Does unemployed training increase individual employability: evidence from Latvian microdata*

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Abstract

In this paper we evaluate the efficiency of unemployed training programmes in Latvia, using propensity score matching. Primary data files provided by the State Employment Agency of Latvia are used to construct the individual database of unemployed and programme participants. 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 investigate the impact of participation in each of those programs on the unemployed transition to employment, examine heterogeneity in programme effect across different socio - demographic (gender, age, education) and regional groups and try to establish an empirical link between targeting of the programme and its efficiency. We also test the sensitivity of our results to the so called "hidden" bias.

The results reveal that 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. The effect of occupational training does not vary significantly with respect to the gender or ethnicity, but it is heterogenous with respect to the age (stronger among young unemployed) education (increasing in its level), working experience of the unemployed or their region of residence. The effect of modular training is higher among men, unemployed without work experience and rural area inhabitants, while modular training in other skills has the strongest impact on women, young unemployed, unemployed without work experience and Latvians.

Keywords: policy evaluation, unemployed training, propensity score matching, sensitivity analysis. **JEL Classification :** C13, J68, H43.

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1 Introduction

This paper aims to assess a comprehensive evaluation of microeconomic effects of training programmes on job seeker individual employability in Latvia.

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, re-qualification 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 paper is organized as follows. Section 2 gives more details on the evaluated

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

measures and provides descriptives on participation in the ALMP programmes in Latvia. The evaluation methodology is presented in section 3. Section 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 5, while section 6 concludes and derives policy suggestions.

2 Evaluation context

The aim of this paper 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 paper (see details in section 4) gives the possibility to derive the 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 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). 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

[2]This programme is evaluated from macroeconomic perspective in Dmitrijeva and Hazans [2007].

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.

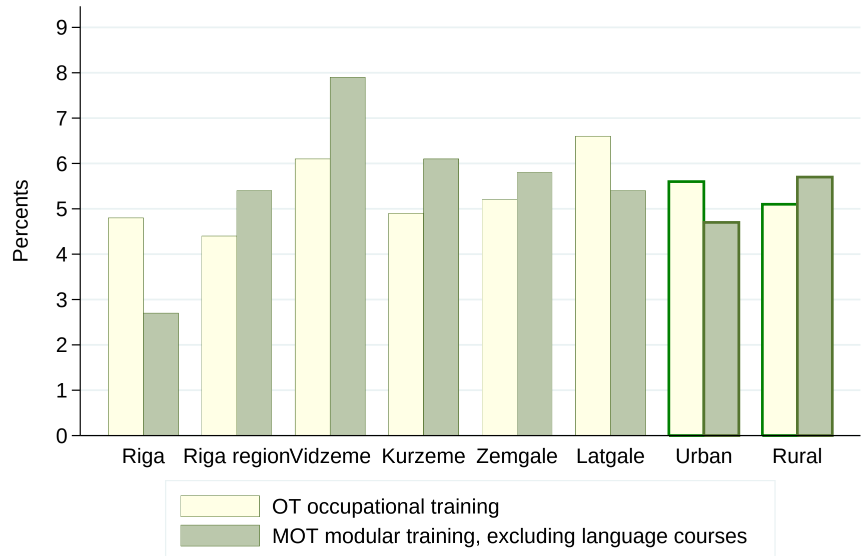
Modular training in other skills (MOT) covers training in foreign language (English, German); computer literacy or improving of computer skills; training in project management, accounting, record keeping, marketing or business operation; receipt of driving licence and qualification (various categories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

Figure 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.

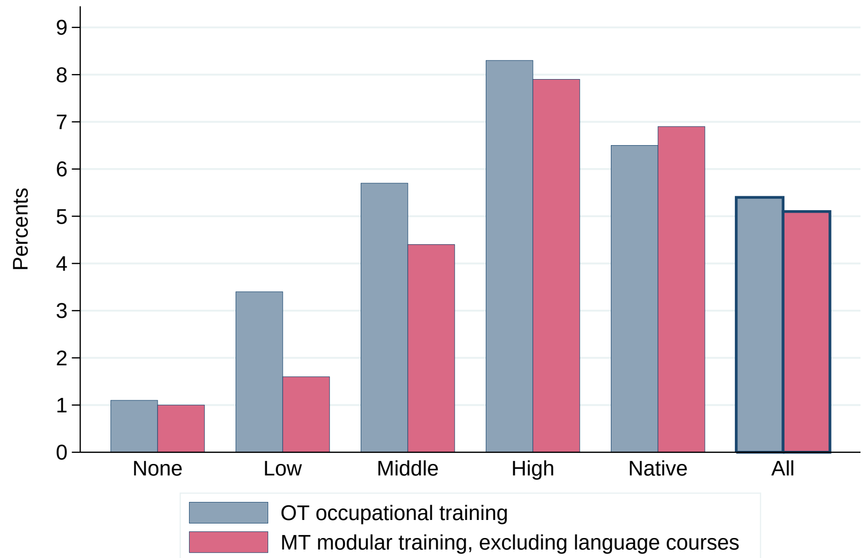
modular training in each of these groups.

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 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 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

Figure 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.

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.

3 Evaluation methodology: Propensity score matching

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:

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

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:

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0) \tag{2}$$

For treated unemployed ($T_i = 1$) only a realization of $Y_i(1)$ is observable (the variable $(1 - T_i)$ in the equation 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:

$$C = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)] \tag{3}$$

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:

$$C_0 = E[Y(1) - Y(0)|_{T=0}] = E[Y(1)|_{T=0}] - E[Y(0)|_{T=0}] \tag{4}$$

[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.

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:

$$C_1 = E[Y(1) - Y(0)|_{T=1}] = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] \tag{5}$$

The first component of equation 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:

$$E[Y(0)|_{T=1}] = E[Y(0)|_{T=0}] = E[Y(0)] \tag{6}$$

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 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).

$$\Delta = E[Y(1)|_{T=1}] - E[Y(0)|_{T=0}] = C_1 \tag{7}$$

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 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 (6) and introduce bias in "naive" estimator Δ:

$$\Delta = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] + E[Y(0)|_{T=1}] - E[Y(0)|_{T=0}] = C_1 + B_{TT} \tag{8}$$

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:

$$(Y(1), Y(0)) \amalg T|X \tag{9}$$

Being in the heart of evaluation studies, the assumption 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:

$$E[Y(0)|_{T=1,X}] = E[Y(0)|_{T=0,X}] \tag{10}$$

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

$$C_1 = E[Y(1)|_{T=1}] - E[Y(0)|_{T=1}] = E_X(E[Y(1)|_{T=1,X}] - E[Y(0)|_{T=1,X}]|_{T=1}) \tag{11}$$

And using CIA:

$$C_1 = E_X(E[Y(1)|_{T=1,X}] - E[Y(0)|_{T=0,X}]|_{T=1}) = E_X(E[Y|_{T=1,X}] - E[Y|_{T=0,X}]|_{T=1}) \tag{12}$$

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.

$$\pi(X) = Pr(T = 1|X) = Pr(T|X) \tag{13}$$

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]).

$$(Y(1), Y(0)) \amalg |X \Longrightarrow Y(1), Y(0)) \amalg T|\pi(X) \tag{14}$$

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

$$C_1 = E_{\pi(X)}(E[Y(1)|_{T=1,\pi(X)}] - E[Y(0)|_{T=0,\pi(X)}]|_{T=1}) \tag{15}$$

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:

$$0 < \pi(X) < 1 \tag{16}$$

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

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 Dataset, definitions

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 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

[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.

[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). We briefly describe the contents and structure of primary data files, as well as the procedure of building a unified data set and examine its adequacy with respect to aggregate data in the appendix. 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.

[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.

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 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).

4.2 Characteristics of treatment and comparison groups

The descriptive statistics on the estimation sample separated by participation status is given in tables 2 -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 often unspoken) for such unemployed.

In terms of age, the share of prime age individuals (24 to 44 years old) is almost identical

[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.

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.

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

[8]See below the definition of main variables.

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), 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 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].

[9] NUTS 4 level division.

[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

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 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.

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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.

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.

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 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.

5.2 Treatment effects

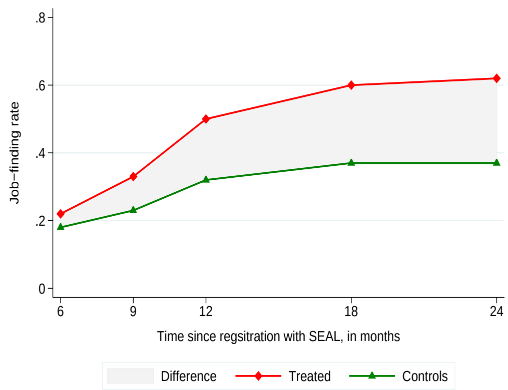
Let us now turn to the results of programme evaluation, being displayed in tables 5 - 7 in the appendix.

Generally, the matching quality is sufficiently high for the results to be interpreted with confidence. Figures 8 and 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 (5 to 6), 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.

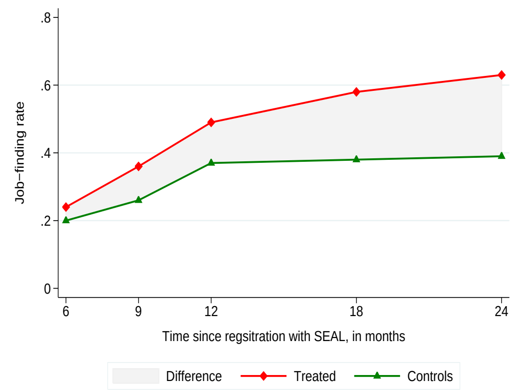
Figure 3 below compares the average employment outcomes - a shift from unemployment to employment within 6, 9, 12, 18 and 24 months since registration with SEAL - of trained (treated) and untrained (controls) individuals[12]. The results are displayed separately for each of training programmes (OT, MLT MOT) and are sorted by the year of inflow into unemployment programs (2003, 2004 or 2005-2006).

[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.

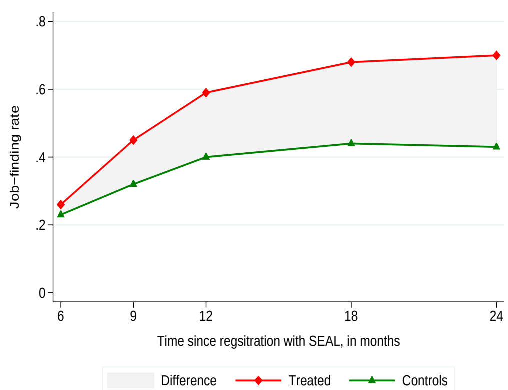
Figure 3: Policy evaluation results, by year of inflow into unemployment



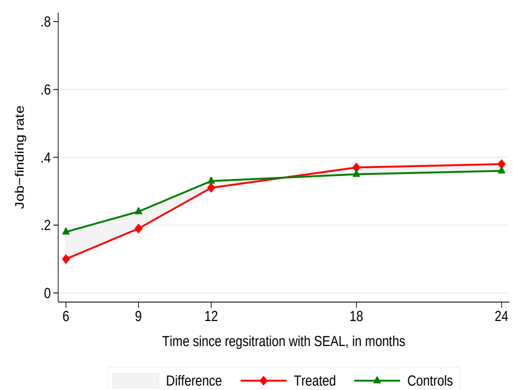
(a) OT, registration in 2003



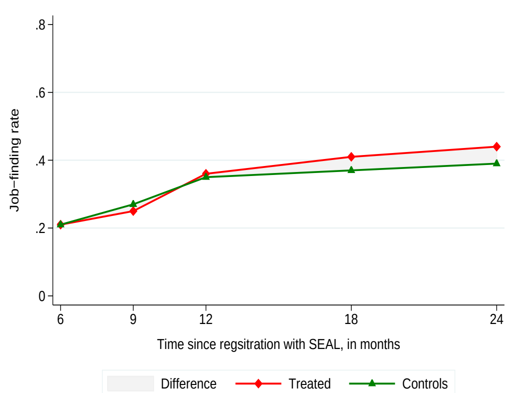
(b) OT, registration in 2004



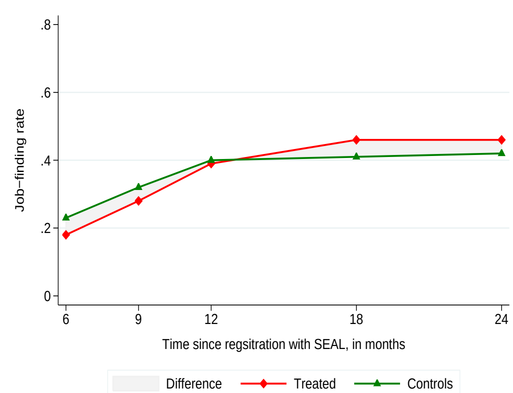
(c) OT, registration in 2005-2006



(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).

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 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 7). 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 7 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 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

[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.

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.

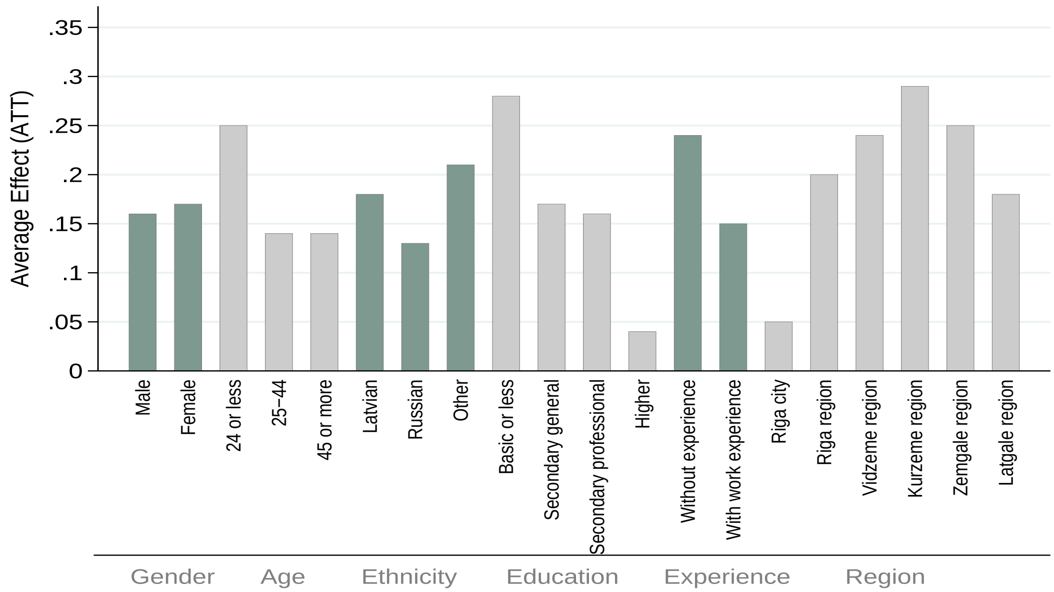
The figure 4 displays the average affect of OT programme (ATT) in different socio-demographic groups of unemployed. We compare the average effect of the programme on the job finding indexes at 12 month horizon (for other time horizons the results are qualitatively similar). The effect of occupational 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.

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 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.

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

Figure 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.

The figures 5 - 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.

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. 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.

Figure 5: Average effect of MLT programme in different groups of unemployed

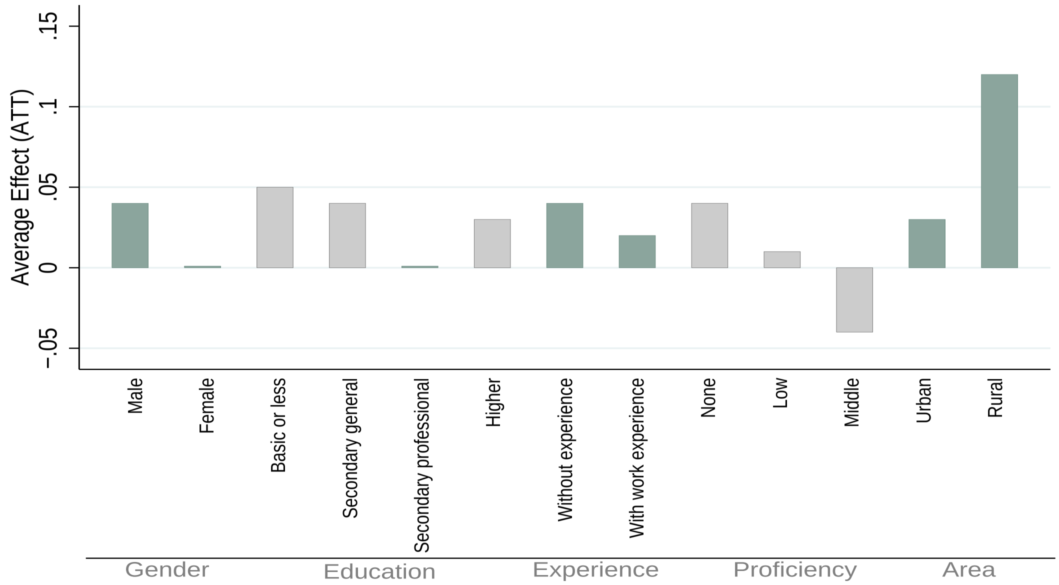
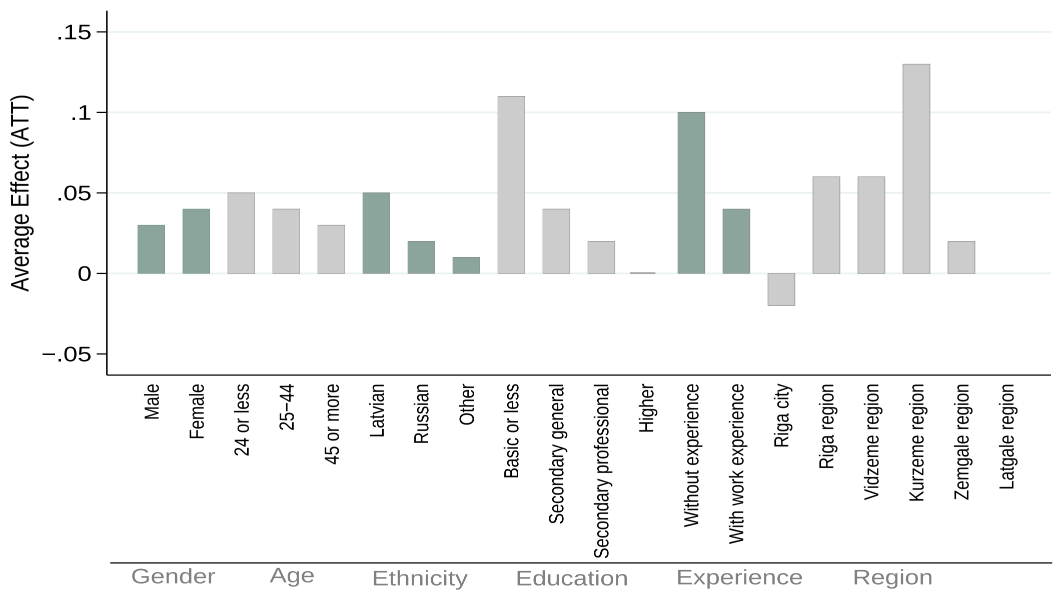


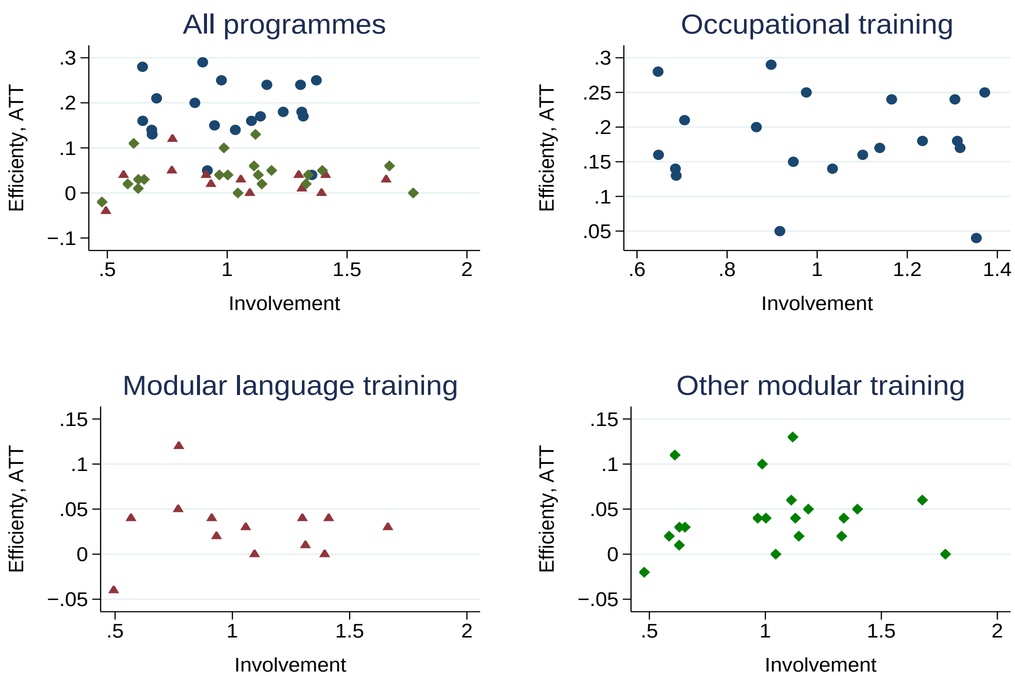
Figure 6: Average effect of MOT programme in different groups of unemployed



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

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 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 $L_i = \frac{T_i/T}{N_i/N}$.

Figure 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.

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.

6 Conclusions and policy suggestions

This paper 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 Dmitrijeva and Hazans [2007]), 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.

References

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.

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.

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. 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.

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.

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.

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.

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, 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.W. Imbens. Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86(1):4–29, 06 2004.

J Kluve, editor. *Active Labor Market Policies in Europe: Performance and Perspectives*. Springer, Ney York, 2007.

J. Kluve, H. Lehmann, and C.M. Schmidt. Disentangling treatment effects of polish active labor market policies: Evidence from matched samples. Technical report, 2002.

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.

R. Leetmaa and A. Vork. Evaluation of active labour market programs in estonia. PRAXIS Working Paper No.9/2003, 2003.

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.

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 sub-classification 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.

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.

7 Appendixes

Table 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 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 3: **Modular Training: Descriptive statistics on estimation sample (employment within 12 months from registration**

	Modular training					
	Other than language				Language	
Registration in	2004		2005 - 2006		2005 - 2006	
	Controls	Treated	Controls	Treated	Controls	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

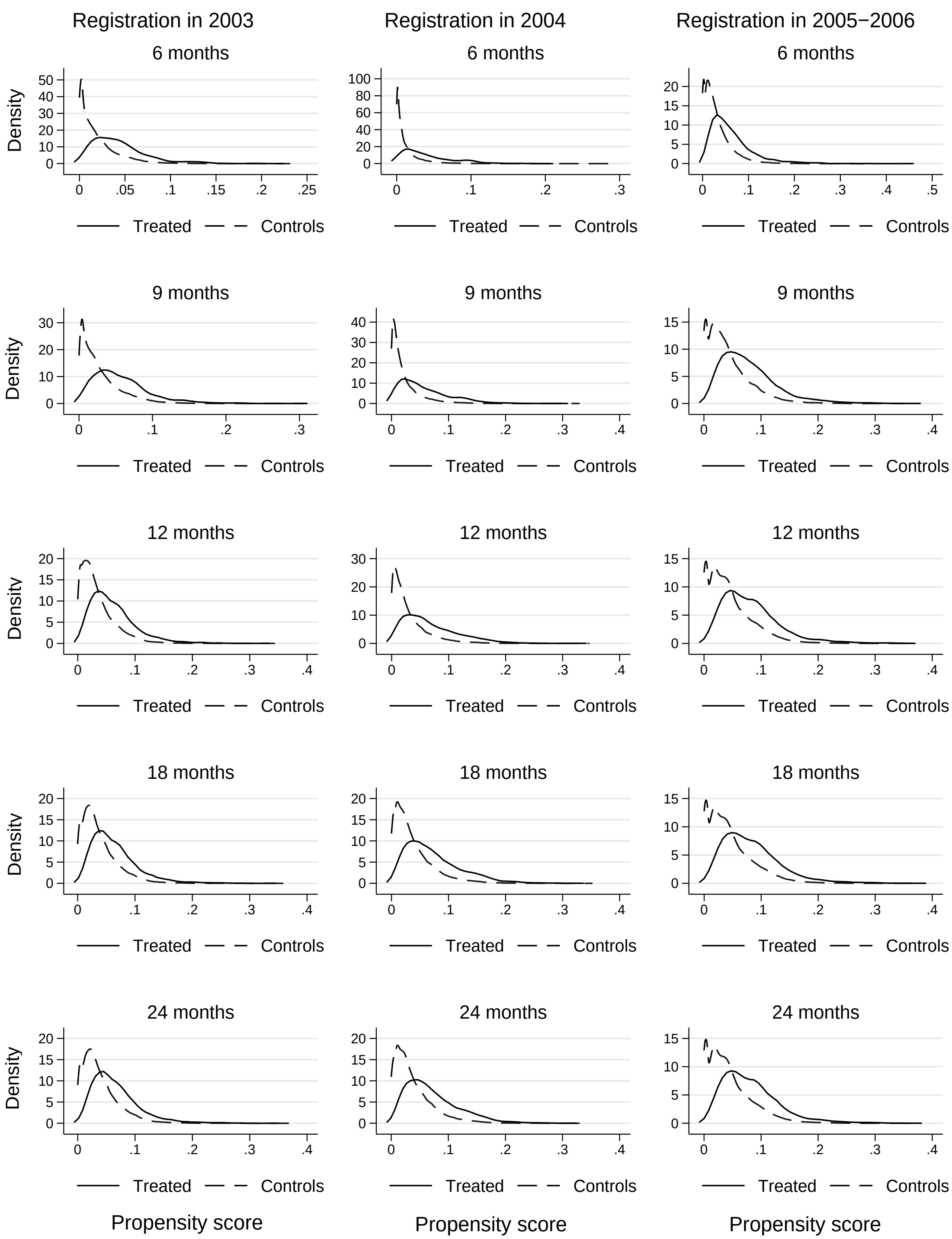
Notes: (1) Urban areas include cities and district centers. (2) When evaluating language courses, those fluent in Latvian or native speakers are excluded from the sample.

Table 4: **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.

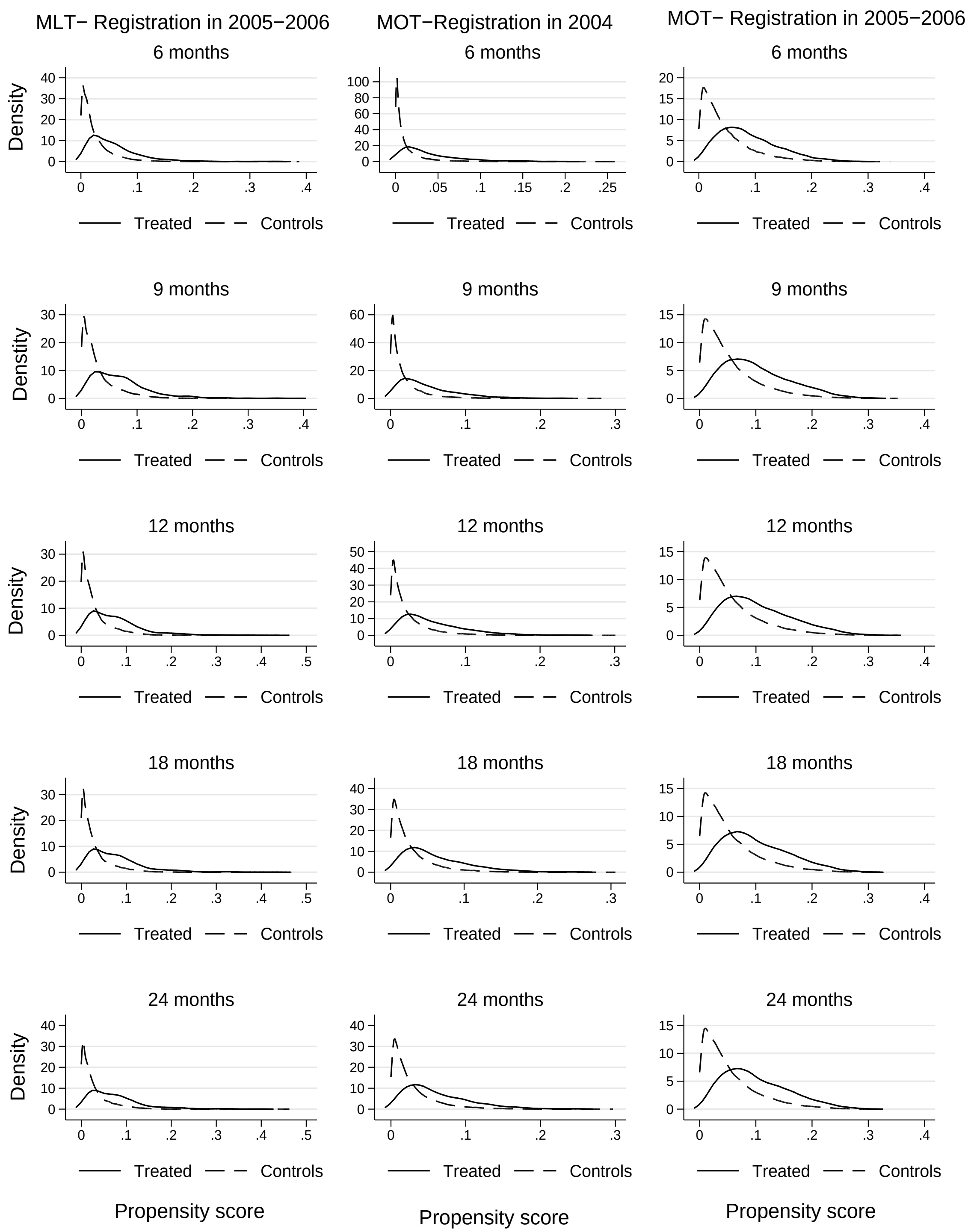
Figure 8: Evaluation of occupations training (OT) programs
Distribution of propensity scores for treatment and control groups



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 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 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 6.

Table 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 6.

Table 7: **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.