Evaluating Training Programs for Economically Disadvantaged. The case of the Czech Republic

Thematic areas: Labour Markets, Education, Educational Policy, Reform.
JEL cassification: I28, O15, C14

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Abstract

In view of the fact that economic and social development is conditioned on sufficient qualificational and educational level of population, significant attention is paid to development of the system of life-long learning, received in formal or informal training as well as self-education. At present the life-long learning becomes one of the most important factors of employability of a person on the labour market. Therefore, European Employment Strategy focuses on training as an instrument for increasing employment rate. This paper analyses how further training helps economically disadvantaged groups of the population to improve their labour market situation. The paper uses microeconomic data from a survey of the training activities, which was conducted in the Czech Republic in 2003 as well as data from the regular Labour Force Survey. Matching and difference-in-difference estimators are used to avoid the selection bias which is likely to arise in estimation of the training effect. It was found that training has positive and lasting effect for its participants. Both in the short run and in the long run the effect is positive and significant.

1. Introduction

The role of the Active Labour Market Programs in the Czech Republic has increased during the past few years. During the period from 1997 to 1999 the unemployment rate has increased from 3.5% to 9% and it remained at this level since then. As reaction to the increasing unemployment the funds allocated to the ALMP significantly increased. If prior to 1997 the Czech Republic spent on ALMP much less funds relatively to the other European countries, gradually, with increasing unemployment, the funds spent on ALMP approached the European level. In 1999 similarly as in other European countries the Czech government accepted National Plan of Employment and in the following year National Action Plan of Employment, which states the goals and priorities similar to those declared in other European countries, based on the directives given in 1997 by the European Commission. In 2000 the European Union accepted the Lisbon Strategy, which set priorities of the European Employment Strategy. This strategy aims at increasing employment rate, human resource development and inclusion into the labour market of the socially excluded groups. The focus groups are young school-graduates, women and older workers. In order to increase their employability the European Employment Strategy defines training and life-long learning as one of the most important tool.

Realization of the ALMP requires significant financial resources and, in relation to this, there is a question about the performance of these programs. In the European Union and the OECD countries the evaluation of the effect of ALMP is given much attention. Evaluation of the programs requires comparison with a situation when no measures are taken. This evaluation is conducted by the labour offices as well as by the research institutions. The labour offices are using a set of performance indicators as a basis for evaluation of ALMP as well as follow program participant in their future labour market performance after completion of the training. The interest in the evaluation of the ALMP was recently growing partially caused by the fact that the provision of the funds by European Social Fund to the EU member states significantly increased. The European Commission emphasizes importance of ALMP evaluation for the future allocation of the funds. In the Czech Republic very few studies tried to evaluate the effect of ALMP. One of these studies is Sirovatka et al. (2007).

The effect of the training programs in the new member states, that joined European Union in May 2004, were not sufficiently explored. This effect was investigated mainly on the macroeconomic level, due to the lack of microeconomic data. The benefit of microeconomic evaluation is that it allows addressing the issue of sample selection problem. This problem arises from the fact that participants of the training programs are not directly comparable with non-participants. In order to estimate the true effect, one has to construct an adequate control group, which can be done only with microeconomic data

This paper evaluates training programs using data collected as the part of the Labour Force Survey in the Czech Republic in 2003. The data contains more than 60 thousands people from all age categories and economic status. The survey was specifically focused on the training courses, including formal and informal training as well as self-education the people received during the previous year. In addition the structure of the Labour Force Survey allows following the same individuals during the subsequent year, which allows examining the effect of the training on the employment status of the people.

The paper uses difference-in-difference matching approach which allows avoiding the fundamental evaluation problem. In this approach the comparison is made between people with similar observable characteristics. All the other observations, which do not have counterparts in the control or treatment groups, are excluded from the analysis. The matching, therefore, allows constructing of a sub-sample of the non-experimental data, which by its properties approaches experimental data and allows avoiding bias due to selection on observables. In addition difference-in-difference estimator allows to control for selection based on unobservable characteristics.

Evaluation of training programs has a long tradition especially in the United States, where the studies focus on the earning effects of the programs. An example of such study is Ashenfelter (1978). On the other hand the European studies focus more on the unemployment effect of the training. Recent examples are Eichner and Lechner (2002), Gerfin and Lechner (2002), Fitzgenberger, Osikominu and Volter (2006), Pratap and Quintin (2006).

The matching approach has been used in most of the recent studies. The methodology is well described in Hujer and Caliendo (2000), Hujer and Wellner (2000), and Lechner (2000). The study by Heckman, Ichimura and Todd (1997) analyzed statistical properties of the matching technique and found that it eliminates much of the bias from the sample selection. A good overview of assumptions that are used not only in the matching approach but also in other estimation techniques in labour economics are provided by Friedlander, Greenberger and Robins (1997) and Angrist and Krueger (1999).

The paper is organized as follows. The next section describes ALMP programs in the Czech Republic. The emphasis is put on the aim of the programs and how the individuals are selected to the programs. In section 3 I describe the data. Section 4 presents the difference-in-difference matching methodology. Section 5 presents results. Section 6 concludes.

2. Labour Market and the ALMP in the Czech Republic

The labour market in the Czech Republic has experienced a significant change in the period from 1997 to 2000. During this period, caused by the economic recession, the unemployment rate has increased from 3.5% to about 9%. The years 1997 and 2000 can be considered as turning points in the ALMP provision. Before 1997 the expenditures on the ALMP were very little. Unemployment in this period remained on a low level and, therefore, expenditures on the ALMP were even decreasing in time. Correspondingly, the number of participant in the ALMP was also decreasing. Among the different programs of the ALMP the emphasis was put more on the community services, time-limited working opportunities consisting of maintenance of public buildings or other activities for the community or state institutions, provided by employers to unemployed for no longer than 12 consequent months. The number of individuals participating in training was low.

During 1997 – 2000, in relation to growing unemployment, the ALMP was given more importance. There was a growth in funds allocated to ALMP and number of people participating in ALMP also increased. If in 1997 only 11% of unemployed participated in the ALMP, in 2000 this share was 20%. In this period emphasis was put on creation of so called socially useful work places. These work places were created by employers for unemployed registered in the labour offices and employers were given a financial contribution for creation of such places. The share of training programs was still low.

In 2000 the economy started to grow and the following years were characterized by growing GDP. However, the unemployment rate decreased only slightly. In addition the share of long-term unemployed also increased. The growing economy did not result in creation of new places. Therefore, even more importance was put on the ALMP and emphasis was shifted to the training programs. The funds allocated to ALMP increased even more, which allowed increasing the quality of the programs. The programs became more profound and better fitted to the needs of unemployed. New types of ALMP were introduces, such as training internships and creation of individual action plans. The individual action plans are created for each individual based on his particular situation and define training courses that will help him best.

Assignment of individuals to the programs

Since 2001 the goal of ALMP is to focus more on the groups that face highest risk in the labour market. More funds for ALMP are allocated to the regions with highest long-term unemployment rate. A significant emphasis is put on ALMP for school leavers, who lack a necessary work experience in order to find a work place. However, according to the statistics from labour offices in 2001 short-term unemployed were more likely to participate in the training courses. Unemployed individuals younger than 24 are also more likely to participate in the training courses. There are also differences in training participation rate by the level of education. Individuals with secondary education with Graduate Certificate of Education (GCE) more often participate in the training then individuals with secondary education without GCE. It shows that unemployed with higher level of education are more likely to participate in further training.

The ALMP participation rate of long-term unemployed and people older than 50 is significantly lower. These groups of unemployed are often considered to be difficultly employable, long-term unemployed due to the loss of the skills and significant expenses that are necessary to restore these skills, and unemployed older than 50 because of their ageing. The reasons for decreasing ALMP participation of these groups are related to their lower motivation to take the program. To conclude, the younger the unemployed individual is and the shorter his unemployment period is the more likely he will be selected to a program. Therefore, it is likely that the participants and non-participants are very different group of people.

3. Data

The data comes from the survey that was organized as part of the regular Labour Force Survey (LFS) in the Czech Republic in 2003. The Labour Force Survey is the official source of information about labour market. The survey is conducted in correspondence with definitions and recommendations of the International Labour Organization as well as methodology of the Eurostat, which guarantees standard interpretation of the specific characteristics of the labour market.

The sample of the survey consists of around 25 thousands households, in which about 60 thousands individuals are interviewed. The households are selected randomly, and in a selected households all people are interviewed. This guarantees that the survey represents all age groups, economic sectors and social groups of the population. The validity of the data entry is checked using a number of filters, which guarantees a good quality of the data. In addition each person participating in the survey is assigned a weight, which is based on his district, gender and age-group. The weights are based on the recent demographic census. The weights serve to correct some possible deviation of the sample from the true structure of the population.

The survey was conducted in the second quarter of 2003. The questions on the training activity of the respondents are divided into ones related to the last 4 weeks and ones related to the last 12 month. The survey inquires information on all types of educational activities: formal, informal and self-education. Formal education is education which a person completes in an educational institution and leads to achieving a certain educational level. It can be vocational training, university courses or distance learning. Informal education is provided by employer or a training institution. It can be language courses, computer courses or re-qualification training within the active labour market policy programs. Self-education is education which a person undertakes without a lecturer. In addition the data contains information on the field of study and whether it relates to the job of the respondent.

The Labour Force Survey contains all the information about the individual status, age, education, duration of unemployment and other characteristics, which allows estimating the probability of training participation in the first stage of the analysis. The survey follows each individual for five quarters, so it is possible to observe the changes in the individual labour market position during the subsequent year after the training activity. In the first dataset I use the following characteristics: gender, age, education, area of education, family status and health disability. In the second dataset in addition to above mentioned characteristics I also use duration of unemployment, industry of the last job, availability of work experience, receiving unemployment benefits and type of activities prior to becoming unemployed.

I construct two different datasets. The first dataset is based on the data from 2nd quarter of 2003. This data contains information about the respondents' situation one year before, i.e. we can identify individuals that were unemployed before the start of the training. The data contains information about trainings received during one year prior to the interview as well as the employment status at the time of the interview. Graph 1 in appendix shows a time line and the sequence of the events in the first dataset.

The second dataset uses data from several quarters of the LFS survey. The data comes from eight quarters starting from 1st quarter 2003 till 4th quarter 2004. Merging two quarters we receive additional information about the unemployed individuals prior to receiving training: duration of unemployment, industry of the last job, activities prior to becoming unemployed (such as child care or military service), and receiving unemployment benefits. All these characteristics can be important for the selection into the training group. Unfortunately in this dataset I do not have information about training received during the whole year but only during the last 4 weeks prior to the interview. Since the interviews were done every 3 month some information about the received training may be lost. The sample of unemployed who receive training in the last 4 weeks is relatively small for each particular quarter; therefore, I pool data from 8 consequent quarters in order to increase the sample size.

An explicit goal of the ALMP is to help unemployed to find a job. Therefore, as an outcome variable I have chosen a dummy variable for becoming employed during the next 12 and 3 month after receiving training for the first and second dataset respectively.

Comparison of participants and non-participants groups

Table 1 in appendix presents characteristics of participants and non-participants for the first and second datasets. We can see that there are significant differences in the characteristics of the two groups. Participants have much lower share of males. Participants have higher level of education than non-participants. About 10% of participants have higher education and 48% of them have secondary education with Graduate Certificate of Education, while for non-participants these shares are 3% and 21% respectively. This fact shows that people who already have high level of education are more likely to participate in ALMP programs. This selection bias leads to upward bias of the estimates. The differences in age and family status are not significant; however, there are some differences in share of people with health disability, only 5% in the participant group and 8% in non-participants group. We can also see some differences in the area of study of the two groups: higher share of participants are educated in teaching, philology and economics subjects, which is also related to the fact that among participants there are higher share of individuals with higher education.

Similarly for the second dataset we may observe differences between the groups of participants and non-participants. The share of males is lower and the share of people with higher education is higher among participants than among non-participants. There are also differences in the duration of unemployment. The share of short-term unemployed is much higher among participants, 70% compared to only 52% in non-participant group. The short-term unemployed are likely to have better skills than the long-term unemployed because of the skills obsolescence. This selection bias would also lead to upward bias of the estimates.

We can see from the description of the ALMP and from comparison of the two groups that the selected characteristics are important for program participation. Therefore, these characteristics should be taken into account in the estimation of the training effect. However, there might be some other factors that also affect participation in the training. In order to receive unbiased estimates of the training effect we should accept conditional independence assumptions, i.e. given the set of observable characteristics we have, the probability of participation in the training is the same for participants and non-participants. However, if this condition is not fulfilled and there are some unobservable factors which affect training participation, then the estimates might still be biased. Therefore, I also use difference-in-difference estimator which can control for selection on unobservables. In order to use the difference-in-difference estimator, in second dataset I select individuals that had no training in the first period and had training in the second period. I compare their probability to find employment in the first and second period assuming that their unobservable characteristics did not change. This allows to control for unobservable characteristics.

4. *Methodology*

Fundamental evaluation problem is that we do not observe what outcome an individual would have, had he not participated in the program. Therefore, we use the group of people who did not participate in the program as the control group. However the characteristics of the last group can be very different from the one that participated in the program. This leads to biased estimates of the treatment effect.

It became common to study this problem in framework of Roy-Rubin model. In this model there are two potential outcomes (Y^1, Y^0) for each individual, where Y^1 represents his outcome in case if he participates in the program and Y^0 if he does not. Let D be a dummy variable for participation in the program. The true program effect is the difference between the two potential outcomes:

$$\theta = Y^1 - Y^0 \qquad (1)$$

The fundamental problem arises since we can observe each individual only in one state:

$$Y = D * Y^1 + (1 - D)Y^0 \qquad (2)$$

Therefore in equation (1) we always have an unobservable component, which is called counterfactual outcome. In this study I estimate the average treatment effect on the treated. This effect is defined as following:

$$E(\theta \mid D = 1) = E(Y^1 - Y^0 \mid D = 1) = E(Y^1 \mid D = 1) - E(Y^0 \mid D = 1) \qquad (3)$$

This effect is the average gain of training for the participants compared to the hypothetical situation had they not participated in the training. The identification of this effect still encounters the problem that the second term in equation (3) is not observable. Therefore, it is commonly accepted method to estimate the second term using the group of non-participants. This estimator can be written as follows:

$$\gamma = E(Y^1 \mid D=1) - E(Y^0 \mid D=0) \qquad (4)$$

It can be rewritten as follows:

$$\gamma = \{E(Y^1 \mid D=1) - E(Y^0 \mid D=1)\} + \{E(Y^0 \mid D=1) - E(Y^0 \mid D=0)\}$$

$$= E(\theta \mid D=1) + B$$

In other words the estimator in (4) is the true effect of the program plus bias (B). This estimator represents the true effect if the bias is zero. The necessary condition for this is :

$$E(Y^0 \mid D=1) = E(Y^0 \mid D=0) \qquad (5)$$

In other words, when potential outcome of non-participation is the same for participants and non-participants. This condition however does not hold if the two groups have very different characteristics. In order to solve this problem we should put additional assumptions such as conditional independence assumption.

Matching

The solution of this problem can be parametrical or non-parametrical. The parametric approach is to include control variables on the right-hand side of the equation. The non-parametric approach is to match individuals from control and treatment groups based on observable characteristics of individuals. The matching approach is simulating data similar to the experimental design and, therefore, it is better than the parametric approach (Hujer and Caliendo, 2000).

Matching originates from the work of Rubin (1974) and Rosenbaum and Rubin (1983), it was further developed by Heckman, Ichimura and Todd (1997). The idea behind matching is to construct the control group with similar observable characteristics as the treatment group has. However, when we try to compare individuals based on N characteristics it is very difficult to find pairs that have all of the characteristics similar. In order to solve this problem Rosenbaum and Rubin (1983) suggest using the balancing score, i.e. function of the relevant observed characteristics. This allows comparison of observations not on N characteristics but on one single balancing score, which satisfies the following condition: the distribution of the observed characteristics should be the same for treatment and control group given the same balancing score. One of the possible balancing scores is propensity score, which is the probability of program participation.

The estimation consists of two steps. In the first step the probability of program participation is estimated based on several observable characteristics. Probit model is used for this purpose. Then, the sample is restricted to the observations that have similar probability of participation in the two groups, i.e. we delete observations with probabilities larger than the smallest maximum and smaller than the largest minimum in the treatment and control group. After that the estimates are computed on the selected sub-sample (Heckman, Ichimura and Todd, 1997, Gerfin and Lechner, 2000).

In order to write it formally, let us denote Z a set of variables that affect the process of selection into the treatment group. We assume that we can observe all these characteristics. Let P(Z = z) be the probability of participation for an individual with the characteristics given by z. Conditional Independence Assumption (CIA) requires that for any participant and non-participant with the same propensity score P the potential outcome of non-participation is the same. Written formally:

$$Y^0 \Pi D \mid P(Z) \tag{6}$$

where Π is a sign for independence.
As a consequence:

$$E(Y^0 \mid P(Z), D=1) = E(Y^0 \mid P(Z), D=0) \tag{7}$$

The benefit of the assumption (6) is that we only need to condition on the propensity score and for this sample of individuals the selection bias specified in (4) is zero. Therefore, the estimator in (4) applied to the sample with similar propensity score represents the true effect.

For each individual in the treatment group I construct a set of individuals from control group with similar characteristics. I use three different matching estimators: “nearest neighbor”, caliper and Epanechnikov kernel. The “nearest neighbor” method selects only one individual from control group with closest propensity score. The caliper method selects all individuals whose propensity score is within interval δ and assign them weights inversely proportional to their distance. Epanechnikov kernel method uses kernel function to assign weights to individuals in control group. The matching estimator formula is:

$$\alpha^M = \frac{1}{n}\sum_{i\in T}\left(E_i^T - \sum_{j\in N} w_{ij} E_j^N\right) \tag{8}$$

where n is the number of individuals in the treatment group,

E_i^T is employment status of individual i from the treatment group, and E_j^N is employment status of individual j from the non-treatment group

w_{ij} are weights of individuals in non-treatment group.

The weights for caliper estimate are computed as follows:

$$w_{ij} = \begin{cases} 0 & \text{if } |p_i - p_j| > \delta \\ \dfrac{\dfrac{1}{|p_i - p_j|}}{\sum_{\{i,j:|p_i - p_j| \le \delta\}} \dfrac{1}{|p_i - p_j|}} & \text{otherwise} \end{cases} \tag{9}$$

And for Epanechnikov kernel:

$$w_{ij} = K\left(\frac{p_i - p_j}{h}\right) \tag{10}$$

where $K(u) = \frac{3}{4}(1-u^2)1_{(|u|\le 1)}$

The parameters δ and h are chosen to be 10^{-3}.

Variance of the estimates is computed using bootstrap. I use sampling variability of the propensity score, estimated using probit model. I resample the coefficients of the probit estimates for the propensity score in order to bootstrap the standard errors of the estimated treatment effects. The estimates are based on 20 replications.

The matching technique allows to receive unbiased estimates if the conditional independence assumption is fulfilled. However, there might be some unobservable characteristics which can affect selection into a training programs. Therefore, I also use difference-in-difference estimator. I select those individuals who switched from no-training group to training group. Assuming that their unobservable characteristics remained the same I compare their probability to find employment while they had no training and after they received training. This method, therefore, controls for the selection on unobservables. The difference-in-difference estimator is:

$$\alpha^{MD} = \frac{1}{n} \sum_{i \in N \to T} \left(\left(E_i^{T,t+1} - E_i^{N,t} \right) - \sum_{j \in N \to N} w_{ij} \left(E_j^{N,t+1} - E_j^{N,t} \right) \right) \tag{11}$$

where $E_i^{T,t+1}$ is employment status of person who switched from no-training at time *t* to training at time *t+1*.

$E_j^{N,t}$ employment status of selected individual from no-training group at time t

Propensity score

The key element of the matching approach is estimation of the propensity score. I use probit model and a set of related covariates Z. The model can be written as following:

$$P_i = Z_i \beta + u_i \tag{12}$$

where Z_i – set of covariates.

The related covariates are based on the predictions of the human capital theory, such as one that probability of training participation is higher for young individuals, as well as on the mechanism how individuals are assigned to the programs, for example, that people with higher education are more likely to participate in the training.

Table 2 shows estimates of the probit model for the probability of participation in the program. The estimates show that gender, educational level and age are important determinants of the program participation. Females, individuals with higher education and young individuals have higher probability of participation in the training.

For the second sample we can see that gender, education, age, industry of the last job, duration of unemployment and type of activities prior to becoming unemployed are all important factors in the selection into training. Similarly as for the previous dataset females, individuals with higher level of education and young individuals are more likely to be included into ALMP trainings. In addition we can see that individuals that were working in agriculture or services have lower probability of participation in the training than those working in the state sector. Short-term unemployed have higher probability of participation, which can probably be explained by lower motivation of long-term unemployed. Individuals who prior to becoming unemployed were on the child care also have lower probability of participation than the ones who prior to becoming unemployed had a regular job.

Based on this model I estimate the probability of participation (propensity score) for each individual. Graph 3 in appendix presents distribution of the propensity score for participants and non-participants in the training programs for the first dataset. As we can see from this graph the distribution for non-participants is very different from the distribution for participants. Graph 4 in appendix presents similar graph for the participation in self-education courses, also based on the first sample. Similarly, Graph 5 presents distribution of propensity scores for the second dataset.

Construction of the control group

To construct the control group we should select from non-participants a group most similar to the group of participants. I use the following procedure:

1. Estimate propensity score for participants and non-participants.
2. Reduce the sample to common support. Observations with propensity scores higher than maximum or lower than minimum in the other group are deleted.
3. Select an observation from participants.
4. Select observations from non-participants with similar propensity scores, using nearest neighbor, caliper and Epanechnikov kernel methods. Compute weights for each non-participant based on the selected method.
5. Do not remove selected non-participants, so they can be chosen again for the other participants.
6. Repeat steps 3 – 5 until there are no participants left and each participant have its control group.

5. Results

Table 3 presents share of individuals who found employment in participants and non-participants groups. In the first dataset there were 1763 individuals in the sample who were unemployed in the second quarter of 2002. Out of this group 120 individuals participated in some form of training during one year, and the other did not. Among those who participated in training 65.8% found employment until the second quarter of 2003, and among those who did not participate in training only 35.7% did. The second dataset contains 12675 individuals who were unemployed three month before the interview. Among this group 277 individuals had training during the last 4 weeks prior to the interview. Out of those who had training courses 27.4 % found employment, and out of those who did not have training only 13.9 % found employment.

These results show much higher probability to find employment for training participants. However, this conclusion would be valid only in case if the participants in the training were randomly selected. However, as we saw in the previous section the selection of individuals is not random and there are many factors that influence it. Therefore, the two groups of participants and non-participants are very different and we cannot compare them. For example, since the group of participants has on average higher educational level and higher share of short-term unemployed than the group of non-participants does, the first group would still had higher probability of finding employment than the second one had it not participated in the program.

Table 4 shows estimates of the OLS regression. The estimates are for unemployed and employed groups. In case of unemployed the estimates show increase in probability to find employment and in case of employed the increase in probability to remain employed. The estimates for the first dataset show increase in probability to find employment of 22% for unemployed and increase in probability to remain employed of 4% for employed. For the second dataset the corresponding estimates are 9% for unemployed. The estimate for employed is not statistically significant.

Table 5 presents results of nearest neighbor, caliper and Epanechnikov kernel estimators for the first data set. We can see that estimates are similar to the OLS results: about 24% increase in probability to find employment for unemployed and 4% increase in probability to remain employed. Estimated standard deviation shows that all the estimates are statistically significant. Table 6 shows estimates for the self-education. The estimates show 4% increase in probability to find employment for unemployed and this effect is statistically significant.

In the second dataset we have additional information about the characteristics of unemployed individuals at the time when they were still unemployed. These characteristics include: duration of unemployment, industry of the last job, type of activities prior to becoming unemployed and whether the individual received unemployment support. As we saw in the previous section all of these characteristics are important determinants of program participation. Therefore, inclusion of these variables into the estimation of the propensity score allows better matching between participant and non-participant groups.

Table 7 shows estimates for the second dataset. The nearest neighbor estimate is only 4% and the caliper and Epanechnikov kernel estimates are about 7% for unemployed. In case of employed the effect is small and statistically insignificant.

Table 8 shows the difference-in-difference estimates. Only caliper matching estimate was computed. The estimates show 8% increase in probability to find employment for unemployed. This effect is statistically significant. The effect for employed is not statistically significant. From Table 3 we saw that among those who did not have training only about 14% found employment during the period of 3 month. From Table 8 we can see that training increase the probability to find work by 8%, so it increases probability to find work from 14% to 22%, which is 1.5 times. We can, therefore, state that after controlling for observable and unobservable characteristics the net effect of training is positive and significant.

6. Conclusion

In this study I evaluate the effect of ALMP on the labour market performance of the unemployed. It was found that the effect of training is positive and significant. Participation in training for unemployed increase probability to find work in a period of one year from 35% to

57%. Training also increase probability to remain employed for those who are currently employed from 93% to 97%. In the period of three month, the training results in a 9% increase in probability of finding employment. These findings correspond to the studies by Larson (2003) and Hujer and Welner (2000) who also found smaller effects in the short run and larger effects in the long run. We can say that the training has a lasting effect and its benefits are revealed in time.

The data used in this study allows us to control for a number of individuals' characteristics, such as gender, age, education, duration of unemployment, industry of last job. All of these characteristics are shown to have significant effect on individual participation in the training. Since these characteristics are also correlated with the outcome variable, the probability of finding employment, we encountered the problem of selection bias, which lead to biased estimates of the training effect.

I solve this problem using difference-in-difference matching technique. In the first stage the characteristics of the two groups, participants and non-participants, were analyzed. It was shown that the two groups are very different. The group of participants consisted of more educated people, higher share of short-term unemployed and young individuals. Therefore, the two groups are not directly comparable. Using matching technique I construct a control group which by its characteristics is very similar to the treatment group. In order to do this I estimate probability of participation in the program for all individuals in both groups and restrict the sample to common support, i.e. remove from the first group those individuals who have very different probability of participation which cannot be found in the other group. Then for each individual in the treatment group I find the comparison group among non-participants. In this way I avoid bias due to selection on observables. In addition I control for selection on unobservable characteristics using difference-in-difference estimator.

The results received in this paper show that training programs are effective for unemployed. The results of OLS, matching and difference-in-difference estimators show positive and significant effect. Even after controlling for observable and unobservable characteristics the effect of training remains significant.

Appendix: Tables and graphs

Table 1: Characteristics of participants and non-participants groups (share of individuals that have a given characteristic)

	First dataset		Second dataset	
	Non-participants	Participants	Non-participants	Participants
Male	0.44	0.28	0.45	0.31
Education				
Secondary w/o GCE	0.47	0.34	0.49	0.32
Secondary with GCE	0.21	0.48	0.23	0.51
Higher education	0.03	0.1	0.03	0.12
Area of education				
Teaching, Philology, Economics	0.16	0.27	0.16	0.3
Biology, IT, Agriculture	0.43	0.48	0.45	0.36
Medical science	0.02	0.02	0.02	0.08
Services	0.07	0.08	0.08	0.12
Age	37	35	37	33
Married	0.45	0.43	0.44	0.4
Health disability	0.08	0.05	0.1	0.06
Worked before			0.86	0.78
Industry of the last job				
Agriculture			0.04	0.01
Manufacturing			0.37	0.28
Services			0.25	0.24
Duration of unemployment				
< 1 year			0.52	0.7
1-2 years			0.18	0.16
> 3 years			0.3	0.14
Prior to being unemployed				
Child care			0.06	0.03
Military service			0.02	0.01
Receives unemployment support			0.34	0.4
N	1643	120	12675	277

Table 2: Estimates of the probit model

	First dataset		Second dataset	
Male	-0.27	(0.11)	-0.16	(0.06)
Education				
Secondary w/o GCE	0.41	(0.26)	0.45	(0.15)
Secondary with GCE	0.95	(0.24)	0.86	(0.14)
Higher education	1.25	(0.31)	1.15	(0.17)
Area of education				
Teaching, Philology, Economics	-0.09	(0.23)	-0.03	(0.12)
Biology, IT, Agriculture	0.03	(0.22)	-0.13	(0.12)
Medical science	-0.48	(0.42)	0.27	(0.16)
Services	-0.09	(0.27)	0.03	(0.13)
Age	-0.01	(0.004)	-0.01	(0.003)
Married	0.04	(0.11)	0.06	(0.06)
Health disability	-0.03	(0.20)	-0.01	(0.10)
Worked before			0.1	(0.09)
Industry of the last job				
Agriculture			-0.59	(0.25)
Manufacturing			-0.08	(0.08)
Services			-0.19	(0.08)
Duration of unemployment				
< 1 year			0.28	(0.08)
1-2 years			0.18	(0.09)
Prior to being unemployed				
Child care			-0.33	(0.14)
Military service			-0.31	(0.21)
Receives unemployment support			-0.06	(0.06)
Constant	-1.6	(0.21)	-2.29	(0.14)
N	1763		12952	
R2	0.08		0.1	

* Standard errors in parenthesis

Table 3: Number of individuals and probability to find employment

	First dataset		Second dataset	
	Number of individuals	Found employment in 1 year	Number of individuals	Found employment in 1 year
Received training	120	65.80%	277	27.40%
Did not receive training	1,643	35.70%	12,675	13.90%
Total	1,763	37.70%	12,952	14.20%

Table 4: OLS regression

	First dataset				Second dataset			
	For unemployed		For employed		For unemployed		For employed	
Training	0.22	(0.04)	0.04	(0.004)	0.09	(0.02)	0.001	(0.001)
Male	0.11	(0.02)	0.03	(0.004)	0.02	(0.01)	0.001	(0.002)
Education								
Secondary w/o GCE	0.06	(0.07)	0.04	(0.01)	-0.01	(0.02)	0.001	(0.001)
Secondary with GCE	0.16	(0.06)	0.06	(0.01)	0.01	(0.02)	0.001	(0.001)
Higher education	0.27	(0.09)	0.07	(0.01)	0.07	(0.02)	0.001	(0.001)
Area of education								
Teaching, Philology, Economics	0.11	(0.07)	0.01	(0.01)	0.06	(0.02)	0.001	(0.001)
Biology, IT, Agriculture	0.10	(0.06)	0.02	(0.01)	0.05	(0.02)	0.003	(0.001)
Medical science	0.07	(0.10)	0.04	(0.01)	0.09	(0.03)	-0.001	(0.001)
Services	0.12	(0.07)	0.01	(0.01)	0.07	(0.02)	-0.001	(0.001)
Age	-0.01	(0.001)	-0.001	(0.000)	-0.002	(0.000)	0.002	(0.001)
Married	0.08	(0.02)	0.03	(0.004)	0.02	(0.01)	0.001	(0.002)
Health disability	-0.15	(0.04)	-0.18	(0.01)	-0.04	(0.01)	-0.004	(0.001)
Worked before					-0.01	(0.01)		
Industry of the last job								
Agriculture					0.03	(0.02)	-0.71	(0.004)
Manufacturing					0.01	(0.01)	-0.74	(0.002)
Services					0.01	(0.01)	-0.73	(0.002)
Duration of unemployment								
< 1 year					0.08	(0.01)	0.008	(0.002)
1-2 years					-0.04	(0.01)	0.002	(0.002)
Prior to being unemployed								
Child care					-0.05	(0.01)		
Military service					-0.02	(0.02)	-0.72	(0.01)
Receives unemployment support					0.03	(0.01)	-0.39	(0.002)
Constant	0.44	(0.04)	0.88	(0.01)	0.12	(0.01)	0.99	(0.002)
N	1,763		26,448		12,952		141,817	
R2	0.12		0.03		0.06		0.87	

* Standard errors in parenthesis

Table 5: Matching estimates, first dataset

	For unemployed			For employed		
	Nearest Neighbor	Caliper	Epanechnikov	Nearest Neighbor	Caliper	Epanechnikov
Effect	0.234	0.239	0.252	0.043	0.040	0.043
SD	0.019	0.017	0.014	0.004	0.005	0.003

Table 6: Matching estimates for self-education

	For unemployed		
	Nearest Neighbor	Caliper	Epanechnikov
Effect	0.041	0.038	0.043
SD	0.021	0.016	0.011

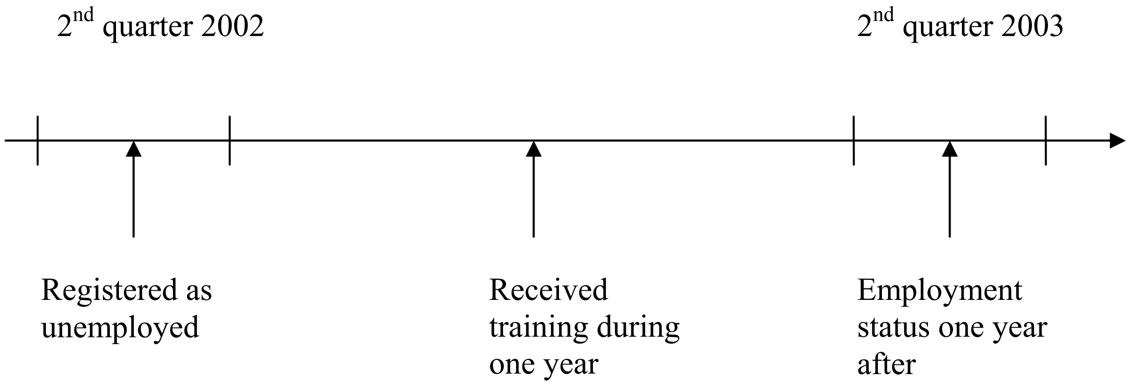
Table 7: Matching estimates, second dataset

	For unemployed		
	Nearest Neighbor	Caliper	Epanechnikov
Effect	0.039	0.076	0.077
SD	0.018	0.010	0.012

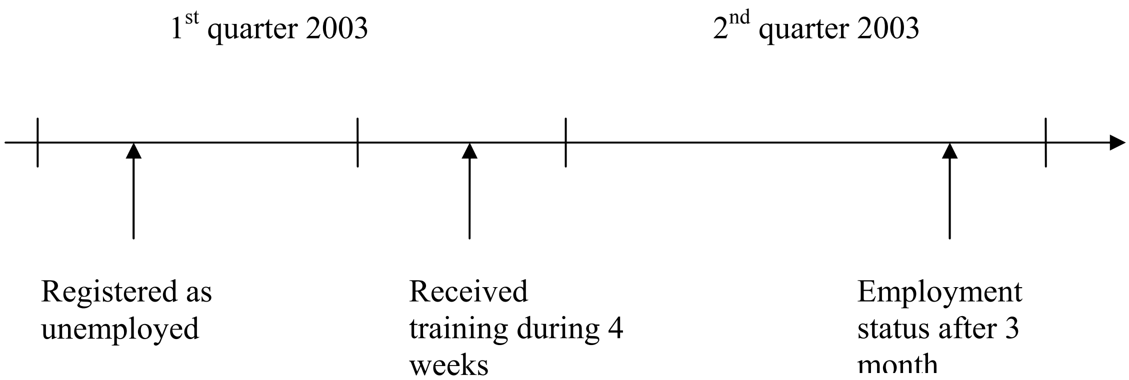
Table 8: Difference-in-difference estimates, second dataset

	For unemployed Caliper	For employed Caliper
Effect	0.082	-0.003
SD	0.042	0.006

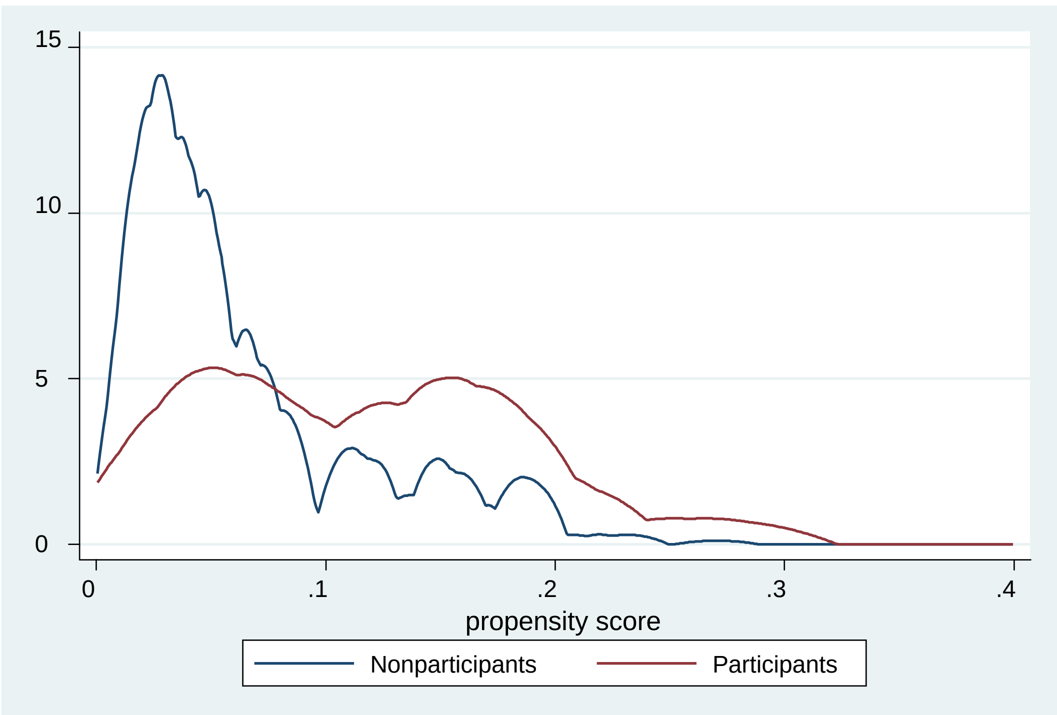
Graph 1: Time line and sequence of events for the first dataset



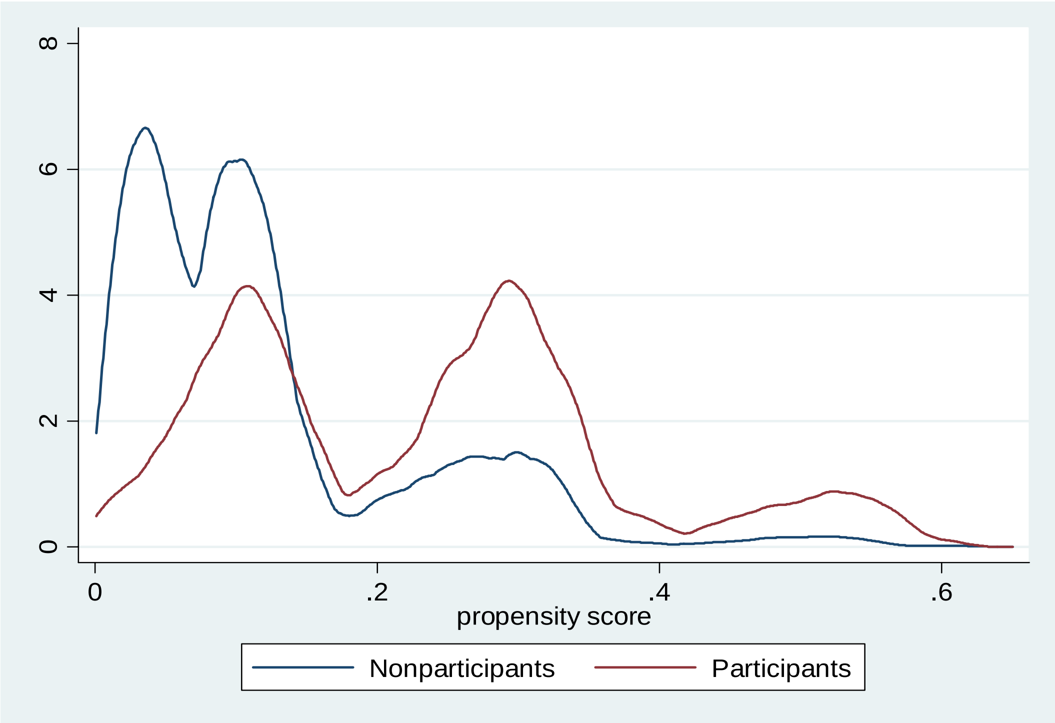
Graph 2: Time line and sequence of events for the second dataset



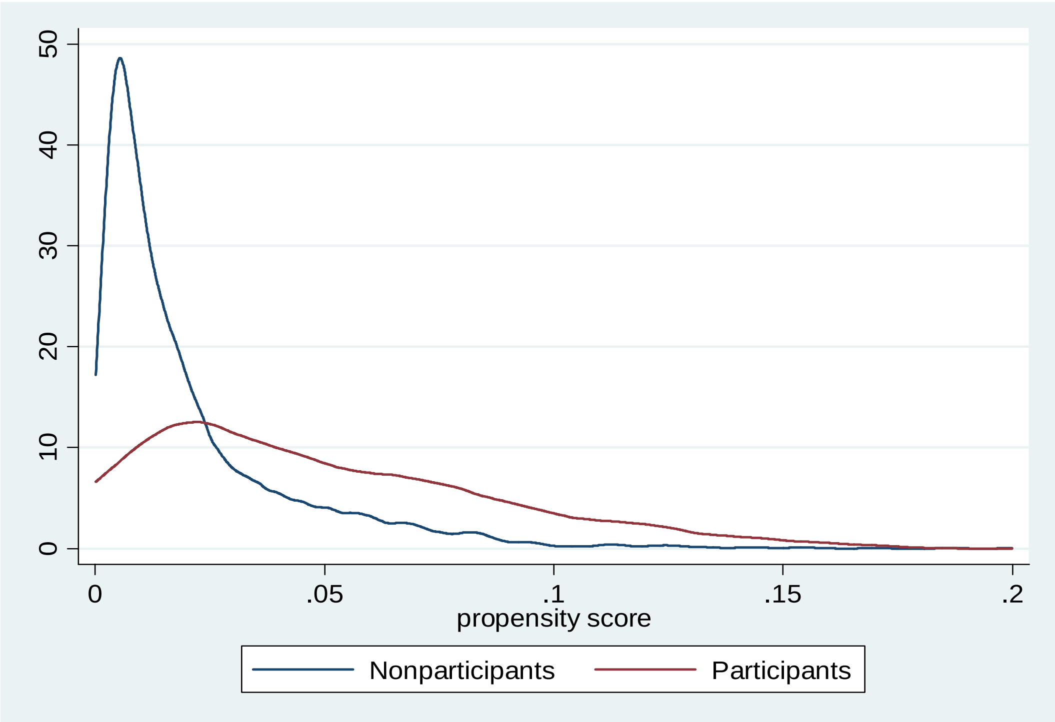
Graph 3: Distribution of the propensity score for the training in the first dataset



Graph 4: Distribution of propensity score for self-education in the first dataset



Graph 5: Distribution on propensity score for training in the second sample



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