588	0.26	0.25	0.01	0.01	1.21	0.160	2063	0.000	13.4
AFTER (Matched, ATT)	9	1356	52588	0.26	0.28	-0.01	0.02	-0.82	0.009	35	0.976	1.7
BEFORE (Unmatched)	12	1435	50948	0.40	0.32	0.08	0.01	6.21	0.159	2092	0.000	12.8
AFTER (Matched, ATT)	12	1407	50948	0.40	0.43	-0.03	0.02	-1.32	0.008	32	0.995	2.1
BEFORE (Unmatched)	18	1442	49914	0.46	0.35	0.11	0.01	8.62	0.146	1922	0.000	11.0
AFTER (Matched, ATT)	18	1414	49914	0.46	0.43	0.03	0.02	1.67	0.009	36	0.978	1.7
BEFORE (Unmatched)	24	1425	49382	0.48	0.36	0.13	0.01	9.73	0.144	1872	0.000	10.9
AFTER (Matched, ATT)	24	1397	49382	0.48	0.43	0.05	0.02	2.6	0.009	36	0.981	1.6

Evaluation results within groups: Modular training (MOT) - cont.

Sample					Results					Covariate Balancing			
Subsample (1)		THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi 2$ (13)	Median Biais (14)
Ethnicity: Latvian													
BEFORE	(Unmatched)	6	4178	88785	0.20	0.23	-0.03	0.01	-4.16	0.112	3813	0.000	10.1
AFTER	(Matched, ATT)	6	4095	88785	0.20	0.25	-0.05	0.01	-5.09	0.004	42	0.948	1.1
BEFORE	(Unmatched)	9	4938	85017	0.30	0.30	0.00	0.01	-0.43	0.102	3899	0.000	9.1
AFTER	(Matched, ATT)	9	4840	85017	0.29	0.32	-0.03	0.01	-2.76	0.003	34	0.995	0.9
BEFORE	(Unmatched)	12	5142	82829	0.40	0.36	0.04	0.01	6.28	0.094	3686	0.000	8.7
AFTER	(Matched, ATT)	12	5040	82829	0.40	0.39	0.01	0.01	0.9	0.003	48	0.819	1.4
BEFORE	(Unmatched)	18	5231	81681	0.46	0.38	0.08	0.01	11.45	0.084	3334	0.000	8.6
AFTER	(Matched, ATT)	18	5127	81681	0.46	0.41	0.05	0.01	4.47	0.003	40	0.963	1.0
BEFORE	(Unmatched)	24	5193	81214	0.48	0.39	0.09	0.01	12.6	0.082	3239	0.000	8.6
AFTER	(Matched, ATT)	24	5090	81214	0.47	0.41	0.06	0.01	5.73	0.004	50	0.762	0.9
Ethnicity: Russian													
BEFORE	(Unmatched)	6	1170	62028	0.15	0.17	-0.02	0.01	-1.95	0.158	1841	0.000	13.9
AFTER	(Matched, ATT)	6	1147	62028	0.15	0.19	-0.04	0.02	-2.62	0.009	28	0.999	1.6
BEFORE	(Unmatched)	9	1392	59448	0.23	0.23	0.00	0.01	0	0.147	1946	0.000	12.2
AFTER	(Matched, ATT)	9	1365	59448	0.23	0.27	-0.04	0.02	-2.49	0.008	31	0.997	1.9
BEFORE	(Unmatched)	12	1450	57943	0.35	0.29	0.06	0.01	4.57	0.137	1866	0.000	11.1
AFTER	(Matched, ATT)	12	1421	57943	0.34	0.34	0.00	0.02	-0.04	0.009	36	0.983	2.2
BEFORE	(Unmatched)	18	1476	57039	0.40	0.31	0.09	0.01	7.25	0.122	1686	0.000	10.2
AFTER	(Matched, ATT)	18	1447	57039	0.40	0.38	0.02	0.02	0.95	0.007	29	0.997	1.8
BEFORE	(Unmatched)	24	1461	56668	0.42	0.32	0.10	0.01	8.25	0.121	1649	0.000	10.2
AFTER	(Matched, ATT)	24	1432	56668	0.42	0.39	0.03	0.02	1.54	0.010	38	0.966	1.9
Ethnicity: Other													
BEFORE	(Unmatched)	6	585	29229	0.15	0.17	-0.03	0.02	-1.6	0.150	863	0.000	12.7
AFTER	(Matched, ATT)	6	574	29229	0.15	0.21	-0.06	0.02	-2.58	0.019	31	0.994	3.3
BEFORE	(Unmatched)	9	710	27824	0.22	0.23	-0.01	0.02	-0.74	0.138	914	0.000	11.6
AFTER	(Matched, ATT)	9	696	27824	0.22	0.23	-0.01	0.02	-0.56	0.011	21	0.999	2.1
BEFORE	(Unmatched)	12	740	27060	0.32	0.30	0.02	0.02	1.39	0.135	920	0.000	10.4
AFTER	(Matched, ATT)	12	726	27060	0.32	0.35	-0.03	0.03	-1.35	0.017	35	0.983	2.2
BEFORE	(Unmatched)	18	742	26661	0.37	0.32	0.06	0.02	3.33	0.122	834	0.000	10.5
AFTER	(Matched, ATT)	18	728	26661	0.37	0.36	0.01	0.03	0.31	0.012	25	0.999	2.7
BEFORE	(Unmatched)	24	736	26502	0.39	0.32	0.07	0.02	3.89	0.121	818	0.000	10.3
AFTER	(Matched, ATT)	24	722	26502	0.39	0.34	0.04	0.03	1.65	0.016	33	0.993	2.6
Education: Basic or less													
BEFORE	(Unmatched)	6	1077	52655	0.13	0.15	-0.02	0.01	-1.52	0.165	1740	0.000	15.6
AFTER	(Matched, ATT)	6	1058	52655	0.13	0.15	-0.02	0.02	-1.35	0.009	26	1.000	1.8
BEFORE	(Unmatched)	9	1260	50565	0.20	0.19	0.02	0.01	1.51	0.156	1844	0.000	13.2
AFTER	(Matched, ATT)	9	1235	50565	0.20	0.19	0.01	0.02	0.38	0.009	30	0.996	1.2
BEFORE	(Unmatched)	12	1289	49388	0.29	0.22	0.06	0.01	5.13	0.149	1792	0.000	12.2
AFTER	(Matched, ATT)	12	1264	49388	0.28	0.23	0.06	0.02	3.17	0.010	34	0.987	1.8
BEFORE	(Unmatched)	18	1311	48707	0.34	0.24	0.10	0.01	7.93	0.137	1668	0.000	10.9
AFTER	(Matched, ATT)	18	1285	48707	0.33	0.23	0.11	0.02	5.66	0.010	35	0.985	2.0
BEFORE	(Unmatched)	24	1298	48386	0.35	0.24	0.10	0.01	8.56	0.136	1635	0.000	11.2
AFTER	(Matched, ATT)	24	1273	48386	0.34	0.24	0.11	0.02	5.65	0.009	30	0.996	1.5
Education: Secondary general													
BEFORE	(Unmatched)	6	1564	48891	0.19	0.20	-0.01	0.01	-1.34	0.144	2001	0.000	14.0
AFTER	(Matched, ATT)	6	1533	48891	0.19	0.23	-0.04	0.02	-2.78	0.008	35	0.973	1.7
BEFORE	(Unmatched)	9	1840	46817	0.26	0.26	0.00	0.01	0.21	0.131	2059	0.000	10.4
AFTER	(Matched, ATT)	9	1804	46817	0.26	0.29	-0.03	0.02	-1.95	0.008	38	0.939	1.8
BEFORE	(Unmatched)	12	1920	45623	0.37	0.33	0.04	0.01	3.71	0.124	1987	0.000	8.5
AFTER	(Matched, ATT)	12	1882	45623	0.37	0.34	0.03	0.02	1.79	0.006	33	0.985	1.7
BEFORE	(Unmatched)	18	1952	45018	0.43	0.35	0.07	0.01	6.68	0.113	1842	0.000	8.5
AFTER	(Matched, ATT)	18	1913	45018	0.43	0.39	0.04	0.02	2.29	0.007	38	0.940	1.8
BEFORE	(Unmatched)	24	1940	44719	0.44	0.36	0.08	0.01	7.24	0.112	1801	0.000	8.5
AFTER	(Matched, ATT)	24	1902	44719	0.44	0.39	0.05	0.02	2.98	0.006	29	0.997	1.6

Evaluation results within groups: Modular training (MOT) - cont.

Sample					Results					Covariate Balancing			
Subsample		THO	NOC Treated	NOC Controls	Treated	Controls	Difference	S.E.	T-stat	R2 (pseudo)	LR	$P > \chi2$	Median Biais
(1)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Education: Secondary professional													
BEFORE	(Unmatched)	6	2371	63030	0.18	0.22	-0.04	0.01	-4.55	0.139	2825	0.000	13.1
AFTER	(Matched, ATT)	6	2325	63030	0.18	0.23	-0.05	0.01	-3.77	0.005	30	0.996	1.3
BEFORE	(Unmatched)	9	2805	60256	0.28	0.29	-0.01	0.01	-1.29	0.131	3011	0.000	11.9
AFTER	(Matched, ATT)	9	2749	60256	0.28	0.32	-0.03	0.01	-2.62	0.004	30	0.997	1.1
BEFORE	(Unmatched)	12	2923	58536	0.39	0.37	0.03	0.01	2.88	0.123	2881	0.000	9.9
AFTER	(Matched, ATT)	12	2866	58536	0.39	0.41	-0.01	0.01	-1	0.004	34	0.983	1.3
BEFORE	(Unmatched)	18	2975	57545	0.45	0.39	0.06	0.01	6.17	0.112	2654	0.000	9.1
AFTER	(Matched, ATT)	18	2916	57545	0.45	0.43	0.02	0.01	1.08	0.004	33	0.987	1.5
BEFORE	(Unmatched)	24	2946	57156	0.47	0.40	0.07	0.01	7.33	0.110	2582	0.000	8.4
AFTER	(Matched, ATT)	24	2888	57156	0.46	0.44	0.03	0.01	1.85	0.005	39	0.936	1.2
Education: Higher													
BEFORE	(Unmatched)	6	921	15939	0.27	0.30	-0.04	0.02	-2.31	0.114	815	0.000	8.9
AFTER	(Matched, ATT)	6	903	15939	0.27	0.35	-0.08	0.02	-3.69	0.008	21	0.999	2.0
BEFORE	(Unmatched)	9	1135	15172	0.35	0.40	-0.05	0.02	-3.32	0.099	815	0.000	8.8
AFTER	(Matched, ATT)	9	1113	15172	0.36	0.43	-0.07	0.02	-3.18	0.010	31	0.990	2.4
BEFORE	(Unmatched)	12	1200	14804	0.50	0.50	-0.01	0.02	-0.45	0.092	786	0.000	8.2
AFTER	(Matched, ATT)	12	1176	14804	0.50	0.54	-0.04	0.02	-1.7	0.008	26	0.999	1.7
BEFORE	(Unmatched)	18	1211	14673	0.57	0.52	0.04	0.01	2.84	0.081	694	0.000	7.4
AFTER	(Matched, ATT)	18	1187	14673	0.56	0.56	0.00	0.02	0.12	0.007	23	0.999	1.9
BEFORE	(Unmatched)	24	1206	14640	0.58	0.53	0.05	0.01	3.6	0.080	686	0.000	7.2
AFTER	(Matched, ATT)	24	1182	14640	0.58	0.57	0.01	0.02	0.58	0.010	33	0.984	1.9
Work experience: Without													
BEFORE	(Unmatched)	6	1067	27812	0.13	0.11	0.02	0.01	2.16	0.159	1451	0.000	13.9
AFTER	(Matched, ATT)	6	1046	27812	0.13	0.12	0.02	0.02	0.95	0.012	34	0.991	2.3
BEFORE	(Unmatched)	9	1162	27317	0.19	0.14	0.05	0.01	5.27	0.161	1565	0.000	14.0
AFTER	(Matched, ATT)	9	1139	27317	0.19	0.16	0.03	0.02	1.71	0.012	38	0.976	2.2
BEFORE	(Unmatched)	12	1168	26622	0.24	0.16	0.09	0.01	7.72	0.151	1463	0.000	10.8
AFTER	(Matched, ATT)	12	1145	26622	0.24	0.18	0.06	0.02	3.2	0.016	49	0.788	2.2
BEFORE	(Unmatched)	18	1156	26124	0.28	0.17	0.11	0.01	10.09	0.142	1356	0.000	10.7
AFTER	(Matched, ATT)	18	1133	26124	0.28	0.18	0.10	0.02	5.4	0.012	37	0.981	1.9
BEFORE	(Unmatched)	24	1135	25902	0.30	0.17	0.12	0.01	10.78	0.142	1340	0.000	10.2
AFTER	(Matched, ATT)	24	1113	25902	0.30	0.20	0.10	0.02	5.07	0.014	43	0.924	1.9
Work experience: With													
BEFORE	(Unmatched)	6	4866	152135	0.20	0.22	-0.02	0.01	-3.15	0.139	6034	0.000	12.3
AFTER	(Matched, ATT)	6	4769	152135	0.20	0.25	-0.06	0.01	-6.43	0.003	46	0.882	0.8
BEFORE	(Unmatched)	9	5878	145491	0.29	0.29	0.00	0.01	0.72	0.129	6410	0.000	11.8
AFTER	(Matched, ATT)	9	5761	145491	0.29	0.33	-0.04	0.01	-4.79	0.003	47	0.837	1.0
BEFORE	(Unmatched)	12	6164	141727	0.41	0.36	0.05	0.01	8.52	0.122	6255	0.000	10.3
AFTER	(Matched, ATT)	12	6041	141727	0.41	0.42	-0.02	0.01	-1.7	0.003	53	0.668	0.9
BEFORE	(Unmatched)	18	6293	139817	0.47	0.38	0.09	0.01	14.25	0.111	5777	0.000	9.9
AFTER	(Matched, ATT)	18	6168	139817	0.47	0.43	0.04	0.01	3.73	0.003	49	0.796	1.0
BEFORE	(Unmatched)	24	6255	138997	0.48	0.39	0.10	0.01	15.65	0.109	5641	0.000	9.8
AFTER	(Matched, ATT)	24	6130	138997	0.48	0.44	0.04	0.01	4.35	0.003	50	0.779	0.9
Region: Riga city													
BEFORE	(Unmatched)	6	650	53192	0.21	0.23	-0.01	0.02	-0.78	0.117	823	0.000	11.7
AFTER	(Matched, ATT)	6	637	53192	0.21	0.27	-0.07	0.02	-2.69	0.010	18	0.999	1.9
BEFORE	(Unmatched)	9	921	51107	0.28	0.30	-0.02	0.02	-1.05	0.113	1050	0.000	10.8
AFTER	(Matched, ATT)	9	904	51107	0.28	0.36	-0.08	0.02	-3.44	0.008	20	0.999	1.6
BEFORE	(Unmatched)	12	1010	50027	0.46	0.39	0.07	0.02	4.47	0.111	1099	0.000	11.8
AFTER	(Matched, ATT)	12	992	50027	0.46	0.52	-0.05	0.02	-2.31	0.006	15	0.999	1.8
BEFORE	(Unmatched)	18	1044	49702	0.54	0.41	0.12	0.02	7.86	0.102	1039	0.000	10.5
AFTER	(Matched, ATT)	18	1027	49702	0.53	0.56	-0.02	0.02	-0.89	0.006	18	0.999	1.7
BEFORE	(Unmatched)	24	1039	49666	0.55	0.42	0.13	0.02	8.51	0.100	1016	0.000	10.4
AFTER	(Matched, ATT)	24	1020	49666	0.54	0.55	0.00	0.02	-0.09	0.005	15	0.999	1.4

Evaluation results within groups: Modular training (MOT) - cont.

Sample				Results					Covariate Balancing			
Subsample (1)	THO (3)	NOC Treated (4)	NOC Controls (5)	Treated (6)	Controls (7)	Difference (8)	S.E. (9)	T-stat (10)	R2 (pseudo) (11)	LR (12)	$P > \chi 2$ (13)	Median Biais (14)
Region: Riga region												
BEFORE (Unmatched)	6	927	25400	0.20	0.21	-0.01	0.01	-1.05	0.131	1051	0.000	12.0
AFTER (Matched, ATT)	6	909	25400	0.20	0.27	-0.07	0.02	-3.5	0.011	27	0.998	2.1
BEFORE (Unmatched)	9	1105	24238	0.34	0.28	0.06	0.01	3.98	0.121	1096	0.000	11.7
AFTER (Matched, ATT)	9	1083	24238	0.34	0.34	0.00	0.02	-0.21	0.006	18	0.999	1.7
BEFORE (Unmatched)	12	1128	23541	0.44	0.34	0.10	0.01	6.91	0.110	1010	0.000	10.7
AFTER (Matched, ATT)	12	1106	23541	0.45	0.41	0.04	0.02	1.56	0.010	31	0.991	1.8
BEFORE (Unmatched)	18	1178	23354	0.49	0.36	0.13	0.01	9.22	0.100	949	0.000	10.1
AFTER (Matched, ATT)	18	1155	23354	0.49	0.43	0.06	0.02	2.73	0.008	24	0.999	1.9
BEFORE (Unmatched)	24	1168	23305	0.51	0.36	0.14	0.01	9.77	0.098	915	0.000	10.0
AFTER (Matched, ATT)	24	1145	23305	0.51	0.43	0.08	0.02	3.46	0.012	40	0.929	2.4
Region: Vidzeme												
BEFORE (Unmatched)	6	1106	17516	0.22	0.22	-0.01	0.01	-0.72	0.122	1020	0.000	11.6
AFTER (Matched, ATT)	6	1084	17516	0.22	0.27	-0.05	0.02	-2.42	0.011	33	0.984	1.9
BEFORE (Unmatched)	9	1223	16817	0.31	0.29	0.02	0.01	1.12	0.104	926	0.000	11.5
AFTER (Matched, ATT)	9	1199	16817	0.31	0.30	0.00	0.02	0.2	0.013	43	0.765	2.5
BEFORE (Unmatched)	12	1255	16369	0.42	0.35	0.07	0.01	4.98	0.097	877	0.000	10.3
AFTER (Matched, ATT)	12	1230	16369	0.42	0.41	0.01	0.02	0.34	0.009	31	0.992	1.9
BEFORE (Unmatched)	18	1254	16091	0.47	0.38	0.09	0.01	6.23	0.087	779	0.000	9.3
AFTER (Matched, ATT)	18	1231	16091	0.47	0.41	0.06	0.02	2.68	0.009	30	0.993	2.3
BEFORE (Unmatched)	24	1247	15993	0.49	0.39	0.10	0.01	6.93	0.085	764	0.000	9.0
AFTER (Matched, ATT)	24	1224	15993	0.49	0.42	0.07	0.02	3.25	0.008	29	0.997	1.7
Region: Kurzeme												
BEFORE (Unmatched)	6	930	25635	0.20	0.20	0.00	0.01	-0.06	0.120	966	0.000	12.6
AFTER (Matched, ATT)	6	912	25635	0.20	0.24	-0.04	0.02	-1.86	0.014	34	0.980	1.9
BEFORE (Unmatched)	9	1120	24593	0.29	0.26	0.02	0.01	1.77	0.117	1074	0.000	10.1
AFTER (Matched, ATT)	9	1098	24593	0.29	0.31	-0.02	0.02	-1.14	0.007	22	0.999	1.9
BEFORE (Unmatched)	12	1162	24014	0.40	0.31	0.09	0.01	6.47	0.109	1025	0.000	9.5
AFTER (Matched, ATT)	12	1139	24014	0.40	0.35	0.06	0.02	2.78	0.007	23	0.999	2.2
BEFORE (Unmatched)	18	1203	23719	0.49	0.34	0.15	0.01	10.57	0.100	964	0.000	9.3
AFTER (Matched, ATT)	18	1180	23719	0.48	0.36	0.13	0.02	5.86	0.007	22	0.999	2.0
BEFORE (Unmatched)	24	1205	23593	0.50	0.34	0.16	0.01	11.16	0.098	944	0.000	9.4
AFTER (Matched, ATT)	24	1181	23593	0.50	0.36	0.14	0.02	6.45	0.007	23	0.999	1.8
Region: Zemgale												
BEFORE (Unmatched)	6	1058	23908	0.18	0.17	0.00	0.01	0.37	0.146	1282	0.000	12.7
AFTER (Matched, ATT)	6	1038	23908	0.18	0.21	-0.04	0.02	-1.97	0.006	18	0.999	1.7
BEFORE (Unmatched)	9	1246	22916	0.26	0.23	0.03	0.01	2.62	0.143	1403	0.000	10.9
AFTER (Matched, ATT)	9	1223	22916	0.26	0.26	0.00	0.02	-0.26	0.009	32	0.992	2.1
BEFORE (Unmatched)	12	1326	22380	0.33	0.27	0.06	0.01	5.1	0.137	1399	0.000	10.8
AFTER (Matched, ATT)	12	1300	22380	0.33	0.33	-0.01	0.02	-0.27	0.008	29	0.997	1.5
BEFORE (Unmatched)	18	1346	22117	0.38	0.28	0.09	0.01	7.3	0.126	1297	0.000	9.7
AFTER (Matched, ATT)	18	1320	22117	0.37	0.35	0.02	0.02	1.08	0.009	32	0.986	2.2
BEFORE (Unmatched)	24	1335	22035	0.38	0.29	0.10	0.01	7.69	0.126	1292	0.000	9.8
AFTER (Matched, ATT)	24	1309	22035	0.38	0.36	0.02	0.02	0.87	0.007	25	0.999	1.3
Region: Latgale												
BEFORE (Unmatched)	6	1262	34081	0.13	0.15	-0.02	0.01	-1.48	0.143	1554	0.000	13.8
AFTER (Matched, ATT)	6	1237	34081	0.13	0.18	-0.05	0.02	-2.91	0.011	37	0.951	2.3
BEFORE (Unmatched)	9	1425	32309	0.20	0.20	0.00	0.01	-0.12	0.137	1623	0.000	12.4
AFTER (Matched, ATT)	9	1397	32309	0.19	0.22	-0.02	0.02	-1.49	0.009	35	0.979	1.7
BEFORE (Unmatched)	12	1451	31190	0.28	0.24	0.04	0.01	3.85	0.128	1520	0.000	10.8
AFTER (Matched, ATT)	12	1422	31190	0.28	0.29	-0.01	0.02	-0.47	0.007	29	0.998	2.0
BEFORE (Unmatched)	18	1424	30132	0.33	0.27	0.07	0.01	5.48	0.114	1318	0.000	10.1
AFTER (Matched, ATT)	18	1396	30132	0.33	0.33	0.00	0.02	-0.15	0.011	41	0.886	2.1
BEFORE (Unmatched)	24	1396	29481	0.35	0.27	0.08	0.01	6.22	0.111	1264	0.000	9.4
AFTER (Matched, ATT)	24	1369	29481	0.35	0.30	0.04	0.02	2.31	0.011	40	0.901	2.0

Explanatory notes for tables 4.5 - 4.9:

The table displays the results of evaluation of ALMP programs using Propensity Score Matching (Nearest neighbor matching, 1% caliper). ATT (Average Treatment effect on Treated) is evaluated. (1) Indicates the concerned sample: BEFORE matching (unmatched sample) of AFTER matching (the sample of trained individuals on common support and their twins from the group of control). (2) The year of registration with SEAL (the year of inflow in unemployment). (3) Time horizon for outcome variable (THO) specifies the the outcome variable used: employment within 6,9,12,18 or 24 months since registration. (4),(5) Number of cases in the group of treated unemployed or in control group. (6),(7) The average outcome in the group of treated unemployed or in control group. (8), (9), (10) Difference in average outcome between treated and controls, its standard error and T-statistics. (11), (12), (13) Pseudo R2, likelihood ratio and P-value of the likelihood test from probit estimation on the conditional probability to enter the program, indicating on the explanatory power of regressors X, which are the socio-demographic characteristics on which the propensity scores are estimates. Obviously, if the quality of matching (twin search) is high, none of the regressors explains the probability of treatment, giving R2 close to zero and P-value close to one. (14) Median absolute standardized bias before and after matching (taken over all regressors). Standardisation allows comparisons between varianles X and comparisons before and after matching. Following Rosenbaum and Rubin [1985] for a covariate X bias before matching is defined as $B_{Before}(X) = 100\frac{\overline{X}_1 - \overline{X}_0}{\sqrt{(V_1(X)+V_0(X))/2}}$ and bias after matching is defined as $B_{After}(X) = 100\frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{(V_1(X)+V_0(X))/2}}$. The variables $\overline{X}_1$, $\overline{X}_0$, $\overline{X}_{1M}$, $\overline{X}_{0M}$ denote respectively the sample means over full treated and non-treated sub-samples and over matched treated and non-treated sub-samples. (15), (16) Are the indicators for result sensitivity to potential hidden bias. (15) gives the Mantel and Haenszel test statistics for the situation free of hidden bias ($\Gamma = 1$), while (16) gives the intervals of Γ values, corresponding to the situation when treatement effects turn to be insignificant.

Table 4.10: **Evaluation results: "naive", parametric and nonparametric**

Sample				Naive				Parametric				Nonparametric			
Prog.	YR	THO	NOC	Difference (GM)	S.E.	T-stat	Sig	Difference (ME)	S.E.	Z-stat	Sig	Difference (ATT)	S.E.	T-stat	Sig
OT	2003	6	74751	0.06	0.010	6.4	***	0.04	0.010	4.3	***	0.04	0.02	2.34	**
OT	2003	9	84350	0.13	0.008	15.7	***	0.10	0.009	11.1	***	0.10	0.01	7.16	***
OT	2003	12	84877	0.24	0.008	28.7	***	0.21	0.010	21.8	***	0.17	0.01	12.99	***
OT	2003	18	85162	0.32	0.008	39.0	***	0.29	0.009	31.9	***	0.24	0.01	18.58	***
OT	2003	24	85297	0.32	0.008	40.5	***	0.30	0.009	33.6	***	0.25	0.01	20.04	***
OT	2004	6	80805	0.06	0.012	5.4	***	0.04	0.012	3.2	***	0.04	0.02	2.26	**
OT	2004	9	87696	0.13	0.010	13.2	***	0.09	0.010	8.8	***	0.10	0.02	6.18	***
OT	2004	12	88427	0.19	0.009	21.7	***	0.15	0.010	15.6	***	0.12	0.01	8.18	***
OT	2004	18	89085	0.27	0.008	32.9	***	0.24	0.009	26.7	***	0.20	0.01	15.96	***
OT	2004	24	88576	0.31	0.008	37.6	***	0.28	0.009	31.5	***	0.24	0.01	18.99	***
OT	2005-2006	6	97888	0.04	0.008	5.5	***	0.05	0.008	6.0	***	0.03	0.01	2.51	**
OT	2005-2006	9	91007	0.16	0.007	21.3	***	0.17	0.008	20.6	***	0.13	0.01	11.56	***
OT	2005-2006	12	86621	0.23	0.008	29.8	***	0.25	0.008	30.5	***	0.19	0.01	16.8	***
OT	2005-2006	18	84115	0.30	0.008	37.9	***	0.33	0.008	41.4	***	0.25	0.01	21.41	***
OT	2005-2006	24	83548	0.31	0.008	39.3	***	0.34	0.008	43.3	***	0.27	0.01	23.09	***
MLT	2005-2006	6	46916	-0.09	0.011	-7.8	***	-0.06	0.012	-4.9	***	-0.08	0.01	-5.58	***
MLT	2005-2006	9	43179	-0.06	0.012	-5.3	***	-0.01	0.014	-0.5		-0.05	0.02	-3.11	***
MLT	2005-2006	12	40963	-0.02	0.013	-1.2		0.03	0.014	1.9	*	-0.02	0.02	-1.12	
MLT	2005-2006	18	39659	0.03	0.014	2.1	**	0.08	0.015	5.1	***	0.02	0.02	1.13	
MLT	2005-2006	24	39370	0.04	0.014	2.6	***	0.08	0.015	5.4	***	0.03	0.02	1.22	
MOT	2004	6	86762	0.03	0.012	2.7	***	0.00	0.011	0.0		0.00	0.02	0.05	
MOT	2004	9	87375	0.02	0.010	2.2	**	-0.02	0.010	-2.1	**	-0.01	0.02	-0.91	
MOT	2004	12	87798	0.06	0.010	6.4	***	0.02	0.010	1.6		0.01	0.02	0.62	
MOT	2004	18	88199	0.09	0.009	10.1	***	0.05	0.010	4.9	***	0.05	0.01	3.12	***
MOT	2004	24	87667	0.11	0.009	12.0	***	0.07	0.010	6.6	***	0.05	0.01	3.09	***
MOT	2005-2006	6	100180	-0.04	0.006	-6.8	***	-0.04	0.007	-5.2	***	-0.05	0.01	-6.15	***
MOT	2005-2006	9	92919	-0.01	0.006	-2.3	**	-0.01	0.007	-1.8	*	-0.04	0.01	-3.77	***
MOT	2005-2006	12	88329	0.03	0.007	4.9	***	0.01	0.007	2.0	**	0.00	0.01	-0.24	
MOT	2005-2006	18	85637	0.07	0.007	10.4	***	0.05	0.008	7.1	***	0.05	0.01	4.31	***
MOT	2005-2006	24	85068	0.08	0.007	11.2	***	0.06	0.008	7.7	***	0.04	0.01	4.01	***

Notes: YR - year of registration as unemployed, THO - time horizon for outcome variable, NOC- number of cases in the sample (unmatched). Difference is defined as simple group mean difference for "naive" estimator, as group mean difference in a matches sample (ATT) for non parametric estimator and as marginal effect of treatment variable, evaluated at mean point for parametric estimator. *, **, *** denote the significance of the effect (difference) at respectively, 1, 5 and 10 percent levels.

Chapter 5

Conclusion

5.1 Main objectives, analysis and results

The main objective of this thesis is to assess the process of worker-job matching in several countries of Central and Eastern Europe through the last decade and to investigate the role of active labour market policy programmes in improving the performance of the labour market.

In **chapter 2**, we perform the analysis of the process of worker-firm matching in three new EU member states (Latvia, Slovenia and Estonia) by estimating the aggregate matching function. We address the possible misspecification of the matching function in two ways. First, following Coles and Smith [1998]), Gregg and Petrongolo [2005], Coles and Petrongolo [2003], we allow for stock-flow specification of the matching process. Second, based on the evidence from European labour markets (Burda and Profit [1996], Burgess and Profit [2001], Ahtonen [2005]), we allow for spatial interactions between regions in terms of worker and job flows.

The main results can be summarized as follows:

- The hiring process in three new EU member states is better described by a stock-flow rather than by a traditional matching function. In Latvia matches mostly occur between the stock of unemployed and the inflow of new vacancies, while in

Slovenia the inflows of unemployed also intensively participate in the matching process.

- Slovenian labour market seems to be less subject to frictions, comparing to the Baltic States, but the aggregate efficiency of the labour market in terms of worker-firm matching increases over time in Latvia and seems to decrease in Estonia and Slovenia.

- The role of labour demand in creating new hires stands crucial in three countries, but the results also feature the development of a new trend: after the accession to the EU the role of labour demand in the matching process becomes weaker, while the role of labour supply becomes more significant.

- The efficiency of matching varies across districts and regions and can partially be explained by the population density in the area or by its geographical location (its proximity to the national borders).

  In Slovenia the efficiency of the matching process seems to be lower in the areas where the population density is high, but in Latvia regional differences in matching efficiency can not be attributed to varying population densities.

  Both in Latvia and Slovenia, the closeness to the border negatively affects the regional efficiency in matching. In Latvia the matching is persistently the least efficient in the depressed eastern regions (on Russian and Byelorussian borders), while in Slovenia the negative proximity effect becomes weaker after the EU accession (at least at Italian and Austrian borders).

- Spatial spill over effects in matching are confirmed to be statistically significant: unemployed do not limit their search to the region of residence and search in neighboring areas. In Latvia the inflow of new vacancies in the neighboring areas positively affects local outflows to jobs, which is consistent with the dominance of labour demand in creating new matches. At the same time, the rise in foreign unemployment increases competition for vacancies in the local labour market and thus decreases local outflows to jobs. In Slovenia local outflows to jobs increase with the inflows into unemployment in neighboring regions.

- The asymmetry of spill over effects is weak in Latvia, while in Slovenia the magnitude of the effects depends on economic context in neighboring regions. Population density in the region can in part explain the magnitude of spillovers for some variables: vacancy inflow in neighboring districts dumps local hires in dense areas of Latvia, whereas in Slovenia local matches are negatively affected by the inflow of new unemployed in neighboring regions, if local population density is higher than national average.

In **chapter 3** we investigate the role of active labour market policy in improving the efficiency of the matching process. We evaluate the impact of unemployed occupational training on aggregate outflows from unemployment to jobs in Latvia. The analysis is performed by estimating the augmented matching function, which includes policy related variables measuring the participation of unemployed in this ALMP programme.

The main findings are the following:

- The effect of unemployed training on outflows from unemployment to employment is positive and statistically significant. This result is in line with Steiner and al. [1998] (Eastern Germany), Puhani [1999] (Poland) and Dmitrijeva and Hazans [2007] (Latvia), but contrasts with Lehmann [1995] or Gora et al. [1996](Poland), Hagen [2003], Hujer et al. [2002], Hujer and Zeiss [2003](East and West Germany).

- The results also indicate that the efficiency of unemployed training increases over time: the estimated semi elasticity of outflows with respect to the share of trained unemployed is higher after Latvia's accession to the EU, if compared to the pre-enlargement period.

- The costs-benefit analysis held in order to assess the feasibility of programme expansion shows that the costs of training are easily covered at the aggregate level if the average job tenure in the economy approaches 9 months.

- In terms of distribution across districts, both the efficiency of matching and the efficiency of unemployed training vary. The total gap in matching efficiency between Riga (capital city) and other districts is higher when the control for unemployed involvement in training programs is applied.

Taking into account that the macroeconomic efficiency analysis through the estimation of the augmented matching function on aggregate data does not allow measuring the effects of active labour market policy on individual level, we assess this issue in the **chapter 4**.

We use an individual database of Latvian unemployed and programme participants, registered with the SEAL in the time period between January 2003 and August 2006, to evaluate the average treatment effects of the following programmes: (i) unemployed occupational training, (ii) modular training in state language training for non - Latvians; (iii) modular training in other skills, *i.e.* foreign language, computer literacy, project management, driving.

We measure the impact of participation in each of those programmes on the unemployed chances to be employed within 6, 9, 12, 18 and 24 months after the date of registration by using "propensity score matching" (Rosenbaum and Rubin [1983], Heckman et al. [1999]).

The estimation results are the following:

- The participation in occupational training always increases individual employability, while the effects of modular training in state language are often insignificant and the effects of modular training in other skills are weak and only appear in a long run (after 18 months of unemployment).

- In line with the results in the previous chapter, we observe a slight improvement in the efficiency of occupational training programme over time.

- The effect of occupational training does not vary significantly with respect to the gender and is similar for Latvians and Russians, but it is heterogenous with respect to the age, education, working experience of the unemployed or their region of residence. Youngest unemployed (below 25 years) enjoy higher returns to training. The effect of occupational training also decreases with the level of educational attainment and is higher for the unemployed without work experience. From a regional perspective, the highest difference between treated and untreated individuals is observed in Kurzeme and Zemgale regions, but the lowest in Riga city.

- While the overall effect of modular training in state language is weak, it seems to be higher among men and unemployed without work experience. The unemployed without any certificate of proficiency in Latvian language also seem to benefit more from language training, although these effects are not statistically significant. The only group where language training significantly increases job finding rates among participants is the group of rural area inhabitants.

- The effects of modular training in other skills, are the highest among women, young unemployed, unemployed without work experience, Latvians and the residents of Riga, Vidzeme and Kurzeme regions.

- Despite the strong heterogeneity of treatment effects across socio-demographic groups, we do not find any empirical link between targeting of the programme and its efficiency: the targeted groups do not always enjoy higher returns to training, while the best performing groups are not always the best represented.

5.2 Policy recommendations

Summarizing the results of the analysis, the main findings concern *(i)* the important role of labour demand in creating new hires in transition countries; *(ii)* the positive effects of occupational training on employment at both macroeconomic and individual levels in Latvia; *(iii)* weak effect of other training programmes, especially modular training in state language.

The policy recommendations based on these results are the following:

First, the important role played by new vacancies in the outflows from unemployment, suggests the intensive use of programmes aiming at the creation of new jobs. Therefore, **wage subsidies to the private sector, credits to self-employed or other employment incentives should be extensively promoted**.

Second, despite the driving role of labour demand, occupational training has an important effect on unemployment reduction. Given the financial feasibility of this programme at the aggregate level and given the potentiality of important social effects (reducing discouragement and social exclusion) the **further promotion of occupational training programme** is strongly suggested.

Third, the weak effects of language training are presumably related to the absence of any certification procedure at the end of the programme. Meanwhile the certificate of proficiency is often required by the employers. Therefore the implementation of a **certification procedure after modular training** should be considered.

Fourth, unemployed with weak proficiency in Latvian language often display the lack of other basic and comprehensive skills, up to date education and qualifications, which makes them a group at high risk of unemployment, long-term unemployment and social exclusion. For such unemployed (and for the unemployed at high unemployment risk in general) **language training should be more often combined with occupational training or modular training in computer skills, management, driving**.

Fifth, given that also non-language modular training programme does not deliver a certificate, employers may have doubts on the quality of the training provided by SEAL and on the effective capacity of the participants to perform at the work place. Accounting in addition for the usual "fear factor" working for the employers when hiring unemployed, there is a necessity to send a positive signal to the employer concerning the skills and working ability of the unemployed. Such signal may be sent by allowing the employer to test the adequacy of job seeker skills. It could be interesting **to introduce a combined training/practice at the work place programme**. This programme may consist of the usual training programme followed by a work/internship period with an employer. Apart positive signalling, this programme may also be viewed as a tool for providing work experience to the unemployed, increasing their social skills and motivation.

5.3 Directions for further research

In this section we discuss the directions for further research.

In chapter 2, we have analyzed different aspects of the process of worker-firm matching in selected countries of Central and Eastern Europe: Latvia, Estonia and Slovenia.

The results suggest that this process does not only rely on the stocks of unemployed and vacancies at the beginning of the period as traditionally supposed. Inflows into the pools of unemployed and vacancies also intensively contribute in the process of match creation. Still we have detected cross country differences in the nature of the hiring process: in Latvia due to job shortage and limited labour demand, hires mainly occur between the stock of unemployed and the inflow of new vacancies; in Slovenia the inflow of new unemployed also plays an important role in match creation.

From this perspective it would be interesting to extend the performed analysis to a larger set of countries and to detect what are the main configurations prevailing in the labour markets of new EU member states.

Another possible improvement concerns the method we have employed for analyzing spatial spillovers in the matching process: more rigorous conclusions on the migration and commuting behavior of job seekers may be derived if instead of simple binary neighborhood indicators, the distances between the observational units (districts, regions) is used.

In chapter 3, we have augmented the matching function with the variables measuring unemployed participation in occupational training programme in order to evaluate the aggregate implications of this policy measure in Latvia. The analysis is based on the assumption that trained and untrained unemployed have different search effectiveness and therefore differ in their chances to be hired.

One of the limits of our analysis is the fact that we assume the increase in search efficiency due to training to be homogenous across Latvian districts. Relaxing such assumption and allowing this parameter to vary across observational units would capture potential regional variation in programme efficiency among Latvian districts.

Another limit of the analysis concerns the fact that we do not take into account possible interactions between the programme participants and other unemployed and disregard, thus, general equilibrium effects of unemployment training programmes (raise in productivity, competition with insiders, substitution). Performing both programme evaluation and cost-benefit analysis of the programmes in a more complete general equilibrium framework would allow to have a more precise evaluation of both positive and negative effects.

In chapter 4, we focused on the evaluation of individual treatment effects of several unemployed training programmes (occupational training, modular training in state language and modular training in other skills) implemented by the Latvian State Employment Agency.

The analysis was performed by applying the propensity score matching method, which is widely used for evaluation purposes. A major drawback of our study concerns the inability to account for censored observations. Instead of withdrawing them, we could borrow from the techniques of survival analysis to handle this issue. A duration model could be used to estimate the propensity scores, as in Brodaty et al. [2000]. Following Crepon and Duguet [2004] we could also consider a survival function as outcome variable.

Besides, it could be interesting to consider an alternative estimation strategy, suggested by Abbring and van den Berg [2003]. Based on the nonparametric identification of treatment effects in a duration model framework, this approach would allow a more flexible representation of transitions out of unemployment by introducing duration dependence and the timing of events. The long term effect of the programme could also be assessed by following Crepon et al. [2005] or Crepon et al. [2007], who investigate the relationship between the participation in the programme and the recurrence of unemployment spells through a multivariate specification which includes subsequent employment durations.

Finally, it could be interesting to enlarge the scope of evaluated programmes to non-training programmes, such as subsidies to private sector or self-employment credits (usually the most efficient programmes, according to the evaluation results from other European countries). The programme heterogeneity (in terms of type, intensity or duration) may be accounted for in a multiple treatment setting (Imbens [2000], Lechner [2001], Frolich [2004]).

Bibliography

A. Aakvik. Bounding a matching estimator: The case of a norwegian training program. *Oxford Bulletin of Economics and Statistics*, 63(1):115–43, February 2001.

A. Abadie and G.W. Imbens. On the failure of the bootstrap for matching estimators. NBER Technical Working Papers 0325, National Bureau of Economic Research, Inc, June 2006.

J.H. Abbring and G. van den Berg. The nonparametric identification of treatment effects in duration models. *Econometrica*, 71(5):1491–1517, 09 2003.

S.M. Ahtonen. Matching across space: Evidence from finland. *Labor*, 19(4):749–765, December 2005.

P.M. Anderson and S.M. Burgess. Empirical matching functions: Estimation and interpretation using dissagregate data. *Review of Economics and Statistics*, 82(1): 93–102, 2000.

S. Anspal and A. Vork. Labour market institutions and productivity in the new eu member states. PRAXIS Working Paper No.27, 2007.

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

N. Beck and J.N. Katz. Nuisance vs. substance: Specifying and estimating time series cross section models. *Political Analysis*, 6:1–36, 1996.

S.O. Becker and M. Caliendo. mhbounds - sensitivity analysis for average treatment effects. Technical report, 2007.

S.O. Becker and A. Ichino. Estimation of average treatment effects based on propensity scores. *Stata Journal*, 2(4):358–377, November 2002.

K. Benett, M. G. Coles, and J. C. van Ours. Temporal aggregation bias in stock-flow models. CEPR Discussion paper No.967, 1994.

G. Betcherman, K. Olivas, and A. Dar. Impacts of active labor market programs: New evidence from evaluations with particular attention to developing and transition countries. World Bank Social Protection Discussion Paper Series No.0402, 2004.

O. Blanchard and P. Diamond. The beveridge curve. *Brooking Papers on Economic Activity*, 1:1–60, 1989.

T. Boeri. Transition with labor supply. IZA Discussion Paper No. 257, 2001.

T. Boeri and M.C. Burda. Active labor market policies, job matching and the czech miracle. *European Economic Review*, 40:805–817, 1996.

T. Boeri and K. Terrell. Institutional determinants of labor reallocation in transition. *Journal of Economic Perspectives*, 16(1):51–76, 2002.

I. Bolvig, P. Jensen, and M. Rosholm. The employment effects of active social policy. IZA Discussion Papers 736, Institute for the Study of Labor (IZA), March 2003.

T. Brodaty, B. Crepon, and D. Fougere. Using matching estiamtors to evaluate youth employment programs: Evidence from france, 1986-1988. Econometric Society World Congress 2000 Contributed Papers 0576, Econometric Society, August 2000.

T. Brodaty, B. Crepon, and D. Fougere. Do long term unemployed workers benefit from active labour market programs? evidence from franece, 1986-1998. mimeo, Econometric Society, 2002.

M.C. Burda. Unemployment, labor markets and structural change in eastern europe. *Economic Policy*, 16:102–137, 1993.

M.C. Burda and M. Lubyova. The impact of active labor market policies : a closer look at the czech and slovak republics. In D. Newberry, editor, *Tax and benefit reform in Cental and Eastern Europe*. 1995.

M.C. Burda and S. Profit. Matching across space: Evidence on mobility in czech republic. *Labor Economics*, 3:255–278, 1996.

M.C. Burda and C. Wyplosz. Gross worker and job flows in europe. *European Economic Review*, 38(6):1287–1315, June 1994.

S. Burgess and S. Profit. Externalities in the matching of workers and firms in britain. *Labor Economics*, 8(3):313–333, 2001.

M. Caliendo and S. Kopeinig. Some practical guidance for the implementation of propensity score matching. IZA Discussion Papers 1588, Institute for the Study of Labor (IZA), May 2005.

M. Caliendo, R. Hujer, and S. L. Thomsen. Identifying effect heterogeneity to improve the efficiency of job creation schemes in germany. IAB Discussion Paper 200508, IAB - Institute for Employment Research, Nuremberg, Germany, April 2005a.

M. Caliendo, R. Hujer, and S. L. Thomsen. The employment effects of job creation schemes in germany: A microeconometric evaluation. IZA Discussion Papers 1512, Institute for the Study of Labor (IZA), March 2005b.

L. Calmfors. Active labour market policy and unemployment - a framework for the analysis of crucial desing features. OECD Economic Studies 22, OECD, 1994.

L. Calmfors, A. Forslund, and M. Hemstrom. Does active labour market policy work? lessons from the swedish experiences. Working Paper Series 2002:4, IFAU - Institute for Labour Market Policy Evaluation, January 2002.

W. Cochran and S. Chambers. The planning of observational studies of human populations. *Journal of the Royal Statistical Society, Series A*, 128(2):234–266, 1965.

W. Cochran and D. Rubin. Controlling bias in observational studies. *Sankyha*, 35: 417–446, 1973.

B. Cockx. Vocational training of unemployed workers in belgium. IZA Discussion Papers 682, Institute for the Study of Labor (IZA), January 2003.

B. Cockx and C. Gobel. Subsidized employment for young long-term unemployed workers an evaluation. mimeo, 2004.

M. Coles and B. Petrongolo. A test between unemployment theories using matching data. IZA Discussion Paper No. 723, 2003.

M. Coles and J. Smith. Cross section estimation of the matching function: Evidence from england and wales. *Economica*, 63(252):589–598, 1996.

M. Coles and J. Smith. Marketplaces and matching. *International Economic Review*, 39(1):239–254, 1998.

B. Crepon and E. Duguet. Bank loans, start-up subsidies and the survival of the new firms: an econometric analysis at the entrepreneur level. Labor and Demography 0411004, EconWPA, November 2004.

B. Crepon, M. Dejemeppe, and M. Gurgand. Counseling the unemployed: Does it lower unemployment duration and recurrence? IZA Discussion Papers 1796, Institute for the Study of Labor (IZA), October 2005.

B. Crepon, M. Ferracci, and D. Fougere. Training the unemployed in france: How does it affect unemployment duration and recurrence? IZA Discussion Papers 3215, Institute for the Study of Labor (IZA), 2007.

R.H. Dehejia and S. Wahba. Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84(1):151–161, February 2002.

R.H. Dehejia and S. Wahba. Causal effects in non-experimental studies: Re-evaluating the evaluation of training programs. *Journal of American Statistical Association*, 94 (448):1053–1062, 1999.

J. Dmitrijeva and M. Hazans. A stock-flow matching approach to evaluation of public training programme in a high unemployment environment. *Labor*, 21(3):503–540, September 2007.

M. Eichler and M. Lechner. An evaluation of public employment programmes in the east german state of sachsen-anhalt. *Labour Economics*, 9(2):143–186, April 2002.

R. Fahr and U. Sunde. Regional dependencies in job creation: an efficiency analysis for western germany. *Applied Economics*, 38(10):1193–1206, June 2006a.

R. Fahr and U. Sunde. Spatial mobility and competition for jobs: Some theory and evidence for western germany. *Regional Science and Urban Economics*, 36(6):803–825, November 2006b.

R. Fay. Enhancing the effectiveness of active labor market policies: Evidence from programme evaluations in oecd countries. Labor Market and Social Policy Occasional Papers No.18, Paris, 1996.

P. Fredriksson and P. Johansson. Employment, mobility, and active labor market programs. Working Paper Series 2003:3, IFAU - Institute for Labour Market Policy Evaluation, January 2003.

M. Frolich. Programme evaluation with multiple treatments. *Journal of Economic Surveys*, 18(2):181–224, 04 2004.

K. Galuscak and D. Munich. Structural and cyclical unemployment: What can we derivate from the matching function? CNB Working Paper No. 2/2005, 2005.

M. Gora, H. Lehmann, M. Socha, and U. Sztanderska. Labor market policies in poland. In OECD, editor, *Lessons from labor market policies in transition countries*. 1996.

P. Gregg and B. Petrongolo. Stock flow matching and the performance of the labor market. *European Economic Review*, 49, 2005.

T. Hagen. Three approaches to the evaluation of active labor market policy in east germany using regional data. ZEW Discussion Paper No.03-27, 2003.

K. Hamalainen and V. Ollikainen. Differential effects of active labour market programmes in the early stages of young people's unemployment. VATT Research Reports 115, Government Institute for Economic Research (VATT), December 2004.

M. Hazans. Unemployment and the earnings structure in latvia. World Bank Policy Research Working Paper No. 3504, 90 pp. World Bank: Washington DC, 2005.

M. Hazans, J. Dmitrijeva, and I. Trapeznikova. Reasons and duration of unemployment and social exclusion in latvia. Latvian Ministry of Welfare, Riga, 2007.

J.J. Heckman, R.J. LaLonde, and J.A. Smith. The economics and econometrics of active labor market programs. *Handbook of labor economics*, 3A,chapter 31, 1999.

G. Hughes and B. McCormick. Did migration in the 1980s narrow the north-south divide? *Economica*, 61(244):509–27, November 1994.

R. Hujer and C. Zeiss. Macroeconomic impacts of almps on the matching pross in west germany. IZA Discussion Paper No.915, 2003.

R. Hujer, U. Blien, M. Caliendo, and C. Zeiss. Macroeconomic evaluation of active labor market policies in germany: A dynamic panel approach using regional data. IZA Discussion Paper No.616, 2002.

R. Hujer, M. Caliendo, and Radi D. Estimating the effects of wage subsidies on the labor demand in west germany using the iab establishment panel. In Statistisches Bundesamt, editor, *MIKAS Mikroanalysen und amtliche Statistik, Wiesbaden: Statistisches Bundesamt*. 2004.

G. Imbens. The role of propensity score in estimating dose response functions. *Biometrica*, 87(3):706–710, 2000.

G.W. Imbens. Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86(1):4–29, 06 2004.

S. Kano and M. Ohta. Estimating a matching function and regional matching efficiencies: Japanese panel data for 1973-1999. *Japan and the World Economy*, 17(1): 25–41, January 2005.

J. Kluve, editor. *Active Labor Market Policies in Europe: Performance and Perspectives*. Springer, Ney York, 2007.

J. Kluve, H. Lehmann, and C. Schmidt. Active labor market policies in poland: Human capital enhancement, stigmatization, or benefit churning? *Journal of Comparative Economics*, 27, 1999.

J. Kluve, H. Lehmann, and C.M. Schmidt. Disentangling treatment effects of polish active labor market policies: Evidence from matched samples. Technical report, 2002.

R. Layard, S. Nickell, and R. Jackman. *Unemployment: Macroeconomic Performance and the Labor Market*. 1991.

M. Lechner. Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. In M. Lechner and F. Pfeiffer, editors, *Econometric Evaluation of Labour Market Policies*. 2001.

M. Lechner. Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. pages 43–58. Heidelberg: Physica Verlag, 1999a.

M. Lechner. An evaluation of public-sector-sponsored continuous vocational training programs in east germany. IZA Discussion Papers 93, Institute for the Study of Labor (IZA), December 1999b.

M. Lechner, R. Miquel, and C. Wunsch. Long-run effects of public sector sponsored training in west germany. IZA Discussion Papers 1443, Institute for the Study of Labor (IZA), December 2004.

R. Leetmaa and A. Vork. Evaluation of active labour market programs in estonia. PRAXIS Working Paper No.9/2003, 2003.

H. Lehmann. Active labor market policies on oecd and in selected transition economies. World Bank Policy Research Working Paper No. 1502, Washington D.C., 1995.

J. Lopez-Tamayo, J. Surinach, and E. Lopez-Bazo. Returns to matching: The effect of spatial interactions in labour markets. Department of Econometrics,University of Barcelona, 2000.

T. Loretzen and E. Dahl. Active labour market policies in norwey: are they helpful for social assistance recepients? *International Journal of Social Welfare*, 14:86–98, 2005.

D. Munich, J. Svejnar, and K. Terrell. Worker-form matching ad unemployment in transition to market economy: (why) were the czech more successful that others? William Davidson Institute Working Paper No. 107, 1999.

B. Petrongolo and C.A. Pissarides. Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, 39(2), 2001.

B. Petrongolo and E. Wasmer. Matching et spillovers rgonaux en grande-bretagne et en france. In Lesueur J.-Y. Catin M. and Zenu Y., editors, *Dveloppements Rcents en Economie Spatiale: Emploi, Concurrence Spatiale et Dynamiques Ronales*. 1999.

C.A. Pissarides. Unemployment and vacancies in britain. *Economic Policy*, 3:676–690, 1986.

S. Profit. Twin peaks in regional unemployment and returns to scale in job matching in the czech republic. Discussion paper No.63, Humboldt University, Berlin, 1997.

P. Puhani. Estimating the effects of public training on polish unemployment by way of the augmented matching function approach. CEPR Discussion Paper No.2244, 1999.

O. Raaum, H. Torp, and T. Zhang. Do individual programme effects exceed the costs? norwegian evidence on long run effects of labour market training. Memorandum 15/2002, Oslo University, Department of Economics, June 2003.

P.R. Rosenbaum. *Observational Studies.* Springer, 2nd edition, New York, 2002.

P.R. Rosenbaum and D.B Rubin. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55, January 1983.

P.R. Rosenbaum and D.B Rubin. Reducing bias in observational studies using subclassification on the propensity score. *Journal of American Statistical Association*, 79:516–524, January 1984.

P.R. Rosenbaum and D.B Rubin. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–387, 1985.

A. Roy. Some thoughts on the distribution of earnings. *Oxford Economic Papers*, 3(2): 135–145, 1951.

D. Rubin. Estimating casual effects to treatments in randomised and nonrandomised studies. *Journal of Educational Psychology*, 66:688–701, 1974.

D. Rubin. Comments on "randomisation analysis of experimental data:the fisher randomisation test by d. bazu". *Journal of the Americal Statistical Association*, 75: 591–593, 1980.

U. Rutkaste. Darbaspeka migracija: attistibas tendences, ekonomiskie efekti, problemas risinajuma varianti, 2006.

J. Rutkowski. Labor market developments during economic transition. Policy Research Working Paper Series 3894, The World Bank, April 2006.

SEAL. Regionalie petijumi par bezdarbnieku socialpsihologisko portretu: Latvija. petijuma atskaite. Latvian State Employment Agency, Riga 2006, 2006.

B. Sianesi. An evaluation of the swedish system of active labour market programmes in the 1990s. IFS Working Papers W02/01, Institute for Fiscal Studies, January 2002.

J. Smith and P. Todd. Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1-2):305–353, 2005.

V. Steiner and al. Strukturanalyse der arbeitsmarktentwicklung in den neuen bundeslndern, endbericht fr das bundesministerium fr wirtschaft. Zentrum fr Europische Wirtschaftsforschung and Rheinisch-Westflisches Institut fr Wirtschaftsforschung, Mannheim, 1998.

J. Svejnar, K. Terrell, and D. Munich. Unemployment in the czech and slovak republics. In J. Svejnar, editor, *The Czech Republic and Economic Trasition in Eastern Europe*. 1995.

J.M. Wooldridge. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge,MA, 2002.

Abstract

During the transition to market economy and the accession to the EU Central and Eastern European countries have witnessed remarkable changes in the structure and functioning of national economies. This thesis aims to assess the development of aggregate and regional labour markets in new EU member states through this eventful period and to investigate the role of active labour market policy in moderating the consequences of transitional shock and improving the performance of the labour market. The analysis of the process of worker-firm matching in Latvia, Slovenia and Estonia reveals that in transition - EU accession context the hiring process is labour demand driven and displays the existence of stock-flow patterns and spatial spillovers. The effects of ALMP programs are confirmed to be positive at both macroeconomic and individual levels : involvement of unemployed in training increases aggregate outflows from unemployment to jobs and increases individual employability of participants.

Keywords : Unemployment, transition economy, evaluation of public policy, training programmes, matching functions, stock-flow matching, spatial spillovers, treatment effects and matching methods.

Résumé

Transition vers l'économie de marché et accession a l'Union Européenne ont profondément modifié la structure et le fonctionnement des économies d'Europe Centrale et de l'Est. Cette thèse propose une analyse des évolutions observées sur les marchés du travail régionaux et nationaux des nouveaux pays membres de l'Union Européenne ainsi qu'une évaluation des politiques publiques mises en œuvre dans ce contexte de transition économique. L'analyse du processus d'appariement entre travailleurs et employeurs révèle l'importance de la demande de travail dans la création de nouvelles embauches en Lettonie, Slovénie et Estonie et souligne la nécessité d'intégrer flux (chômeurs et emplois vacants) et effets spatiaux dans la modélisation. L'efficacité des politiques publiques est attestée au niveau macro et microéconomiques et démontre l'influence positive des programmes de formation sur les sorties du chômage et l'employabilité des participants.

Mots clef : Marché du travail, chômage et emploi, économie en transition, évaluation des politiques publiques, programmes de formation, fonctions d'appariement, appariement stock-flux, interactions spatiales, effets de traitement, méthodes d'appariement.

JEL Classification : C13, J41, J64, J68, H43.