RegionalCooperationCouncil

This project is funded by the European Union

IMPACT ASSESSMENT OF THE ACTIVE LABOUR MARKET MEASURES IN NORTH MACEDONIA

good.
better.
regional.

Title: Impact assessment of the active labour market measures in North Macedonia

Publisher: Regional Cooperation Council
Trg Bosne i Hercegovine 1/V, 71000 Sarajevo
Bosnia and Herzegovina

Phone: +387 33 561 700; Fax: +387 33 561 701

E-mail: rcc@rcc.int

Website: www.rcc.int

Author: Dimitar Nikoloski

Design: Samir Dedić
October, 2021

Contents

1. Introduction

Active labour market measures (ALMMs) aim at bringing unemployed back to work by improving the functioning of the labour market. The active labour market policies have multiple purposes such as: increasing output and welfare by putting unemployed to work, maintain the size of the effective labour force by counteracting high unemployment, help reallocate labour between different segments by improving employability of the labour force, alleviate the moral-hazard problem of unemployment insurance etc. The majority of these measures are general-purpose, i.e. serve relatively broad target population. However, often programs are designed for specific groups in the labour market considered as more vulnerable segments. The current Covid-19 crisis offer unique opportunities for innovation and reset of social objectives and to experiment with different ALMMs.

The importance of active labour market policies for North Macedonia can be viewed from two different perspectives. First, the role of the active labour market policies receives greater weight when skill obsolescence is higher i.e. when the long-term unemployment prevails over the short-term unemployment. Second, the aspiration of the economy in the foreseeable future to start negotiations for European Union (EU) accession imposes ambitious objectives in terms of attaining international labour market competitiveness. With this in mind, we can argue that investment in human capital becomes increasingly valuable and implies a need for reforms of active labour market policies.

Persistently high unemployment in many economies, tight government budgets and the existing scepticism regarding the effects of active labour market policies are the reason for growing interest in evaluating these measures (Hujer and Caliendo, 2000). The main challenge in carrying out effective impact evaluation is to identify the causal relationship between the program and the outcomes of interest. With respect to this, there exist contrasting positions on the effectiveness of active labour market programs. On one hand, proponents of these programs argue that they are both necessary and useful for reducing unemployment. On the other hand, the opponents demonstrate that active labour market programs are provided at high opportunity costs to other social programs and labour market efficiency as a whole (Dar and Tzannatos, 1999; Kluve, 2006; Escudero, 2018).

The aim of this report is to present the results from the impact evaluation of the selected active labour market policies and measures implemented in North Macedonia during the period 2018-2019. In addition, we perform a cost effectiveness analysis in order to assess in monetary terms the short-term outcomes from the ALMMs. The impact evaluation is a part of a general agenda of evidence-based policy making that focuses on redesigning the existing policies in order to achieve the best possible outcomes. In this context, the worldwide experience shows that the effectiveness of ALMMs is considerably improved if impact evaluations are rigorous and the feedback results are channeled into program design. Particularly, the analysis is based on using the EU and International Labour Organization (ILO) standards and the best practices from developed and other former transition economies.

2. Preliminary research

The efforts to increase employment and reduce social exclusion in North Macedonia continue to be high priority due to the need for reducing unemployment, especially among vulnerable groups. In this context, the process of planning, design and implementation of ALMMs has been continually performed since 2007. Among the implemented measures, the usual types of measures are provided on regular basis, while the others are provided sporadically. As regular we can consider the following ALMMs: subsidies for employment, trainings for known employers, trainings for advanced IT skills and trainings for jobs on demand. The non-regular ALMMs are quite heterogeneous and sometimes they have been provided for only couple of years such as trainings for specific fields or specific support for firms regarding new job openings (Krstevska and Ilievska, 2018).

The planned active labour market programs and measures in North Macedonia are systematized in the Operational Plan (OP), which is prepared on yearly basis by the Employment Service Agency (ESA). The OP is an official document that contains detailed explanation of each ALMM including the eligibility criteria, the number of beneficiaries (participants), the selection procedures etc. In the realisation of the OP are involved different institutions such as: ESA, Ministry of Labour and Social Affairs, educational organisations etc. Furthermore, the OP encompasses the financial framework with indicated costs and financial sources for each ALMM. The guiding principles in the realization of the ALMMs according to the OP is providing gender balance and representation of youth (aged under 29) for at least 30 percent.

Even though the implemented ALMMs in North Macedonia are characterized with high level of transparency and accountability, there is a lack of their rigorous assessment. The last published impact evaluation was performed for selected number of active labour market programs implemented by ESA during the period 2008-2012 (Mojsoska-Blazevski and Petreski, 2015). The findings show mixed results in the way that some programs bring comparatively better outcomes for the program participants relative to non-participants. However, the analysis identified programs that were not effective in improving the labour market outcomes of the participants. The results from this analysis can be used as a benchmark for the impact evaluation within the framework of this project.

The need to assess the effects of ALMMs in North Macedonia stems from the fact that public funds are limited and spent at a time of an economic crisis and increased risk of poverty due to the Covid-19 pandemics. In this context, we take into account the specific socio-economic context such as high level of informality, social exclusion and labour market segmentation. The experience from the last 15 years shows that ESA successfully copes with the implementation of planned ALMMs including their monitoring and post-program assessments. However, there exist a lot of challenges regarding the redesign of the actual and introduction of potential new measures, as well as the analysis of their cost-effectiveness.

3. Scope of the assessment

The evaluation of the active labour market policies and measures is focused on the following five ALMMs:

1. Training for drivers (DR) – the aim is to increase the employability of unemployed workers by providing training for the C, D and E category driving license;
2. Training for known employer (TKE) – the aim is to provide unemployed with the required skills according to the employers' needs;
3. Training for advanced IT skills (IT) – the aim is to meet the needs for advanced IT skills among registered unemployed workers;
4. Training for in-demand occupation (IN) – the aim is to meet the needs for demanded occupations, crafts and social services that lead to opening "green jobs";
5. Wage subsidy program (WS) – provides monetary subsidy for employed persons from the target groups for a period of 3, 6 or 12 months;

The ALMPs from 1 to 4 are training programs. Their premise is that a lack of certain technical skills is the reason that particular individuals are unemployed, and that these skills can be taught and learned in a relatively short period of time. In contrast, the wage subsidies lower the cost of a company to hire particular worker, which should lead to an increase in employment. The period under consideration is 2018-2019. The exception is the training for drivers which is analysed for 2016 and 2020. The number of planned participants according to the OPs and actual participants by program is presented in Table 1.

Table 3.1 The number of planned and actual participants by program

Active labour market measure	Operational plan	Number of participants	Realisation of the plan
Training for drivers (DR) 2016	60	65	108.3%
Training for drivers (DR) 2020	50	52	104.0%
Training for known employer (TKE) 2018	200	210	105.0%
Training for known employer (TKE) 2019	707	199	28.1%
Training for advanced IT skills (IT) 2017/18*	220	200	90.9%
Training for advanced IT skills (IT) 2019	193	218	113.0%
Training for in-demand occupations (IN) 2018	400	588	147.0%
Training for in-demand occupations (IN) 2019	500	805	161.0%
Wage subsidy program (WS) 2018	570	1206	212.6%
Wage subsidy program (WS) 2019	1000	1945	194.5%

** The participants in other co-financed programs are not included.*

For majority of the ALMMs the actual number of participants has been higher than the planned according to the OPs. Exceptions are the training for known employer in 2019 and the training for advanced IT skills in 2017/18. The highest discrepancies are observed for the training for in-demand occupations as well as the wage subsidy programs in 2018 and 2019 when the number of actual beneficiaries was about twice as high as the planed number of beneficiaries.

4. Definition of the outcome measures

The analysis is based on observing a wide range of possible outcomes obtained from the ESA Registry or from the survey. The ESA registry provides outcome information about the labour market status of the participants after 6, 12 and 24 months, while additionally for all applicants (including the control group) is provided the current labour market status (August, 2021). The following possible 8 outcomes may arise: Employed person, other person who search for job, unemployed person, unknown status, founder, manager, founder and manager, death or retirement.

In addition, from the survey carried out on a sample of participants and control group applicants we provide information about the following outcome measures:

- Currently employed – defined according to the standard ILO definition and further is disaggregated to the following categories: employer, employed, self-employed and unpaid family worker;
- Currently unemployed which correspond to the ILO definition of a person who does not have a job, is searching for job and is available to take a job within four weeks;
- Inactive – correspond to the ILO definition of inactivity, or more precisely categorizes those who have not searched for a job at least four weeks;
- Type of contract – permanent (open-end), temporary (close-end), seasonal or no contract if the person is employed informally;
- Monthly salary earned on the current job from employed persons or monthly wage earned on the last employment for those who are employed. Instead of asking the respondents about the exact amount of monthly salary, we assign them to classes with predefined ranges;
- Changes in financial conditions after the participation in the program or after the cut-off point for the applicants from the control group. The possible outcomes are categorized as: better, same or worse.
- Changes in employment prospects after the participation in the program or after the cut-off point for the applicants from the control group. The possible outcomes are categorized as: better, same or worse;
- Job search effort – assessed on a five point Likert scale with five options from ‘do not search at all’ to ‘search to great extent’;
- Emigration intention – assessed on a five point Likert scale with five options from ‘do not plan at all’ to ‘plan to great extent’.

5. Explanatory and self-assessment variables

Similar to outcome indicators, the explanatory variables are obtained from the ESA Registry or by the additional survey. The variables under consideration are the following:

- Demographic (age, gender, ethnicity, urban/rural, marital status, disability) – all of these variables except the marital status are provided from the ESA registry; the marital status of respondents has been provided from the survey;
- Household characteristics – Number of household members, Number of household members under 15, Number of employed household members, Number of unemployed household members, Number of retired household persons; this information is provided from the survey;
- Human capital (education, previous work experience) – the education level is categorized in the broad education groups: primary, secondary, higher (2 years), higher (4 years) and specialization which corresponds to the post-graduate and doctoral levels;
- Previous work experience – provided from the ESA registry and measured either as a binary variable or number of months;
- Unemployment history – duration of unemployment prior to application or participation in the program; this information is provided from the ESA registry.

In order to evaluate the targeting of the ALMMs with respect to vulnerable and marginalised groups, we pay particular attention to the coverage of specific categories of workers. As marginalised groups are considered the following: unemployed without work experience, youth (aged under 25), female, those living in rural areas and very-long-term unemployed (those who search for job more than 4 years). Additionally, disabled people and some ethnic minorities such as Roma can be considered as disadvantaged groups, but their underrepresentation in some ALMMs prevents us from undertaking more detailed analyses.

The participants in the ALMMs are assessed with respect to their satisfaction with the provided training or wage subsidy. Particularly they are questioned about the gained knowledge and skills, the appropriateness of the applied training methods, the usefulness of the training materials, the appropriateness of the training environment and whether they would apply for another ALMM. In the case of wage subsidies, the satisfaction is assessed with respect to the job, salary, on-the-job training and superiors. For the purpose of evaluation we use a five point Likert scale in the gradation from ‘not satisfied at all’ to ‘satisfied to great extent’. Having in mind the circumstances engendered by the Covid-19 pandemics, the participants and ALMM applicants have been assessed whether the pandemics imposed a need for new skills. As possible outcomes we assume an increased demand for the following skills: foreign languages, basic IT skills, advanced IT skills, e-commerce, e-banking etc.

6. Data and sample

The data for the analyses are provided from two sources: the registry of the Employment Service Agency as administrative data and a survey carried out on a sample of ALMM participants and applicants. There are several advantages of using administrative data for policy research such as: its superior quality, exhaustive coverage, representativeness etc. (Pierre, 1999). However, the ESA registry does not contain data on all considered attributes. In order to obtain information for additional attributes that are not provided by the ESA registry, an additional survey was carried out on the samples of participants and non-participants. The questionnaires for the survey are presented in Appendix 1a and Appendix 1b.

The sample for analysis consists of treatment and control groups. The treatment group comprises persons who participated in one of the five ALMMs. On the other hand, the control group includes persons who applied but have not been selected (have not participated). The figures regarding the sample size for the treatment and control groups for each ALMM are reported in Table 6.1. In addition to response rate, we present the rates of unreached participants and control group applicants and the rates of rejection.

The response rate varies between 18 and 62 percent among ALMM participants, and between 15 and 41 percent among control group applicants. The most frequent reason for the low response rates is the inability to reach a person, due to lack of correct contact information. Namely, there is a quite large share of persons who could not be reached by provided mobile phones. The rate of unreached participants (attrition) varies between 23 and 55 percent, while the rate of unreached within the control groups varies between 30 and 53 percent. The rejection among ALMM participants happened in the range of 9 and 32 percent, while among control group applicants it varies between 18 and 52 percent.

This attrition is a problem because we might expect the employment outcomes of individuals who refuse to be surveyed or who cannot be found to differ from those who are interviewed. A typical approach has been to compare attrition rates in the treatment and control groups, and then do a bounding exercise if the attrition rates vary (often the control group is slightly less likely to respond). But it is easy to think of problems that can arise even when the attrition rates are the same for both groups: for example, the attritors in the treatment group may be people who went through the training and did not find it useful and have still not found jobs, while those in the control group could be those who are too busy to answer surveys because they are employed in good jobs. This type of differential response would bias the estimated treatment effect upwards, overstating the impact of training (McKenzie, 2017). A second issue with the use of survey measures of employment is the possibility that those in the treatment groups over-report their employment outcomes to express their appreciation for being given the program, while those in the control group potentially under-report these outcomes.

Table 6.1 Total number and sample size of the treatment and control groups

Active labour market measure	Database from ESA		Sample size		Response rate (percent)		Unreached rate (percent)		Rejection rate (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	65	297	31	74	47.7	25.5	43.1	38.3	9.2	36.2
Training for drivers (DR) 2020	52	235	32	88	61.5	40.0	23.1	30.5	15.4	29.5
Training for known employer (TKE) 2018	210	83	61	12	29.0	14.8	44.3	33.3	26.7	51.9
Training for known employer (TKE) 2019	199	97	64	14	32.2	15.9	43.7	38.6	24.1	45.5
Training for advanced IT skills (IT) 2017/18	200	322	73	93	36.5	30.3	32.0	42.3	31.5	27.4
Training for advanced IT skills (IT) 2019	218	244	86	60	39.6	31.6	28.6	38.4	31.8	30.0
Training for in-demand occupations (IN) 2018	588	957	103	150	17.9	27.6	53.0	42.7	29.2	29.7
Training for in-demand occupations (IN) 2019	805	833	315	276	39.1	41.0	35.8	40.6	25.1	18.4
Wage subsidy program (WS) 2018	1206	531	261	121	21.7	22.8	55.6	52.5	22.7	24.7
Wage subsidy program (WS) 2019[1]	1945	281	234	82	35.8	40.2	33.9	33.3	30.3	26.5
Total	**5488**	**3880**	**1260**	**970**	**30.1**	**31.0**	**43.8**	**41.4**	**21.1**	**27.6**

Source: Author's calculations

1 The response, unreached and rejection rates are calculated on the base of a sample of 661 participants.

7. Descriptive statistics

Part of the differences in labour market outcomes between ALMMs participants and the control group is due to the differences in their socio-demographic characteristics. A similar explanation could be offered for the different outcomes across the various programs (aside from the differences stemming from the characteristics and intensity of programs). Given that the treatment and control groups are likely to differ in their observable and unobservable characteristics, a comparison of their employment outcomes can be biased. Specifically, better employment outcomes can be expected for individuals with higher levels of education, those who have prior work experience, those with shorter unemployment spells and so on. In other words, program participants may have better employment outcomes not because of the effectiveness of the programs but because of their better characteristics. Thus, if the groups systematically differ in these characteristics, the differences in employment outcomes may be due to these differences, rather than to differences in program effects.

In this section we only present raw differences between the treatment and the control groups, while in the next section the differences in characteristics are included in the econometric analysis and their impact on outcomes examined in detail. We proceed by analyzing the differences in the main characteristics of the treatment and control groups, for each program. The main socio-demographic characteristics such as age, gender, place of living (urban/rural) and marital status are presented in Table 7.1. The descriptive statistics regarding the educational attainment of the participant and control group applicants are presented in Table 7.2. The unemployment duration categorized from short-term to very-long-term unemployment is presented in Table 7.3. The representation of disadvantaged groups (youth, older, disabled Roma and without work experience) among the participants and control group applicants are presented in Table 7.4.

The statistics regarding the motivation for application for ALMM are presented in Table 7.5. In this context, as possible motivation for application we assume the following: employment, higher wage, gaining additional skills, change of profession, emigration and other. The shares of participants and control group applicants according to the current labour market status (employed, unemployed and inactive) are presented in Table 7.6. Additionally, the statistics regarding the alternative outcomes such as: Financial condition, future employment prospects, search for job and intention for emigration are presented in Table 7.7. Finally, the average monthly salary for participants and control group applicants as an additional outcome variable is presented in Table 7.8. Having in mind the sensitivity of the question regarding the respondents' salaries, instead of asking the exact amount of salary we asked to determine only the class with predetermined range. In this way, we assume to obtain greater response rate to this question.

Table 7.1 Socio-demographic characteristics (sample)

Active labour market measure	Age (average)		Female (percent)		Rural (percent)		Married (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
TRaining for drivers (DR) 2016	31.9	34.7	-	1.3	35.5	21.6	74.2	51.3
Training for drivers (DR) 2020	34.0	34.9	-	1.1	34.4	38.6	65.6	60.2
Training for known employer (TKE) 2018	36.7	36.6	67.2	66.7	29.5	50.0	85.3	50.0
Training for known employer (TKE) 2019	36.0	31.5	35.9	78.6	31.3	28.6	62.5	35.7
Training for advanced IT skills (IT) 2017/18	29.9	28.9	30.1	51.6	8.2	11.8	42.5	66.7
Training for advanced IT skills (IT) 2019	26.4	26.4	29.1	51.7	11.6	10.0	8.1	25.0
Training for in-demand occupations (IN) 2018	36.1	35.7	72.8	74.7	18.4	18.0	50.5	62.7
Training for in-demand occupations (IN) 2019	35.1	35.1	70.8	75.0	24.8	19.6	76.2	89.5
Wage subsidy program (WS) 2018	31.4	33.8	47.1	46.3	25.7	25.6	83.1	90.9
Wage subsidy program (WS) 2019	32.2	27.0	57.7	45.1	30.8	35.4	82.0	79.3

Source: Author's calculations

From Table 7.1 we can notice that generally, there is no significantly differences between the participants and control group applicants with respect to the main socio-demographic characteristics such as: age, sex, place of living and nationality. Women are obviously less represented among participants and control group applicants in the training for the C, D and E category driving license, while rural population is less represented among participants and control group applicants in the training for advanced IT skills.

Table 7.2 Educational attainment (sample)

Active labour market measure	Primary education (percent)		Secondary education (percent)		Higher education[2] (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	6.5	9.5	80.6	72.9	12.9	17.5
Training for drivers (DR) 2020	9.4	23.9	84.4	61.4	6.3	13.7
Training for known employer (TKE) 2018	24.6	50.0	72.1	50.0	3.2	-
Training for known employer (TKE) 2019	25.0	-	51.6	35.7	20.3	57.1
Training for advanced IT skills (IT) 2017/18	-	-	32.9	27.9	67.1	72.1
Training for advanced IT skills (IT) 2019	-	-	51.2	38.3	48.8	61.7
Training for in-demand occupations (IN) 2018	8.7	12.0	62.1	56.7	29.2	31.3
Training for in-demand occupations (IN) 2019	16.8	15.6	54.3	51.1	28.9	33.3
Wage subsidy program (WS) 2018	33.7	21.5	48.6	48.8	17.7	29.7
Wage subsidy program (WS) 2019	29.5	26.8	52.1	52.4	18.4	20.8

Source: Author's calculations

Regarding the educational attainment presented in Table 7.2, it is noticeable that the highest shares of both participants and applicants from the control group have secondary education. Exception is the training for advanced IT skills, where dominant education category represent participants with higher education. In addition, we can conclude that participants with secondary education are more represented compared to the corresponding control group, while the participants with higher education is slightly less represented compared to the corresponding control group.

2 In this education category are included all types of education above secondary education.

Table 7.3 Unemployment duration (sample)

Active labour market measure	Up to 1 year (percent)		1-2 years (percent)		2-3 years (percent)		3-4 years (percent)		More than 4 years (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	45.2	47.3	29	16.2	12.9	14.9	3.2	6.8	9.7	14.9
Training for drivers (DR) 2020	65.6	68.2	6.3	7.9	6.3	6.8	3.1	4.6	18.8	12.5
Training for known employer (TKE) 2018	81.9	83.3	8.2	-	4.9	8.3	1.6	-	3.3	8.3
Training for known employer (TKE) 2019	76.6	71.4	7.8	14.3	4.7	0	3.1	7.1	7.8	7.1
Training for advanced IT skills (IT) 2017/18	89.0	80.7	4.1	6.5	4.1	6.5	0.0	3.2	2.7	3.2
Training for advanced IT skills (IT) 2019	83.7	85.0	9.3	11.7	2.3	3.3	2.3	-	2.3	-
Training for in-demand occupations (IN) 2018	69.9	54.0	10.7	10.7	4.8	6.7	2.9	4.0	11.7	24.7
Training for in-demand occupations (IN) 2019	69.8	66.3	9.8	10.9	6.4	3.6	2.5	2.9	11.4	16.3
Wage subsidy program (WS) 2018	85.1	72.7	8.1	10.7	3.1	2.5	1.9	5.8	1.9	8.3
Wage subsidy program (WS) 2019	82.9	80.5	9.0	12.2	2.1	2.4	2.1	2.4	3.8	2.4

Source: Author's calculations

From Table 7.3 we can conclude that the most represented among participants and control group applicants are the unemployed with previous short-term duration of unemployment. In addition, it is noticeable that significant shares represent those with unemployment duration between 1 and 2 years, while the so-called very-long-term unemployed (those who search for job more than 4 years) are mostly represented in the training for the C, D and E category driving license and in the training for in-demand occupations.

Table 7.4 Shares of disadvantaged groups (sample)

Active labour market measure	Youth (percent)		Older (percent)		Disabled (percent)		Roma (percent)		Without work experience (per.)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	19.3	18.9	-	1.3	-	1.3	3.2	-	32.3	24.3
Training for drivers (DR) 2020	18.8	18.2	3.1	6.8	-	2.3	3.1	10.2	28.1	30.7
Training for known employer (TKE) 2018	21.3	25.0	3.3	-	1.6	-	1.6	-	27.9	58.3
Training for known employer (TKE) 2019	29.7	21.4	12.5	-	-	-	3.1	7.1	28.1	28.6
Training for advanced IT skills (IT) 2017/18	27.4	39.8	1.4	-	1.4	1.1	-	-	26.0	36.6
Training for advanced IT skills (IT) 2019	41.8	48.3	-	-	1.2	-	-	-	41.9	35.0
Training for in-demand occupations (IN) 2018	21.4	16.0	5.8	7.3	1.0	2.0	1.9	4.7	37.9	32.7
Training for in-demand occupations (IN) 2019	24.4	23.9	7.3	5.4	1.0	0.7	4.1	5.1	33.3	32.3
Wage subsidy program (WS) 2018	48.3	32.2	8.4	9.9	1.2	1.7	3.8	5.8	39.9	35.5
Wage subsidy program (WS) 2019	39.3	50.0	9.4	-	2.1	2.4	2.6	4.9	38.5	54.9

Source: Author's calculations

With respect to the representation of disadvantaged groups, from Table 7.4 we can conclude that particularly represented in all programmes are youth and workers without previous work experience. On the other hand, older workers, those with disability and Roma have much lower shares or they do not participate at all. Hence, this could be used as an indicator for improving the targeting of the ALMMs by increasing the participants from these vulnerable segments.

Table 7.5 Motivation for application (sample)

Active labour market measure	Employment (percent)		Greater salary (percent)		New skills (percent)		Change of profession (per.)		Emigration (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	35.5	29.7	16.1	5.4	41.9	64.9	6.4	-	-	-
Training for drivers (DR) 2020	43.8	45.5	12.5	5.7	43.8	48.9	-	-	-	-
Training for known employer (TKE) 2018	72.1	50.0	18.0	16.7	9.8	33.3	-	-	-	-
Training for known employer (TKE) 2019	59.4	28.6	20.3	7.1	20.3	64.3	-	-	-	-
Training for advanced IT skills (IT) 2017/18	41.1	37.6	4.1	2.2	46.6	58.1	8.22	2.2	-	-
Training for advanced IT skills (IT) 2019	34.9	23.3	5.8	5.0	43.0	61.7	16.3	10.0	-	-
Training for in-demand occupations (IN) 2018	42.7	31.3	9.7	6.0	47.6	54.7	-	8.0	-	-
Training for in-demand occupations (IN) 2019	64.4	77.5	5.1	0.7	21.6	18.5	4.8	1.8	1.9	0.4
Wage subsidy program (WS) 2018	88.5	95.0	0.8	-	0.4	-	-	-	-	-
Wage subsidy program (WS) 2019	46.6	63.4	35.0	28.1	6.4	1.2	12.0	7.3	-	-

Source: Author's calculations

From Table 7.5 it is obvious that the main motivations for participation in the ALMMs under consideration is employment and gaining new skills. In addition, greater salary represents an important motivation for participation in the training for drivers and the training for known employers. Generally, emigration does not seem to be an important motivation, while changing profession might be considered as an important motive for the participants in the training for advanced IT skills in 2019.

Table 7.6 Current labour market status, August 2021 (sample)

Active labour market measure	Currently employed (percent)		Currently unemployed (percent)		Inactive (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	58.0	16.2	32.3	83.8	9.7	-
Training for drivers (DR) 2020	53.1	2.3	3.1	97.7	43.8	-
Training for known employer (TKE) 2018	77.0	25.0	21.4	75	1.6	-
Training for known employer (TKE) 2019	65.6	42.9	-	57.1	34.4	-
Training for advanced IT skills (IT) 2017/18	87.7	78.5	5.5	21.5	6.9	-
Training for advanced IT skills (IT) 2019	38.4	48.3	51.2	51.7	10.5	-
Training for in-demand occupations (IN) 2018	37.9	22.0	54.4	73.3	7.8	4.7
Training for in-demand occupations (IN) 2019	70.5	60.1	16.5	37.3	13.0	2.5
Wage subsidy program (WS) 2018	69.0	85.1	23.7	14.9	7.3	-
Wage subsidy program (WS) 2019	89.7	90.2	9.4	9.8	0.9	-

Source: Author's calculations

According to Table 7.6 the current employment prevails over current unemployment among participants in majority of the ALMMs. Exception are the training for IT skills in 2019 and the training for in-demand occupations in 2018. The opposite is true for the applicants in the control groups, where generally the shares of currently unemployed are higher than the shares of the currently employed.

Table 7.7 Alternative outcome variables (sample)

Active labour market measure	Better financial situation (perc.)		Better employment prospects (perc.		Search for another job (perc.)		Intention to emigrate (perc.)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	19.3	2.7	41.9	2.7	67.7	78.4	58.1	52.7
Training for drivers (DR) 2020	25.0	-	25.0	-	59.4	84.0	53.1	51.1
Training for known employer (TKE) 2018	45.9	-	36.0	-	39.3	58.3	24.6	25.0
Training for known employer (TKE) 2019	25.0	-	25.0	-	40.6	64.3	32.8	21.4
Training for advanced IT skills (IT) 2017/18	45.2	19.4	32.9	9.7	21.9	24.7	21.9	14.0
Training for advanced IT skills (IT) 2019	19.8	18.2	21.8	18.7	66.9	58.4	45.7	39.1
Training for in-demand occupations (IN) 2018	18.5	1.3	17.5	1.3	45.6	70.0	31.1	43.3
Training for in-demand occupations (IN) 2019	36.8	25.4	34.3	23.6	23.8	31.2	15.9	4.7
Wage subsidy program (WS) 2018	15.0	14.1	14.2	9.1	19.5	17.4	2.7	-
Wage subsidy program (WS) 2019	9.0	1.2	9.4	3.7	25.2	30.5	27.8	56.1

Source: Author's calculations

Regarding the alternative outcome variables, perception of better financial situation and better employment prospects is generally higher among participants compared to the control groups. In contrast, the control group applicants are more prone to search for job, while results with respect to intention for emigration is mixed.

Table 7.8 Monthly salary (sample)

Active labour market measure	0 – 14.449 (percent)		15.000 – 19.999 (percent)		20.000 – 24.999 (percent)		25.000 – 34.999 (percent)		35.000 and above (percent)	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	-	8.3	44.4	58.3	33.3	33.3	11.1	-	11.1	-
Training for drivers (DR) 2020	5.9	-	52.9	50.0	23.5	50.0	17.6	-	-	-
Training for known employer (TKE) 2018	23.9	-	69.6	100.0	4.35	-	2.17	-	-	-
Training for known employer (TKE) 2019	19.5	-	65.9	-	9.8	100.0	4.9	-	-	-
Training for advanced IT skills (IT) 2017/18	4.5	-	25.0	20.3	45.5	65.2	25.0	14.5	-	-
Training for advanced IT skills (IT) 2019	4.3	1.2	17.1	35.4	50.0	36.6	22.9	26.8	5.7	-
Training for in-demand occupations (IN) 2018	3.2	-	9.7	39.3	71.0	57.1	16.1	3.6	-	-
Training for in-demand occupations (IN) 2019	8.0	4.3	8.0	26.1	40.0	34.8	32.0	34.8	12.0	-
Wage subsidy program (WS) 2018	-	-	61.3	58.9	36.9	41.1	1.8	-	-	-
Wage subsidy program (WS) 2019	2.0	-	41.5	61.1	41.0	33.3	15.5	5.5	-	-

Source: Author's calculations

According to the data from Table 7.8, we can estimate the average monthly salary for treatment and control groups for each ALMM. Namely, the highest average monthly salary is observed among participants in the training for advanced IT skills, followed by participants in the training for drivers, the training for in-demand occupations and the training for known employer. The average salary of the wage subsidy beneficiaries are grater than the salaries of the participants in the training for known employer but lower than the participants in the training for advanced IT skills.

8. Estimation technique

The choice of the evaluation method depends upon data availability, the nature of the program and how selection into treatment occurs. Since we are confined of using post-program data, the analysis is be based on quasi-experimental approach where programs are evaluated ex-post. Namely, because the control group does not exist, it must be created and matched as closely as possible to the observed characteristics of those who participated in the program. These methods are called quasi-experimental, because they attempt to recreate a situation similar to a controlled experiment. In this case there is no single method that is preferable in all circumstances, and various alternative techniques can be applied (Caliendo and Hujer, 2005; Gertler et al., 2016).

The Propensity score matching is used as a principal estimation method. This method is based on the assumption that differences between participants and non-participants that jointly determine their decision to participate and the outcome of interest are all observable in the data. Matching therefore results in comparing participants with non-participants, giving more weight to the non-participants that are most similar to participants. In this context, a logistic regression is used in order to calculate the propensity scores. The outcomes of participants and non-participants with similar propensity scores are compared to obtain the program effect. The technical aspects of estimation based on propensity score matching procedure is developed within the Roy-Rubin framework[3] which is presented in Box 1.

There are several matching algorithms suggested in the literature such as: nearest-neighbour matching, radius calliper matching and Kernel matching (Loi and Rodrigues, 2012). The choice of the matching algorithm is not trivial since it involves trade-off between bias and variance. The quality of the matching procedure is evaluated on the basis of its capability in balancing the control and treatment groups with respect to the covariates used for the propensity score estimation. The basic idea is to compare the distribution of these covariates in the two groups before and after matching on the propensity score.

There are several pros and cons using the propensity score matching method. On one hand it is characterised with its simplicity in computing the standardised bias and joint significant test. Furthermore, the matching method does not require any functional form assumption for the outcome equation and therefore, it is not susceptible to misspecification bias along that dimension. However, in practice it may be the case that some of the participants do not have matched counterparts in the pool of non-participants with similar propensity scores. In technical terms, it is possible a lack of common support, or lack of overlap between the propensity scores of the participants in the program and those of the pool of non-participants. Having in mind these characteristics of the propensity score matching method, for checking the robustness of the estimates alternative methods for estimation are applied as well.

3 Developed by A.D. Roy and D.B. Rubin.

Box 8.1 Propensity score matching

Let denote with YT the outcome when the person gets the treatment, whereas YC denotes the outcome when person does not participate in the ALMM (comparison group).

Additionally, we introduce a binary assignment indicator D that determines whether the individual gets the treatment (D=1) or not (D=0).

The average treatment effect of the treated (ATT) is defined as follows:

$ATT = E(Y^T - Y^C | D=1) = E(Y^T|D=1) - E(Y^C|D=1)$

ATT shows the expected effect of the program for those persons who actually participated. However, we cannot observe the counterfactual $E(Y^C|D=1)$ i.e. the average outcome of those persons who participated in the program had they not participated. Thus, without further assumption ATT is not identified. But if we can observe all factors that jointly influence outcomes and participation decision, then conditional on these factors (X), the participation decision and the outcomes are independent.

The propensity score matching method creates a comparison group from untreated observations by matching treatment observations to one or more observations from the untreated sample, based on observable characteristics. The propensity scores are used to select the comparison group for each treatment group according to the following three steps:

First, a logistic regression model is estimated for each ALMM in which the dependent variable is dichotomous, taking the value 1 for those who took part in the intervention, and 0 if they did not. The explanatory variables include all observables that may affect participation, but that are not affected by the intervention.

Second, the output from these selection models are used to estimate choice probabilities conditional on X (the so-called propensity scores) for each treatment and potential comparison group member. Hence, an individual's propensity score is the fitted value from the participation equation. Having calculated the propensity scores for all observations, the region of common support is identified.

Third, for each treatment group member is selected potential comparison group member based on their propensity scores.

Once the matching is done, a test is performed for balance by comparing the mean characteristics of treatment and comparison groups. There should be no significant difference in average characteristics between the two groups.

Finally, the impact estimate is calculated by first calculating the difference in between the indicator for the treatment individual and the average value for the matched comparison individuals, and second, by averaging over all these differences.

9. Evaluation of the impact by program

For each type of ALMM we determine what outcome would have been for a program participant after participation in the program compared with the counterfactual outcome i.e. if the person had not participated in the program. The difference between the observed outcome and the counterfactual outcome is used as a measure of the impact of the program. One of the main issues in the sample selection is the so-called selection bias, which may affect the accuracy of the estimates. Selection bias means that a better outcome for the participants compared to the non-participants may be observed due to differences in the characteristics of the persons in the two groups and not to participation in the program.

Furthermore, we estimate the individual probabilities to participate to the program, depending on a set of observable characteristics. This is conducted through using standard Probit regression on the treated and the non-treated individuals. The estimated coefficients will provide insights in the factors influencing selection into treatment, but may also capture factors of attrition from the survey, i.e. factors explaining differential non-response rates in the treatment and in the control group. According to the estimated Probit model is than calculated the propensity score for each individual in the treatment and comparison group.

The propensity scores are used to match participants with comparable non-participants. For each treated individual, we look for the one individual among non-participants who is the closest neighbor in terms of the predicted probability of being treated. In other words, for each pair comprising a participant and a non-participant, the absolute difference in terms of the estimated propensity to participate in a certain treatment is minimized. To ensure that the matched pairs have reasonably similar probabilities to be treated, we exclude participants for whom the predicted probability to be in the program is larger than for any individual in the comparison group. In this way we achieve common support. Alternative matching procedures are used as robustness checks.

Moreover, we further explore the impact of ALMMs on the outcome variables for particular disadvantaged segments by disaggregation of the average treatment effect on treated individuals. In this context, particular attention is paid to youth, female, unemployed from rural areas, without work experience and being very-long-term unemployed. The disaggregation is performed only for those outcome variables where statistically significant impact has been identified.

Finally, we conduct evaluation of the matching quality. A way to do so is to compare the standardized mean bias before matching to the standardized mean bias after matching. In addition, we also re-estimate the propensity score on the matched sample to compute the pseudo-R2 before and after matching. The number of observations that are off common support in absolute and relative term is also presented as an additional indicator of matching quality.

9.1 Training for drivers (DR) 2016

Table 9.1.1 Training for drivers (DR) 2016, mean comparison

Observables		Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	31.9	34.7	-2.758	0.130
	Gender (1=male)	1.000	0.986	0.013	0.520
	Rural	0.355	0.216	0.139	0.141
	Married	0.742	0.514	0.228	0.031**
Household	Household size	4.129	2.932	1.197	0.000***
	Number of members under 15	1.032	0.554	0.478	0.010***
	Number of employed members	1.193	0.838	0.356	0.025**
	Number of unemployed members	1.839	1.176	0.663	0.003***
	Number of retired members	0.226	0.365	-0.139	0.250
Human capital	Primary education	0.065	0.094	-0.030	0.619
	Secondary education	0.806	0.729	0.077	0.411
	Higher education	0.129	0.162	-0.033	0.670
	Previous work experience	0.677	0.757	-0.079	0.407
	Short-term unemployed (up to 1 year)	0.452	0.473	-0.021	0.843
Disadvantaged	Very-long-term unemployed (more than 4)	0.097	0.149	-0.052	0.480
	Youth	0.193	0.189	0.004	0.959
	Older	0.000	0.014	-0.009	0.520
	Disabled	0.000	0.013	-0.013	0.520
	Roma	0.032	0.000	0.032	0.123

Outcome variables		Mean treated	Mean control	Difference	p-value
Registry	Currently employed	0.516	0.500	0.016	0.882
	Currently unemployed	0.323	0.148	0.174	0.043**
	Currently unknown	0.161	0.176	-0.014	0.860
Survey data	Employed	0.580	0.162	0.418	0.000***
	Unemployed	0.322	0.837	-0.515	0.000***
	Salary	23055	18958	4097	0.079*
	Permanent contract	0.555	0.083	0.472	0.007***
	Better financial conditions	0.193	0.027	0.166	0.003***
	Better employment prospects	0.419	0.027	0.392	0.000***
	Search for job	0.677	0.784	-0.106	0.254
	Intend to emigrate	0.580	0.527	0.054	0.619

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.1.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: marital status, household size, the number of members under 15, the number of employed and unemployed household members.

Table 9.1.2 Training for drivers (DR) 2016, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	-0.0242313	0.0168915	0.151
	Rural	0.1867401	0.3517583	0.596
	Married	0.0130431	0.4514266	0.977
Household	Household size	0.3036612	0.2599625	0.243
	Number of members under 15	0.0201478	0.266968	0.940
	Number of employed members	0.2243695	0.306956	0.465
	Number of unemployed members	0.2038273	0.25358	0.422
	Number of retired members	-0.141488	0.3352984	0.673

Human capital	Primary education	-1.400754	0.899803	0.120
	Secondary education	-1.201574	0.7465639	0.108
	Higher education	-1.315398	0.765503	0.086*
	Previous work experience	-0.2028059	0.3519685	0.564
	Short-term unemployed (up to 1 year)	0.1358054	0.2969518	0.647

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.1.2, only having higher education appear as statistically significant observable that exerts impact on the probability to participate in the training for drivers. Namely, unemployed with higher education are less likely to participate in this type of training.

Table 9.1.3 Training for drivers (DR) 2016, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.418	0.571	0.088	0.143	4.73	4.00**
Unemployed	-0.515	-0.714	0.086	0.130	-5.96	-5.48**
Salary	4097	3889	2255	2460	1.82	1.58
Permanent contract	0.472	0.444	0.163	0.176	2.90	2.53**
Better financial conditions	0.166	0.190	0.166	0.190	3.03	1.61
Better empl. prospects	0.392	0.429	0.065	0.132	6.04	3.25**
Search for job	-0.106	0.000	0.092	0.161	-1.15	0.00
Intend to emigrate	0.053	0.143	0.107	0.182	0.50	0.78

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.1.3, participation in the training for drivers has statistically significant positive impact on employment, having permanent contract and enjoying better employment prospects, while its impact on the unemployment is negative and statistically significant.

Table 9.1.4 Training for drivers (DR) 2020, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Employed	0.833	0.320	-	0.387	0.091	0.550	0.300	0.476	-	0.464
Unemployed	-0.833	-0.440	-	-0.484	-0.182	-0.650	-0.400	-0.571	-	-0.571
Permanent contract	-	0.385	-	0.500	0.600	0.462	0.750	0.429	-	-
Better empl. prospects	0.333	0.360	-	0.355	0.182	0.400	0.400	0.429	0.667	0.321

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.1.4, we can draw the following conclusions with respect to the impact of training for drivers on disadvantaged groups:

- Youth are better off than mature unemployed vis-à-vis probability of being employed and being unemployed but they perceive lower employment prospects;
- Since the female are not represented among the participants in this ALMM, we are not able to draw conclusion regarding their position compared with male participants;
- Unemployed from rural areas are better off than those from urban areas vis-à-vis probability of being employed but worse of regarding the probability of being unemployed; in addition they enjoy higher probability of having permanent employment but perceive lower employment prospects;
- Unemployed without work experience are worse off than those with work experience vis-à-vis probability of being employed and probability of being unemployed; in addition they enjoy higher probability of having permanent contract and similar perception of employment prospects as unemployed with previous work experience;
- The very-long-term unemployed are worse off compared to those with shorter spells of unemployment regarding the perception of the employment prospects.

The propensity score density functions and the quality of the matching are presented on Figure 9.1.1 and Figure 9.1.2 respectively.

Figure 9.1.1 Training for drivers (DR) 2016, Propensity score density functions

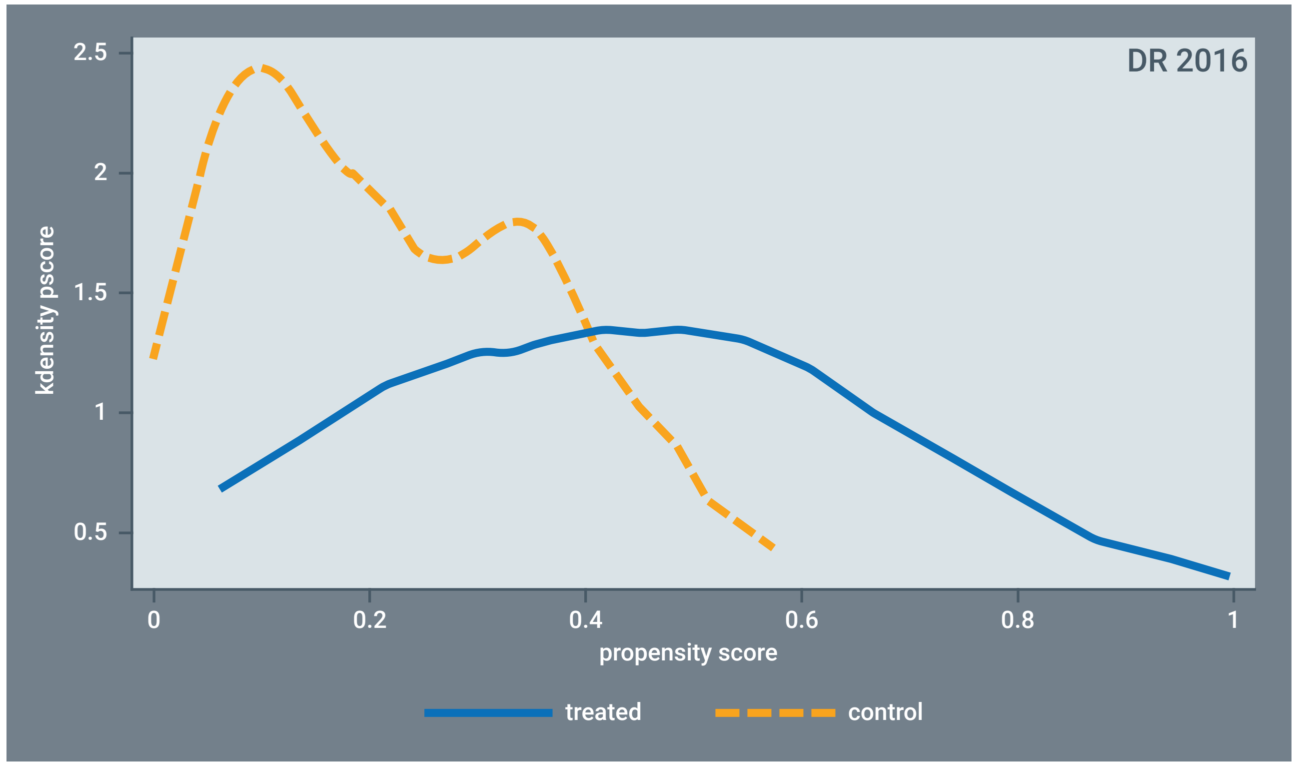
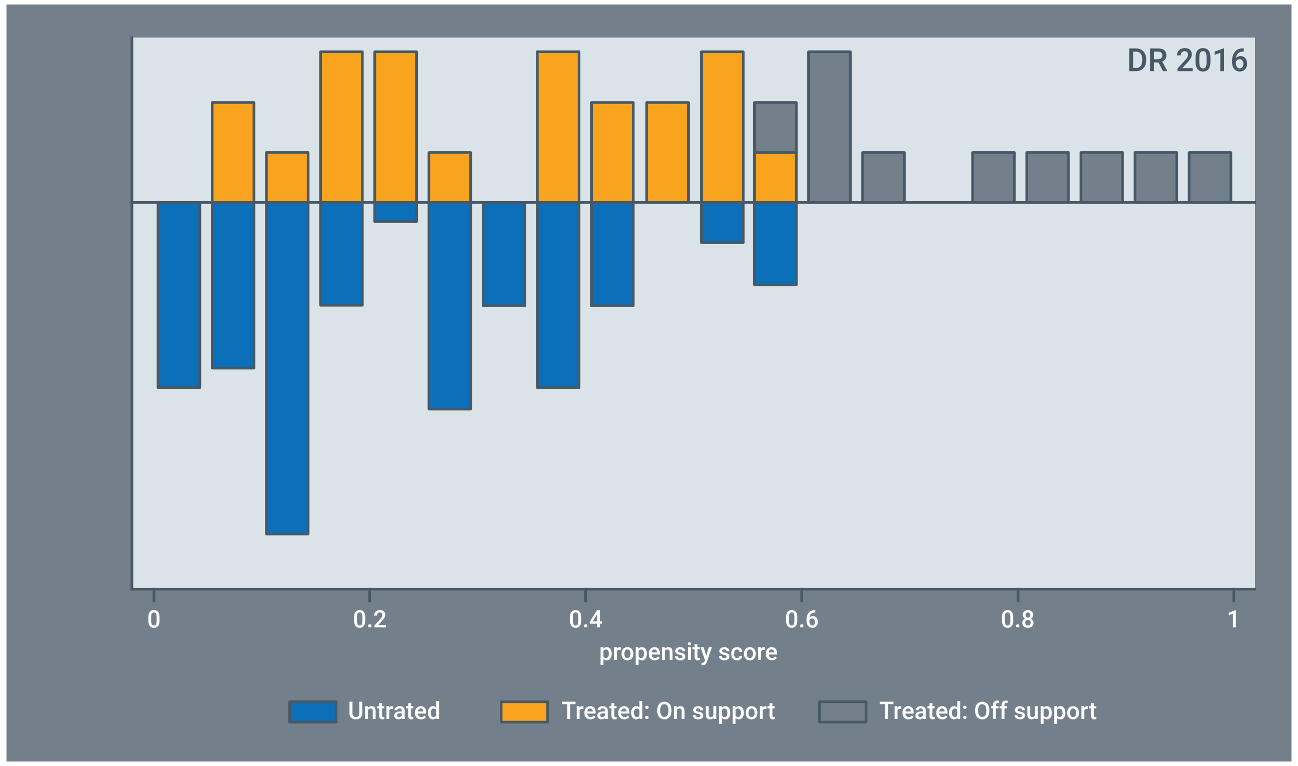


Figure 9.1.2 Training for drivers (DR) 2016, matching quality



9.2 Training for drivers (DR) 2020

Table 9.2.1 Training for drivers (DR) 2020, mean comparison

Observables		Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	34	34.9	-0.900	0.650
	Gender (1=male)	1.000	0.989	0.011	0.549
	Rural	0.344	0.386	-0.043	0.673
	Married	0.656	0.602	0.054	0.594
Household	Household size	4.062	3.057	1.006	0.000***
	Number of members under 15	0.875	0.398	0.477	0.003***
	Number of employed members	1.313	0.909	0.403	0.009***
	Number of unemployed members	1.656	1.329	0.327	0.089*
	Number of retired members	0.281	0.420	-0.139	0.237
Human capital	Primary education	0.094	0.239	-0.145	0.081*
	Secondary education	0.844	0.614	0.230	0.017**
	Higher education	0.063	0.114	-0.051	0.413
	Previous work experience	0.719	0.693	0.026	0.789
	Short-term unemployed (up to 1 year)	0.656	0.682	-0.026	0.794
Disadvantaged	Very-long-term unemployed (more than 4)	0.187	0.125	0.063	0.389
	Youth	0.188	0.182	0.006	0.944
	Older	0.031	0.068	-0.037	0.449
	Disabled	0.000	0.023	-0.023	0.394
	Roma	0.031	0.102	-0.071	0.216
Outcome variables		**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.406	0.307	0.099	0.311
	Currently unemployed	0.500	0.534	-0.034	0.743
	Currently unknown	0.062	0.136	-0.073	0.269

Survey data	Employed	0.531	0.023	0.508	0.000***
	Unemployed	0.031	0.977	-0.946	0.000***
	Salary	20588	20000	588	0.870
	Permanent contract	0.353	0.500	-0.147	0.703
	Better financial conditions	0.250	0.000	0.250	0.000***
	Better employment prospects	0.250	0.000	0.250	0.000***
	Search for job	0.594	0.841	-0.247	0.004***
	Intend to emigrate	0.531	0.511	0.019	0.849

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.2.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: household size, the number of household members under 15, the number of employed members, the number of unemployed members, being with primary education and being with secondary education.

Table 9.2.2 Training for drivers (DR) 2020, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	-0.0138225	0.0132523	0.297
	Rural	-0.1817992	0.298983	0.543
	Married	-0.4348596	0.362445	0.230
Household	Household size	-0.2422613	0.6786035	0.721
	Number of members under 15	0.9418523	0.6900906	0.172
	Number of employed members	0.7594344	0.6950646	0.275
	Number of unemployed members	0.565412	0.6602306	0.392
	Number of retired members	0.0097121	0.7059477	0.989
Human capital	Primary education	-1.318947	0.7361022	0.073*
	Secondary education	-0.8055898	0.6099657	0.187
	Higher education	-1.016871	0.7083994	0.151
	Previous work experience	-0.1893165	0.3543433	0.593
	Short-term unemployed (up to 1 year)	-0.2077803	0.2819056	0.461

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.2.2, only having primary education appear as statistically significant observable that exerts impact on the probability to participate in the training for drivers. Namely, unemployed with primary education are less likely to participate in this type of training.

Table 9.2.3 Training for drivers (DR) 2020, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.508	0.313	0.059	0.110	8.49	2.50**
Unemployed	-0.946	-0.781	0.032	0.067	-29.12	-8.11***
Salary	-	-	-	-	-	-
Permanent contract	-	-	-	-	-	-
Better financial conditions	0.250	0.241	0.046	0.081	5.37	2.98**
Better empl. prospects	0.250	0.241	0.046	0.081	5.37	2.98**
Search for job	-0.247	-0.103	0.084	0.129	-2.95	-0.70
Intend to emigrate	0.019	0.103	0.104	0.167	0.19	0.62

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.2.3, participation in the training for drivers has statistically significant positive impact on employment and enjoying better financial conditions and better employment prospects, while its impact on the unemployment is negative and statistically significant.

Table 9.2.4 Training for drivers (DR) 2020, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Employed	0.833	0.423	-	0.469	0.364	0.619	0.667	0.435	-	0.654
Unemployed	-	-0.923	-	-0.906	-	-0.952	-	-0.913	-	-0.962
Better financial conditions	0.833	0.115	-	0.250	0.273	0.238	0.333	0.217	-	0.308
Better empl. prospects	0.833	0.115	-	0.250	0.273	0.238	0.333	0.217	-	0.308

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.2.4, we can draw the following conclusions with respect to the impact of training for drivers on disadvantaged groups:

- Youth are better off than mature unemployed vis-à-vis probability of being employed and have considerably higher perception of better financial conditions and better employment prospects;
- Since the female are not represented among the participants in this ALMM, we are not able to draw conclusion regarding their position compared with male participants;
- Unemployed from rural areas are worse off than those from urban areas vis-à-vis probability of being employed and have slightly higher perception of better financial conditions and better employment prospects;
- Unemployed without work experience are better off than those with work experience vis-à-vis probability of being employed and have slightly higher perception of better financial conditions and better employment prospects;
- The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in this ALMM.

The propensity score density functions and the quality of the matching are presented on Figure 9.2.1 and Figure 9.2.2 respectively.

Figure 9.2.1 Training for drivers (DR) 2020, Propensity score density functions

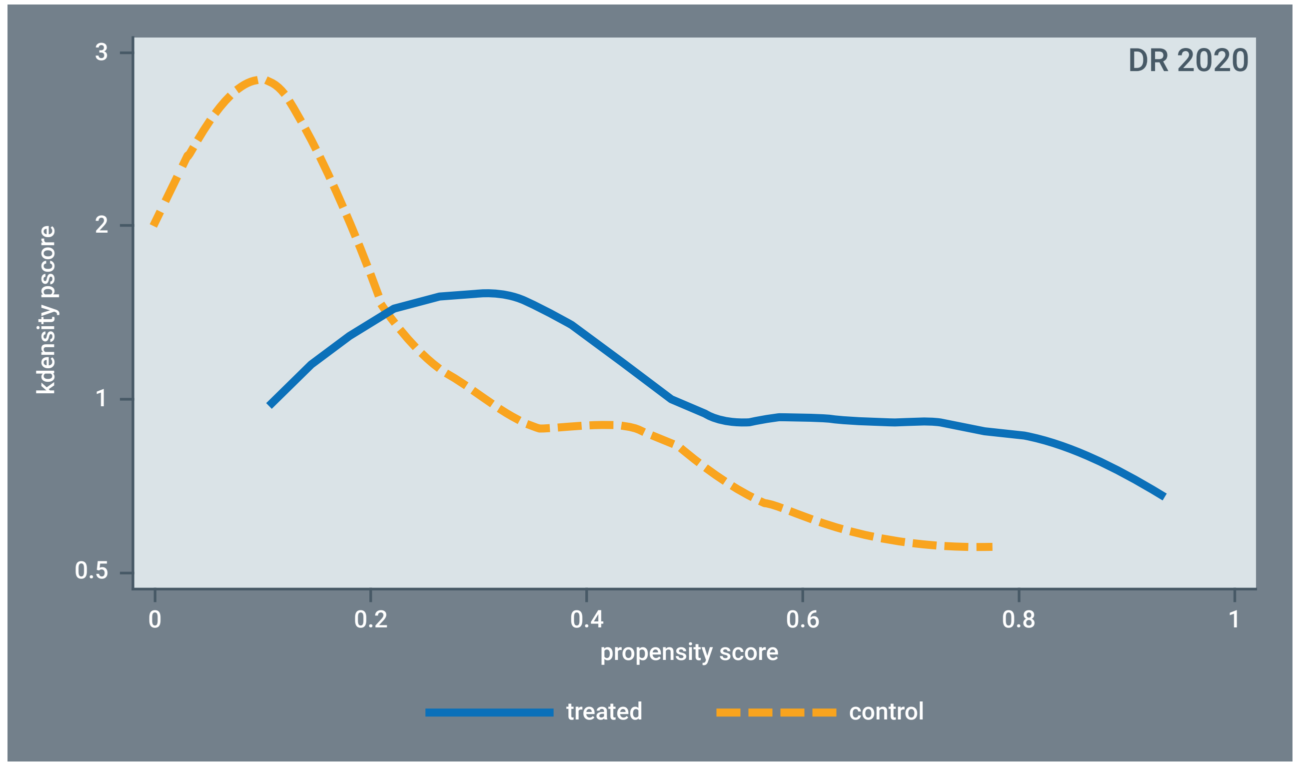
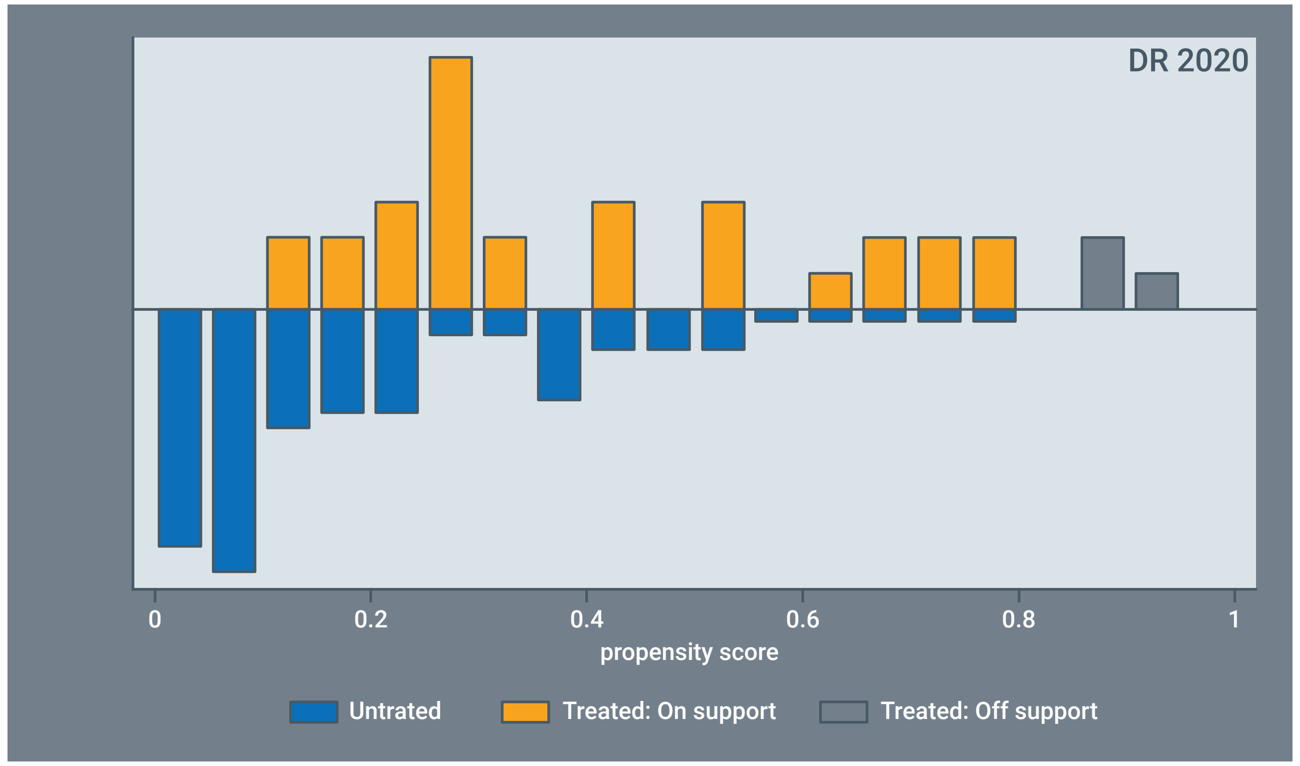


Figure 9.2.2 Training for drivers (DR) 2020, Matching quality



9.3 Training for known employer (TKE) 2018

Table 9.3.1 Training for known employer (TKE) 2018, mean comparison

Observables		Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	36.7	36.6	0.105	0.975
	Gender (1=male)	0.328	0.333	-0.005	0.971
	Rural	0.295	0.500	-0.205	0.172
	Married	0.852	0.500	0.352	0.005***
Household	Household size	3.984	3.833	0.150	0.716
	Number of members under 15	0.869	0.583	0.285	0.372
	Number of employed members	1.590	1.083	0.507	0.054**
	Number of unemployed members	0.885	1.916	-1.031	0.039**
	Number of retired members	0.279	0.250	0.029	0.866
Human capital	Primary education	0.246	0.500	-0.254	0.077*
	Secondary education	0.721	0.500	0.221	0.135
	Higher education	0.016	0.000	0.016	0.660
	Previous work experience	0.721	0.417	0.305	0.041**
	Short-term unemployed (up to 1 year)	0.820	0.833	-0.014	0.912
Disadvantaged	Very-long-term unemployed (more than 4)	0.033	0.083	-0.050	0.427
	Youth	0.213	0.250	-0.037	0.781
	Older	0.033	0.000	0.033	0.531
	Disabled	0.016	0.000	0.016	0.661
	Roma	0.016	0.000	0.016	0.661
Outcome variables		**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.754	0.500	0.254	0.077*
	Currently unemployed	0.147	0.167	-0.019	0.868
	Currently unknown	0.049	0.083	-0.034	0.640
Survey data	Employed	0.770	0.250	0.520	0.000***
	Unemployed	0.213	0.750	-0.537	0.000***
	Salary	17337	17500	-163	0.899
	Permanent contract	0.674	0.333	0.341	0.238
	Better financial conditions	0.459	0.000	0.459	0.002***
	Better employment prospects	0.361	0.000	0.361	0.012***
	Search for job	0.393	0.583	-0.190	0.229
	Intend to emigrate	0.246	0.250	-0.004	0.976

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.3.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: marital status, the number of employed members, the number of unemployed members, being with primary education and having previous work experience.

Table 9.3.2 Training for known employer (TKE) 2018, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	-0.0238225	0.0417944	0.569
	Gender (1=male)	0.3962214	0.4868279	0.416
	Rural	-0.361175	0.5229903	0.490
	Married	1.137009	0.6749109	0.092*
Household	Household size	4.378614	379.481	0.991
	Number of members under 15	-4.295072	379.4812	0.991
	Number of employed members	-3.863669	379.4815	0.992
	Number of unemployed members	-4.302481	379.4811	0.991
	Number of retired members	-3.558763	379.4816	0.993
Human capital	Primary education	-3.674831	2192.383	0.999
	Secondary education	-3.740533	2192.383	0.999
	Previous work experience	0.7123254	0.6178908	0.249
	Short-term unemployed (up to 1 year)	-0.3436768	0.607675	0.572

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.3.2, only marital status appear as statistically significant observable that exerts impact on the probability to participate in the training for known employer. Namely, married unemployed are more likely to participate in this type of training.

Table 9.3.3 Training for known employer (TKE) 2018, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.520	0.063	0.135	0.241	3.79	0.26
Unemployed	-0.537	-0.063	0.132	0.241	-4.00	-0.26
Salary	-	-	-	-	-	-
Permanent contract	-	-	-	-	-	-
Better financial conditions	0.459	0.312	0.146	0.120	3.09	2.61**
Better empl. prospects	0.361	0.312	0.141	0.120	2.51	2.61**
Search for job	-0.190	0.000	0.157	0.248	-1.21	0.00
Intend to emigrate	-0.004	-0.188	0.138	0.228	-0.03	-0.82

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.3.3, participation in the training for known employer has statistically significant positive impact on enjoying better financial conditions and better employment prospects.

Table 9.3.4 Training for known employer (TKE) 2019, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Better financial conditions	0.385	0.479	0.439	0.500	0.222	0.558	0.353	0.500	0.458	0.500
Better empl. prospects	0.385	0.354	0.341	0.400	0.111	0.465	0.294	0.386	0.356	0.386

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.3.4, we can draw the following conclusions with respect to the impact of training for known employer on disadvantaged groups:

- Youth are worse off than mature unemployed vis-à-vis their perception of future financial conditions, but they are slightly better off regarding the perception of employment prospects;
- Female are worse off than male unemployed regarding their perception of future financial conditions and employment prospects;
- Unemployed from rural areas are considerably worse off than those from urban areas vis-à-vis their perception of future financial conditions and employment prospects;
- Unemployed without work experience are worse off than those with work experience regarding their perception of future financial conditions and employment prospects;
- The very-long-term unemployed are slightly worse off compared to those with shorter spells of unemployment regarding their perception of future financial conditions and employment prospects.

The propensity score density functions and the quality of the matching are presented on Figure 9.3.1 and Figure 9.3.2 respectively.

Figure 9.3.1 Training for known employer (TKE) 2018, Propensity score density functions

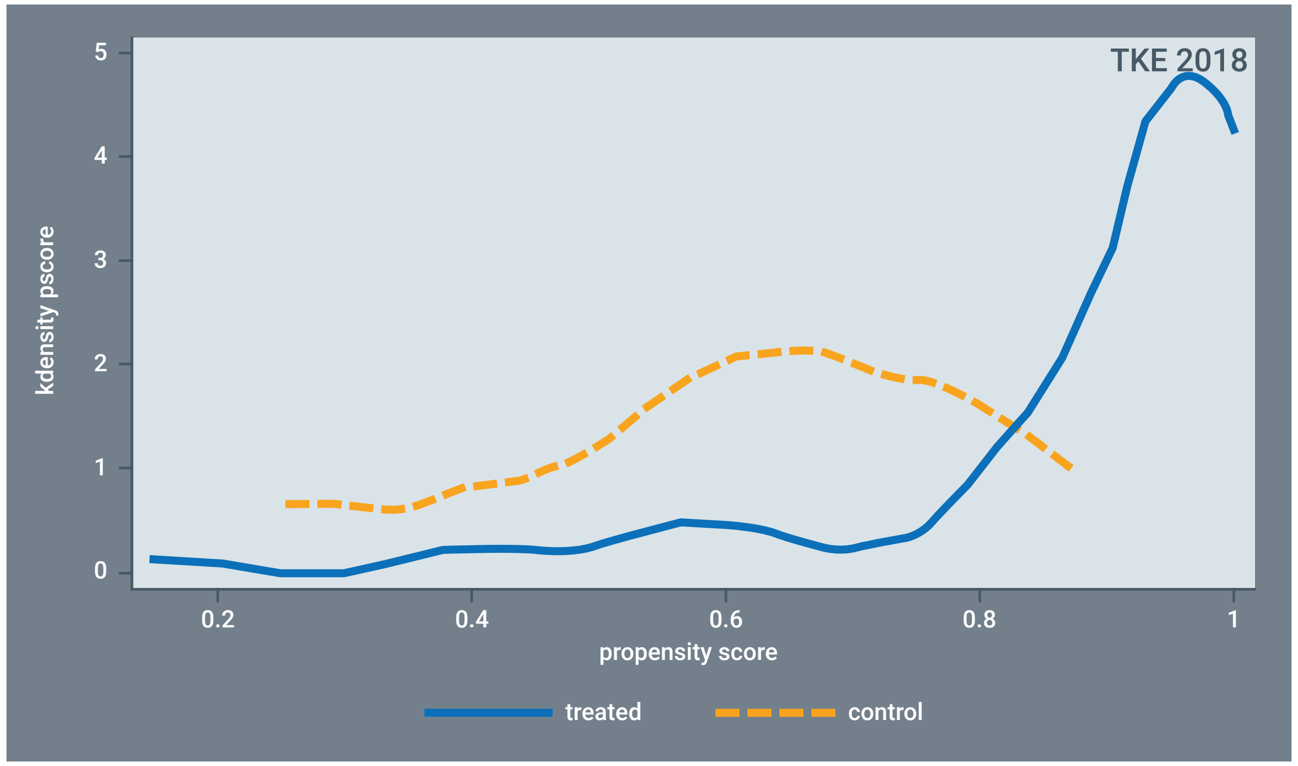
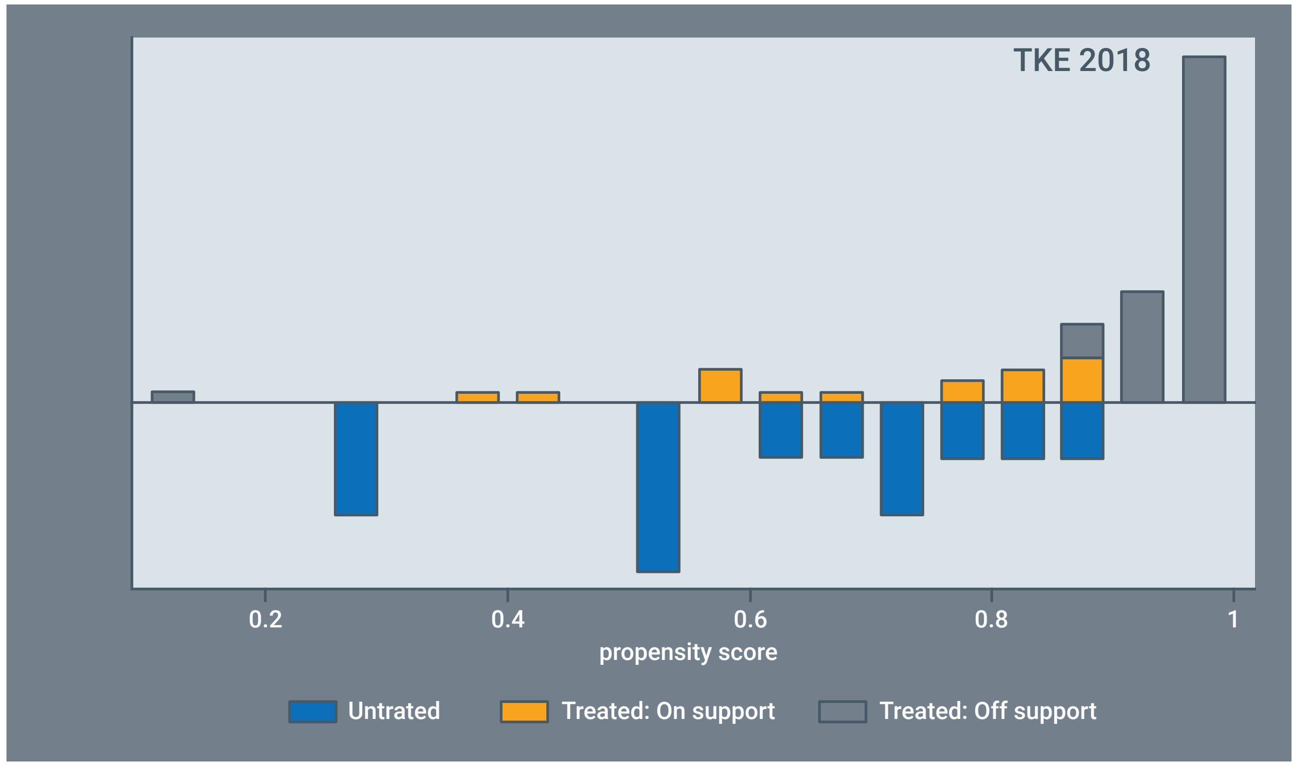


Figure 9.3.2 Training for known employer (TKE) 2018, Matching quality



9.4 Training for known employer (TKE) 2019

Table 9.4.1 Training for known employer (TKE) 2019, mean comparison

	Observables	Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	36.0	31.5	4.5	0.225
	Gender (1=male)	0.640	0.214	0.426	0.003***
	Rural	0.313	0.286	0.027	0.846
	Married	0.625	0.357	0.268	0.068*
Household	Household size	3.719	3.500	0.219	0.512
	Number of members under 15	0.672	0.429	0.243	0.384
	Number of employed members	1.687	1.643	0.045	0.881
	Number of unemployed members	0.984	1.071	-0.087	0.785
	Number of retired members	0.344	0.429	-0.085	0.636
Human capital	Primary education	0.250	0.000	0.250	0.036**
	Secondary education	0.516	0.357	0.158	0.289
	Higher education	0.172	0.571	-0.399	0.001**
	Previous work experience	0.719	0.714	-0.004	0.973
	Short-term unemployed (up to 1 year)	0.766	0.714	0.051	0.690
Disadvantaged	Very-long-term unemployed (more than 4)	0.078	0.071	0.007	0.933
	Youth	0.297	0.214	0.083	0.540
	Older	0.125	0.000	0.125	0.167
	Disabled	0.000	0.000	0.000	-
	Roma	0.031	0.071	-0.040	0.485
	Outcome variables	**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.562	0.428	0.134	0.369
	Currently unemployed	0.250	0.429	-0.178	0.183
	Currently unknown	0.156	0.071	0.085	0.415

Survey data	Employed	0.656	0.428	0.228	0.116
	Unemployed	0.000	0.571	-0.571	0.000***
	Salary	17988	22500	-4512	0.017**
	Permanent contract	0.381	0.500	-0.119	0.586
	Better financial conditions	0.250	0.000	0.250	0.036**
	Better employment prospects	0.250	0.000	0.250	0.036**
	Search for job	0.406	0.643	-0.237	0.110
	Intend to emigrate	0.328	0.214	0.114	0.410

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.4.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: gender, marital status, being with primary education and being with higher education.

Table 9.4.2 Training for known employer (TKE) 2019, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	0.0270224	0.0326845	0.408
	Gender (1=male)	5.951233	2.333583	0.011**
	Rural	-0.4854342	0.7572028	0.521
	Married	2.562273	1.85277	0.167
Household	Household size	2.910188	1.296152	0.025**
	Number of members under 15	-2.683988	1.307096	0.040**
	Number of employed members	-0.7213644	0.7129341	0.312
	Number of unemployed members	-2.189424	1.024646	0.033**
	Number of retired members	-4.820999	2.064769	0.020**
Human capital	Secondary education	-7.330666	3.245723	0.024**
	Higher education	-8.004037	3.210129	0.013**
	Previous work experience	0.0443447	0.8097489	0.956
	Short-term unemployed (up to 1 year)	0.2708259	0.6915306	0.695

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.4.2, gender, household size, number of household members under 15, number of unemployed and retired members, and educational attainment have significant impact on the probability to participate in the training for known employer. Namely, men and those living in bigger households are more likely to participate, while higher number of unemployed and retired household members, as well as higher level of education is associated with lower probability to be participants in this type of training.

Table 9.4.3 Training for known employer (TKE) 2019, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.196	-0.333	0.150	0.211	1.31	-1.58
Unemployed	-0.571	-0.875	0.063	0.215	-7.87	-1.99**
Salary	-	-	-	-	-	-
Permanent contract	-	-	-	-	-	-
Better financial conditions	0.250	0.667	0.117	0.176	2.13	3.16**
Better empl. prospects	0.250	0.667	0.117	0.176	2.13	3.16**
Search for job	-0.237	-0.259	0.146	0.259	-1.62	-1.00
Intend to emigrate	0.114	0.261	0.137	0.261	0.83	-1.28

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.4.3, participation in the training for known employer has statistically significant negative impact on probability to be unemployed, while positive impact on enjoying better financial conditions and better employment prospects.

Table 9.4.4 Training for known employer (TKE) 2019, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Unemployed	-0.368	-0.667	-0.478	-0.634	-0.800	-0.568	-0.667	-0.608	-	-0.644
Better financial conditions	0.316	0.222	0.435	0.146	0.300	0.227	0.333	0.217	-	0.271
Better empl. prospects	0.316	0.222	0.435	0.146	0.435	0.146	0.333	0.217	-	0.271

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.4.4, we can draw the following conclusions with respect to the impact of training for known employer on disadvantaged groups:

- Youth are worse off than mature unemployed vis-à-vis the probability of being unemployed, but they perceive better financial conditions and better employment prospects;
- Female are worse off than male unemployed regarding the probability of being unemployed, but they have more than twice higher perception for better financial conditions and better employment prospects;
- Unemployed from rural areas are better off than those from urban areas vis-à-vis the probability of being, but they perceive better financial conditions and better employment prospects;
- Unemployed without work experience are better off than those with work experience regarding the probability of being unemployed and they perceive better financial conditions and better employment prospects;
- The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in this ALMM.

The propensity score density functions and the quality of the matching are presented on Figure 9.4.1 and Figure 9.4.2 respectively.

Figure 9.4.1 Training for known employer (TKE) 2019, Propensity score density functions

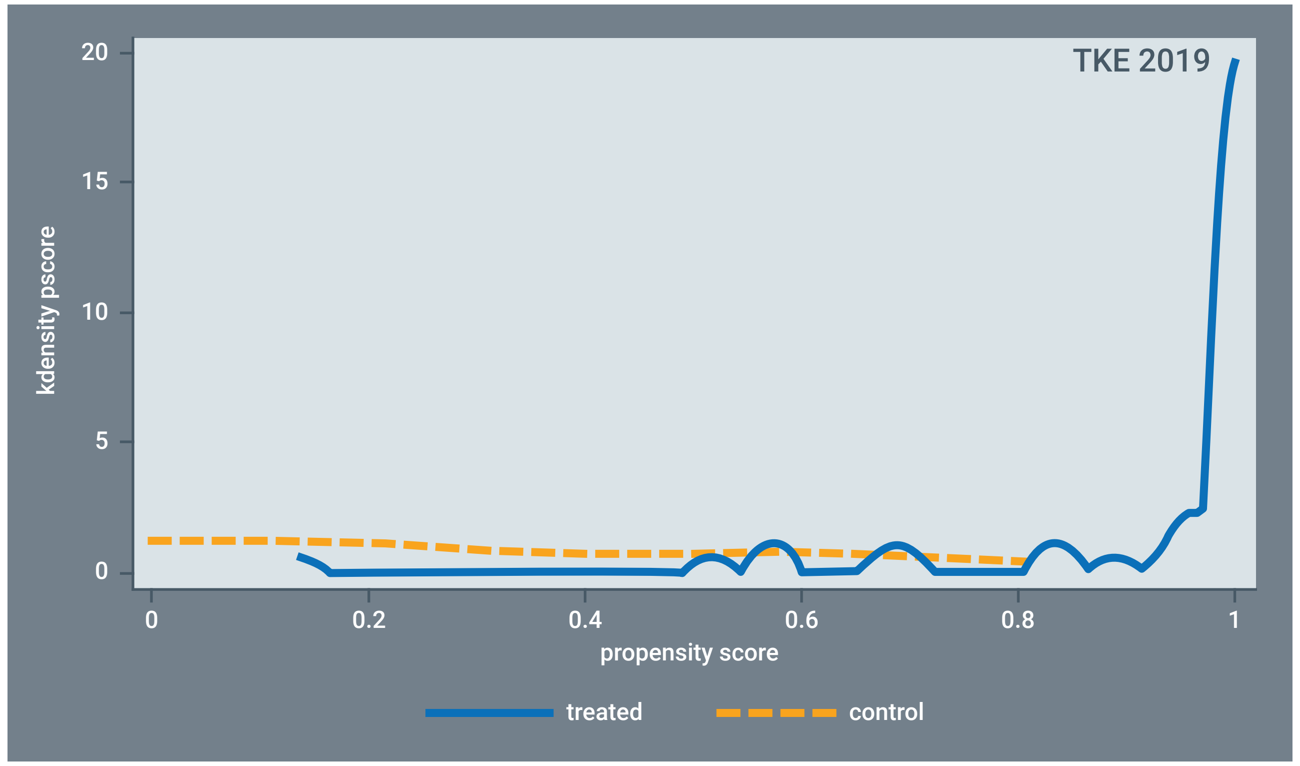
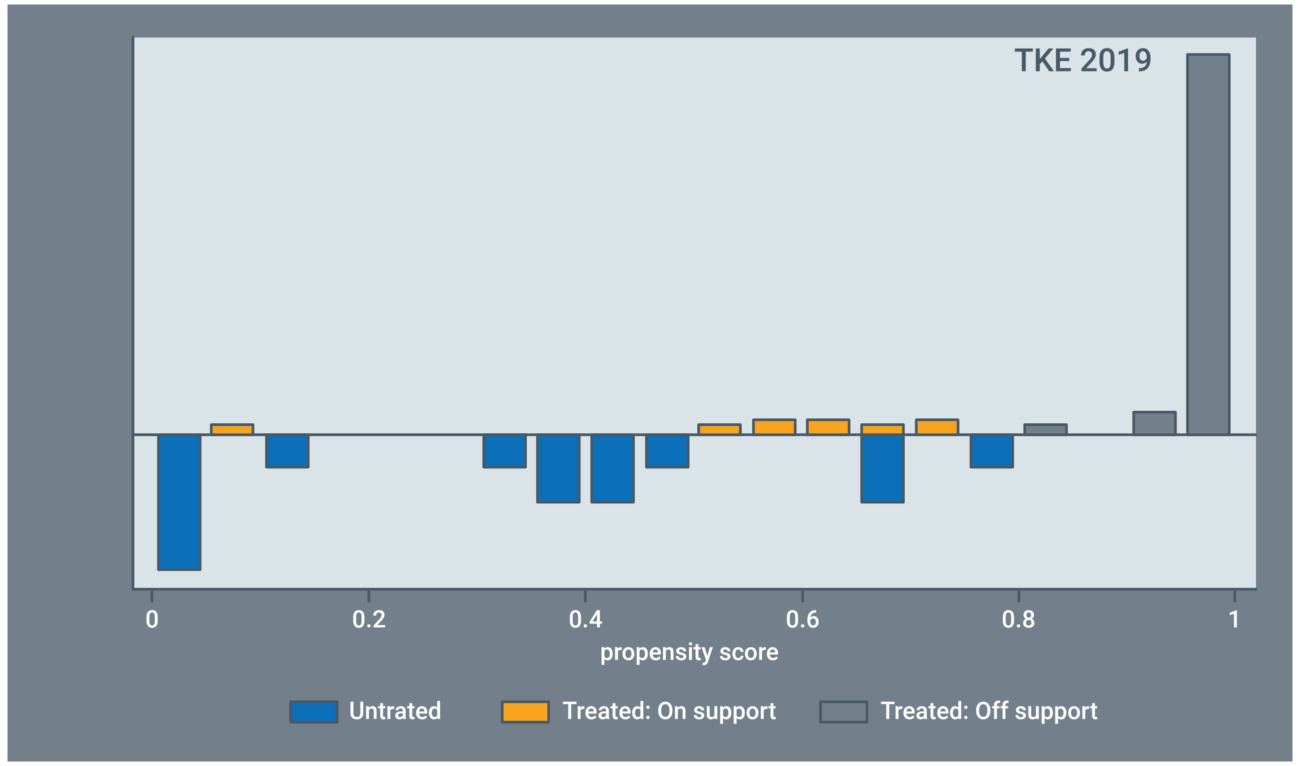


Figure 9.4.2 Training for known employer (TKE) 2019, Matching quality



9.5 Training for advanced IT skills (IT) 2017/18

Table 9.5.1 Training for advanced IT skills (IT) 2017/18, mean comparison

	Observables	Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	29.9	28.9	0.949	0.391
	Gender (1=male)	0.699	0.484	0.215	0.005***
	Rural	0.082	0.118	-0.036	0.450
	Married	0.425	0.667	-0.242	0.002***
Household	Household size	3.260	3.494	-0.234	0.154
	Number of members under 15	0.466	0.699	-0.233	0.078*
	Number of employed members	2.027	2.043	-0.016	0.921
	Number of unemployed members	0.384	0.570	-0.186	0.121
	Number of retired members	0.411	0.194	0.217	0.025**
Human capital	Primary education	-	-	-	-
	Secondary education	0.329	0.279	0.049	0.496
	Higher education	0.548	0.634	-0.086	0.262
	Previous work experience	0.734	0.634	0.105	0.150
	Short-term unemployed (up to 1 year)	0.890	0.806	0.084	0.141
Disadvantaged	Very-long-term unemployed (more than 4)	0.027	0.032	-0.005	0.857
	Youth	0.274	0.398	-0.124	0.096*
	Older	0.014	0.000	0.014	0.260
	Disabled	0.014	0.011	0.003	0.864
	Roma	-	-	-	-
	Outcome variables	**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.767	0.688	0.079	0.262
	Currently unemployed	0.137	0.140	-0.003	0.959
	Currently unknown	0.041	0.140	-0.099	0.033**
Survey data	Employed	0.877	0.785	0.092	0.124
	Unemployed	0.014	0.000	0.014	0.260
	Salary	22386	22283	104	0.883
	Permanent contract	0.703	0.527	0.176	0.035**
	Better financial conditions	0.452	0.194	0.259	0.000***
	Better employment prospects	0.329	0.097	0.232	0.000***
	Search for job	0.219	0.247	-0.028	0.674
	Intend to emigrate	0.219	0.140	0.079	0.183

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.5.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: gender, marital status, the number of household members under 15, the number of retired household members and being youth.

Table 9.5.2 Training for advanced IT skills (IT) 2017/18, propensity score coefficients (Probit model)

	Observables	Coefficient	Std. error	p-value
Socio-dem.	Age	0.0100003	0.0170404	0.557
	Gender (1=male)	0.4278441	0.2274521	0.060**
	Rural	0.0149796	0.3683936	0.968
	Married	-0.7146442	0.3055843	0.019**
Household	Household size	-0.0840098	0.8962292	0.925
	Number of members under 15	0.1294073	0.8966107	0.885
	Number of employed members	-0.0118069	0.9305418	0.990
	Number of unemployed members	-0.3013737	0.9496847	0.751
	Number of retired members	0.1858649	0.9437529	0.844
Human capital	Secondary education	-0.1080907	0.3847408	0.779
	Higher education	-0.3298191	0.3517523	0.348
	Previous work experience	0.2966857	0.2513991	0.238
	Short-term unemployed (up to 1 year)	0.6210604	0.3238033	0.055*

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.5.2, gender, marital status and unemployment history have significant impact on the probability to participate in the training for advanced IT skills. Namely, men and short-term unemployed are more likely to participate, while married unemployed have lower probability to be participants in this type of training.

Table 9.5.3 Training for advanced IT skills (IT) 2017/18, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.092	0.153	0.059	0.086	1.55	1.77
Unemployed	0.014	0.014	0.012	0.014	1.13	1.00
Salary	104	1071	705.3	964.5	0.15	1.11
Permanent contract	0.176	0.136	0.082	0.121	2.13	1.12
Better financial conditions	0.259	0.314	0.070	0.093	3.71	3.37**
Better empl. prospects	0.232	0.286	0.060	0.065	3.86	4.39**
Search for job	-0.028	0.057	0.067	0.091	-0.42	0.63
Intend to emigrate	0.079	-0.014	0.059	0.094	1.34	-0.15

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.5.3, participation in the training for advanced IT skills has statistically significant positive impact on the probability to enjoy better financial conditions and better employment prospects.

Table 9.5.4 Training for advanced IT skills (IT) 2017/18, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Better financial conditions	0.225	0.245	0.318	0.235	0.360	0.224	0.316	0.204	-	0.225
Better empl. prospects	0.475	0.151	0.318	0.196	0.167	0.239	0.421	0.148	-	0.225

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.5.4, we can draw the following conclusions with respect to the impact of training for advanced IT skills on disadvantaged groups:

- Youth are worse off than mature unemployed vis-à-vis the perception of the future financial conditions, but worse of regarding the perception of employment prospects;
- Female are better off than male unemployed with respect to both perceptions of better financial conditions and better employment prospects;
- Unemployed from rural areas are worse off than those from urban areas regarding the perception of the future financial conditions, but worse of regarding the perception of employment prospects;
- Unemployed without work experience are better off than those with work experience with respect to both perceptions of better financial conditions and better employment prospects;
- The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in this ALMM.

The propensity score density functions and the quality of the matching are presented on Figure 9.5.1 and Figure 9.5.2 respectively.

Figure 9.5.1 Training for advanced IT skills (IT) 2017/18, Propensity score density functions

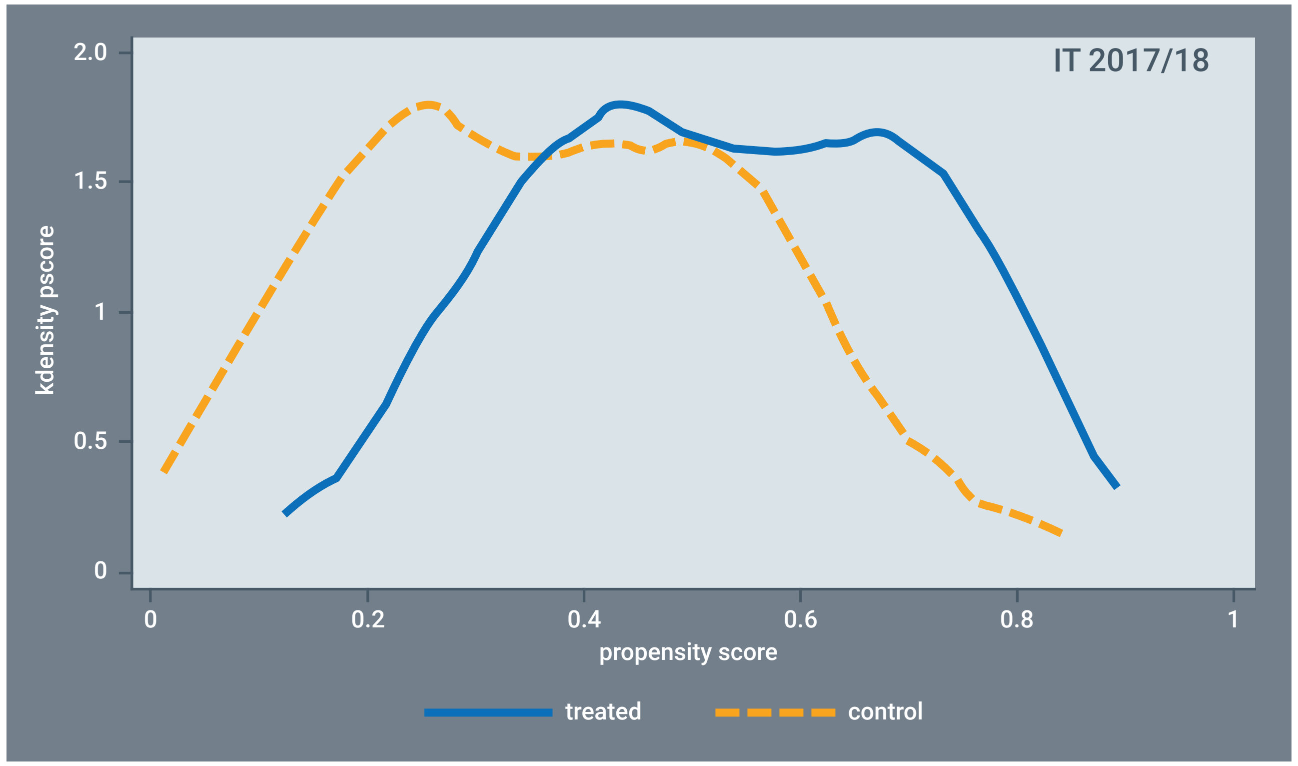
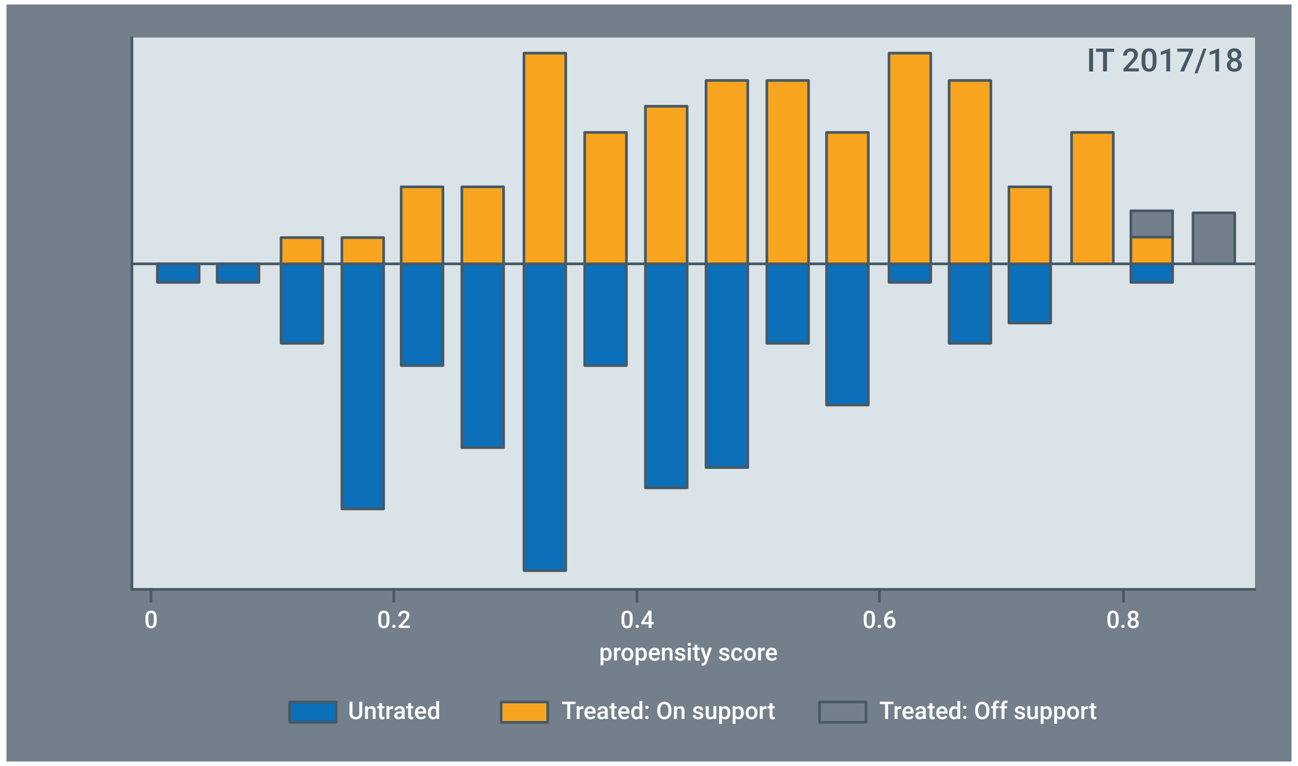


Figure 9.5.2 Training for advanced IT skills (IT) 2017/18, Matching quality



9.6 Training for advanced IT skills (IT) 2019

Table 9.6.1 Training for advanced IT skills (IT) 2019, mean comparison

	Observables	Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	26.4	26.4	-0.01	0.983
	Gender (1=male)	0.709	0.483	0.226	0.006***
	Rural	0.116	0.100	0.016	0.759
	Married	0.081	0.250	-0.169	0.005***
Household	Household size	3.094	3.150	-0.056	0.790
	Number of members under 15	0.129	0.267	-0.137	0.113
	Number of employed members	1.706	1.500	0.206	0.282
	Number of unemployed members	1.094	1.033	0.061	0.701
	Number of retired members	0.271	0.383	-0.113	0.273
Human capital	Primary education	-	-	-	-
	Secondary education	0.512	0.383	0.128	0.128
	Higher education	0.430	0.550	-0.120	0.156
	Previous work experience	0.581	0.650	-0.069	0.407
	Short-term unemployed (up to 1 year)	0.837	0.850	-0.013	0.836
Disadvantaged	Very-long-term unemployed (more than 4)	0.023	0.000	0.023	0.237
	Youth	0.419	0.483	-0.065	0.442
	Older	-	-	-	-
	Disabled	0.011	0.000	0.011	0.405
	Roma	-	-	-	-
	Outcome variables	**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.465	0.550	-0.085	0.316
	Currently unemployed	0.314	0.283	0.031	0.694
	Currently unknown	0.128	0.117	0.011	0.840

Survey data	Employed	0.384	0.483	-0.099	0.234
	Unemployed	0.512	0.517	-0.005	0.953
	Salary	25300	22608	2691	0.201
	Permanent contract	0.303	0.345	-0.042	0.731
	Better financial conditions	0.233	0.200	0.033	0.643
	Better employment prospects	0.233	0.217	0.016	0.823
	Search for job	0.709	0.533	0.176	0.029**
	Intend to emigrate	0.360	0.233	0.127	0.103

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.6.1 we can observe that statistically significant difference between the treatment and control group is found for gender and marital status, while regarding other observables there is no statistically significant difference.

Table 9.6.2 Training for advanced IT skills (IT) 2019, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	0.0775205	0.0395544	0.050**
	Gender (1=male)	0.5246944	0.2448502	0.032**
	Rural	0.0789775	0.369883	0.831
	Married	-0.7285525	0.4405679	0.098*
Household	Household size	-0.5913511	0.3427225	0.084*
	Number of members under 15	0.3000602	0.3730572	0.421
	Number of employed members	0.6992011	0.3738829	0.061*
	Number of unemployed members	0.5704214	0.3790802	0.132
	Number of retired members	0.1731034	0.3781468	0.647
Human capital	Secondary education	0.2201162	0.5261679	0.676
	Higher education	-0.2068993	0.4986387	0.678
	Previous work experience	-0.4982686	0.2985433	0.095*
	Short-term unemployed (up to 1 year)	0.2469896	0.3365752	0.463

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.6.2, age, gender, marital status, household size, number of employed members in the household and previous work experience have significant impact on the probability to participate in the training for advanced IT skills. Namely, an additional year, being male, and additional employed household member increase the probability to participate, while being married, the household size and previous work experience are associated with lower probability to be participants in this type of training.

Table 9.6.3 Training for advanced IT skills (IT) 2019, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	-0.095	-0.195	0.084	0.130	-1.14	-1.50
Unemployed	0.000	0.098	0.085	0.131	0.01	0.74
Salary	2691	5000	2074	6871	1.30	0.73
Permanent contract	-0.042	0.048	0.121	0.218	-0.35	0.22
Better financial conditions	0.035	0.049	0.070	0.117	0.50	0.42
Better empl. prospects	0.019	0.049	0.071	0.117	0.26	0.42
Search for job	0.173	0.232	0.080	0.130	2.14	1.78*
Intend to emigrate	0.131	0.024	0.078	0.125	1.69	0.19

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.6.3, participation in the training for advanced IT skills has statistically significant positive impact on the probability to search for job, while the impact on other outcome variables is not statistically significant.

Table 9.6.4 Training for advanced IT skills (IT) 2019, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Search for job	0.083	0.184	0.250	0.180	0.600	0.160	0.167	0.082	-	0.193

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.6.4, we can draw the following conclusions with respect to the impact of training for advanced IT skills on disadvantaged groups:

- Youth manifest about twice as lower probability to search for job compared to mature unemployed;
- Female participant are characterized with higher probability to search for job compared to male participants;
- Unemployed from rural areas manifest almost four times higher probability to search for job compared to those from urban areas;
- Unemployed without work experience have almost twice as higher probability to search for job compared to those with work experience;
- The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in this ALMM.

The propensity score density functions and the quality of the matching are presented on Figure 9.6.1 and Figure 9.6.2 respectively.

Figure 9.6.1 Training for advanced IT skills (IT) 2019, matching quality

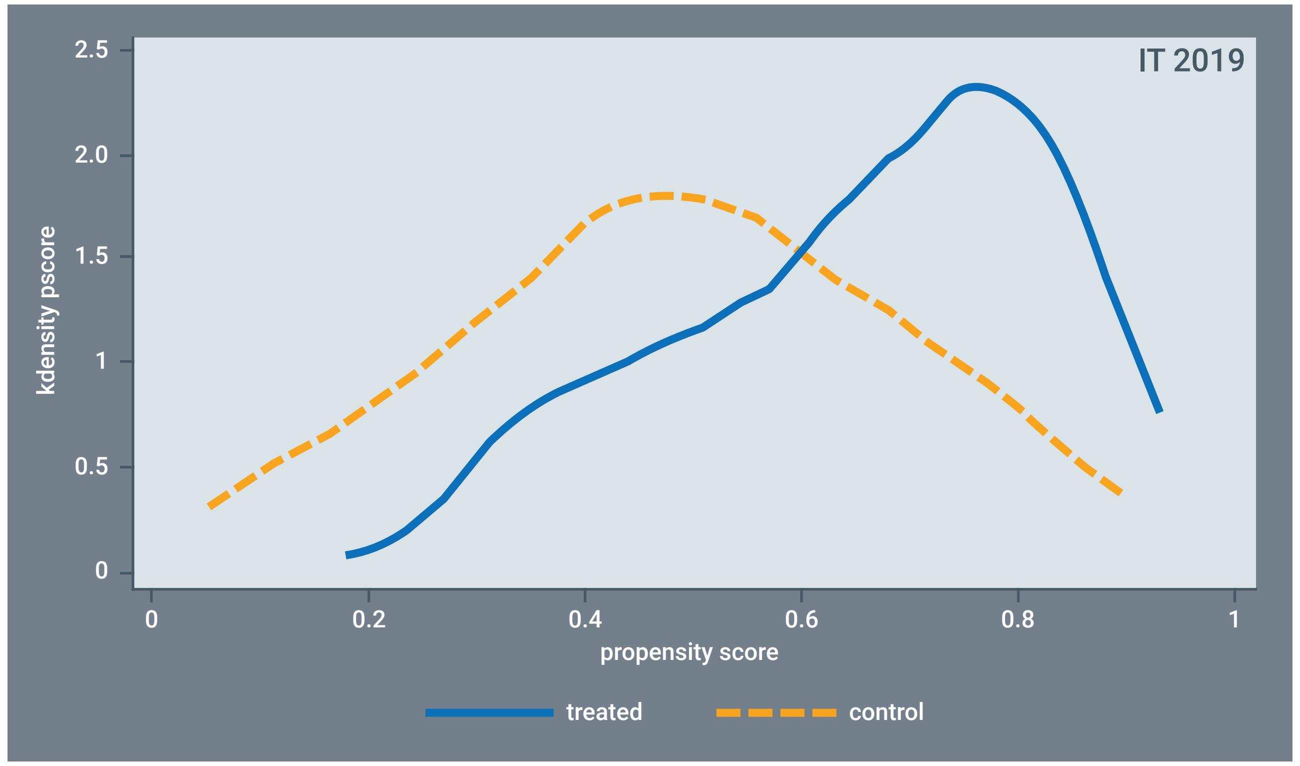
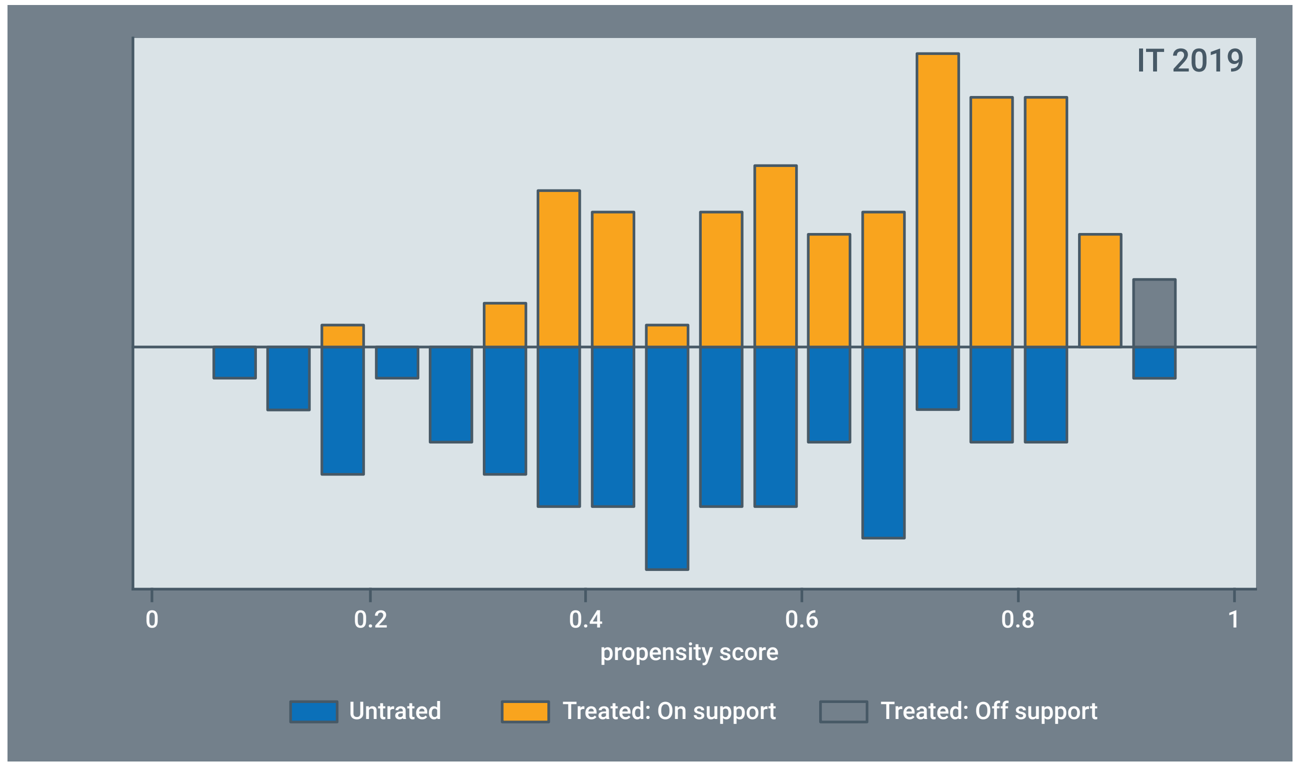


Figure 9.6.2 Training for advanced IT skills (IT) 2019, Matching quality



9.7 Training for in-demand occupation (IN) 2018

Table 9.7.1 Training for in-demand occupations (IN) 2018, mean comparison

Observables		Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	36.1	35.7	0.391	0.776
	Gender (1=male)	0.272	0.253	0.018	0.743
	Rural	0.184	0.180	0.004	0.928
	Married	0.505	0.627	-0.122	0.054**
Household	Household size	3.359	3.267	0.093	0.569
	Number of members under 15	0.466	0.547	-0.081	0.437
	Number of employed members	1.553	1.133	0.420	0.000***
	Number of unemployed members	1.097	1.200	-0.103	0.415
	Number of retired members	0.291	0.393	-0.102	0.205
Human capital	Primary education	0.087	0.120	-0.033	0.411
	Secondary education	0.621	0.567	0.055	0.387
	Higher education	0.243	0.280	-0.037	0.511
	Previous work experience	0.621	0.673	-0.052	0.396
	Short-term unemployed (up to 1 year)	0.699	0.540	0.159	0.011**
Disadvantaged	Very-long-term unemployed (more than 4)	0.117	0.247	-0.130	0.001***
	Youth	0.213	0.160	0.054	0.279
	Older	0.058	0.073	-0.015	0.639
	Disabled	0.009	0.020	-0.010	0.521
	Roma	0.019	0.047	-0.027	0.252
Outcome variables		**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.369	0.333	0.0356	0.561
	Currently unemployed	0.359	0.453	-0.094	0.137
	Currently unknown	0.136	0.140	-0.004	0.927
Survey data	Employed	0.379	0.220	0.159	0.006***
	Unemployed	0.544	0.733	-0.189	0.002***
	Salary	22580	20714	1866	0.015**
	Permanent contract	0.333	0.273	0.061	0.584
	Better financial conditions	0.184	0.013	0.171	0.000***
	Better employment prospects	0.175	0.013	0.161	0.000***
	Search for job	0.456	0.700	-0.244	0.000***
	Intend to emigrate	0.311	0.433	-0.123	0.049**

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.7.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: marital status, the number of employed household members, being short-term unemployed and being very-long-term unemployed.

Table 9.7.2 Training for in-demand occupations (IN) 2018, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	0.0191154	0.0093344	0.041**
	Gender (1=male)	-0.0241643	0.2002749	0.904
	Rural	0.109756	0.229615	0.633
	Married	-0.592555	0.2111202	0.005***
Household	Household size	-0.4301338	0.3529322	0.223
	Number of members under 15	0.5023535	0.361659	0.165
	Number of employed members	0.8054647	0.3736841	0.031**
	Number of unemployed members	0.4801134	0.3649747	0.188
	Number of retired members	0.3731522	0.3656315	0.307
Human capital	Primary education	-0.4181153	0.5195246	0.421
	Secondary education	-0.2210583	0.4430059	0.618
	Higher education	-0.2311485	0.4565281	0.613
	Previous work experience	-0.3371944	0.2038212	0.098*
	Short-term unemployed (up to 1 year)	0.5073236	0.1809044	0.005***

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.7.2, age, marital status, number of employed members in the household, work experience and unemployment history have statistically significant impact on the probability to participate in the training for in-demand occupations. Namely, younger unemployed, those who are not married unemployed, live in households with more employed members, have lower work experience and are short-term unemployed are more likely to be participants in this type of training.

Table 9.7.3 Training for in-demand occupations (IN) 2018, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.158	0.051	0.057	0.062	2.78	0.56
Unemployed	-0.189	-0.112	0.060	0.095	-3.17	-1.18
Salary	1866	1354	746	1051	2.50	1.29
Permanent contract	0.079	0.000	0.112	0.159	0.70	0.00
Better financial conditions	0.171	0.184	0.034	0.046	5.07	3.97**
Better empl. prospects	0.161	0.173	0.033	0.045	4.87	3.81**
Search for job	-0.244	-0.194	0.061	0.095	-3.99	-2.03*
Intend to emigrate	-0.123	-0.163	0.062	0.102	-1.98	-1.61

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.7.3, participation in the training for in-demand occupations has statistically significant positive impact on the perception for better financial conditions and better employment prospects, and negative impact on the probability to search for job.

Table 9.7.4 Training for in-demand occupations (IN) 2018, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Better financial conditions	-0.182	0.197	0.227	-0.071	0.105	0.179	0.051	0.203	0.250	0.154
Better empl. prospects	-0.182	0.185	0.213	-0.071	0.105	0.167	0.026	0.203	0.250	0.143
Search for job	-0.545	-0.309	-0.333	-0.429	-0.053	-0.357	-0.333	-0.406	-0.167	-0.297

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.7.4, we can draw the following conclusions with respect to the impact of training for in-demand occupations on disadvantaged groups:

- Youth perceive lower probability for better financial conditions and better employment prospects than mature participants and they manifest lower probability to search for job;
- Female perceive higher probability for better financial conditions and better employment prospects, and they manifest slightly higher probability to search for job;
- Unemployed from rural areas are worse off than those from urban areas vis-à-vis future financial conditions and employment prospects, and they manifest slightly higher probability to search for job;
- Unemployed without work experience perceive lower probability for better financial conditions and better employment prospects than those with work experience, and they manifest slightly higher probability to search for job;
- The very-long-term unemployed perceive higher probability for better financial conditions and better employment prospects compared to those with shorter spells, and they manifest slightly higher probability to search for job.

The propensity score density functions and the quality of the matching are presented on Figure 9.7.1 and Figure 9.7.2 respectively.

Figure 9.7.1 Training for in-demand occupations (IN) 2018, Propens. score density functions

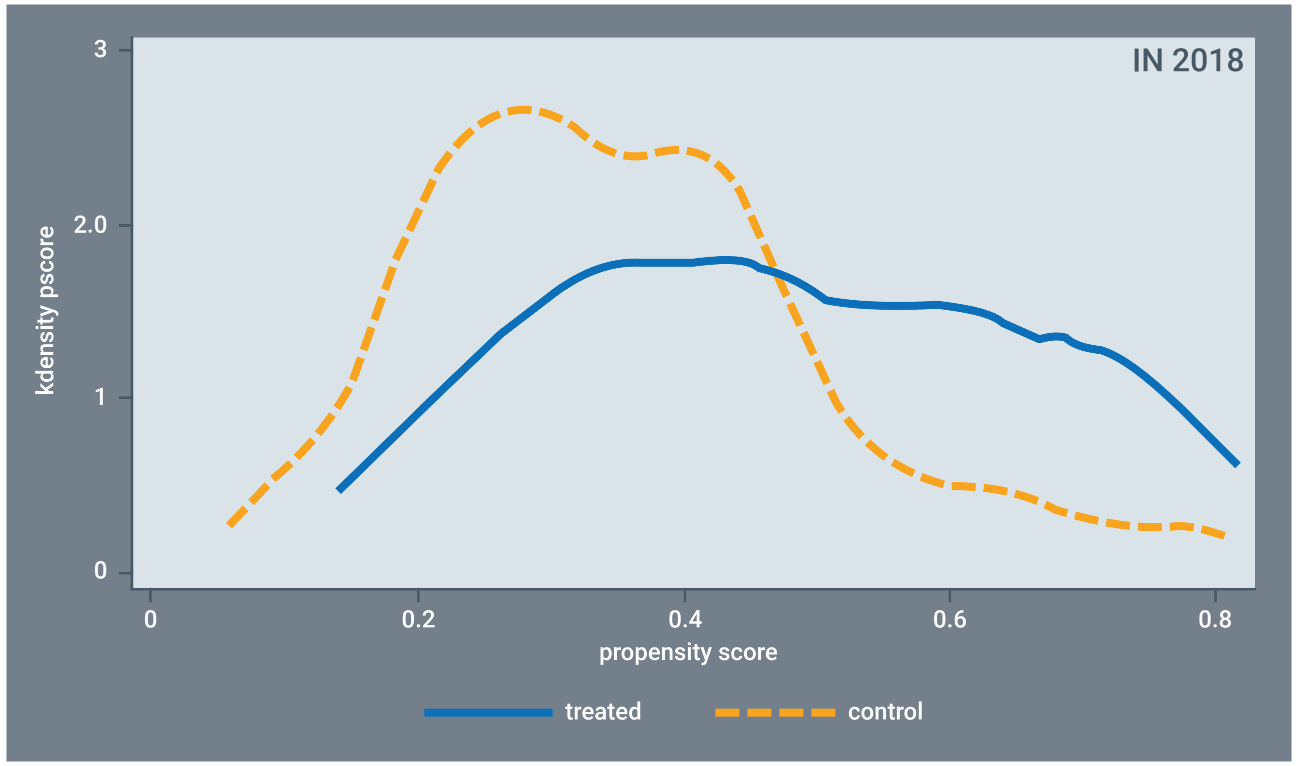
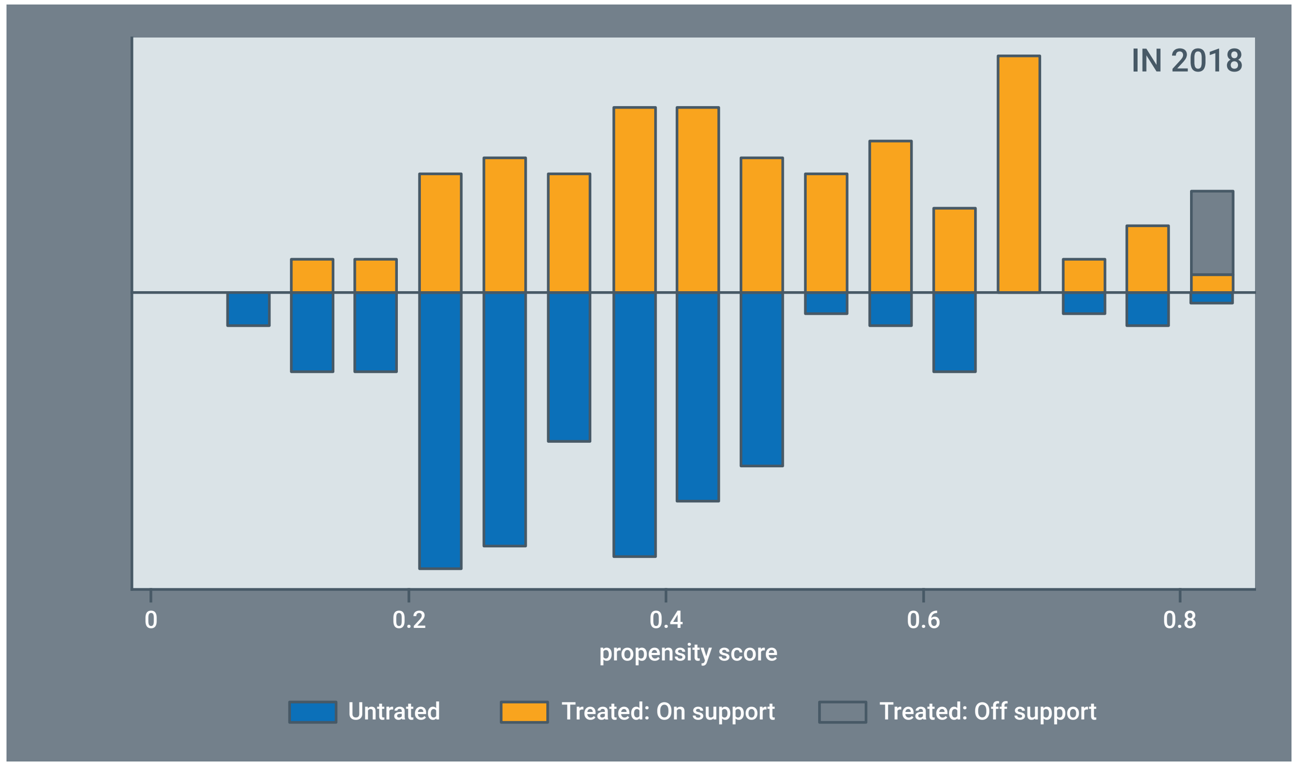


Figure 9.7.2 Training for in-demand occupations (IN) 2018, Matching quality



9.8 Training for in-demand occupation (IN) 2019

Table 9.8.1 Training for in-demand occupations (IN) 2019, mean comparison

Observables		Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	35.7	35.1	0.6	0.553
	Gender (1=male)	0.292	0.250	0.042	0.253
	Rural	0.248	0.196	0.052	0.131
	Married	0.762	0.895	-0.133	0.000***
Household	Household size	3.743	4.003	-0.261	0.015**
	Number of members under 15	0.952	1.141	0.189	0.027**
	Number of employed members	1.669	1.663	0.006	0.920
	Number of unemployed members	0.686	0.797	-0.111	0.091*
	Number of retired members	0.454	0.427	0.026	0.661
Human capital	Primary education	0.168	0.156	0.012	0.683
	Secondary education	0.543	0.511	0.032	0.438
	Higher education	0.232	0.290	-0.058	0.108
	Previous work experience	0.667	0.678	-0.011	0.778
	Short-term unemployed (up to 1 year)	0.698	0.663	0.035	0.358
Disadvantaged	Very-long-term unemployed (more than 4)	0.114	0.163	-0.049	0.086*
	Youth	0.244	0.239	0.005	0.881
	Older	0.073	0.054	0.019	0.357
	Disabled	0.010	0.007	0.003	0.763
	Roma	0.041	0.051	-0.010	0.584
Outcome variables		**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.326	0.366	-0.039	0.321
	Currently unemployed	0.448	0.402	0.045	0.266
	Currently unknown	0.159	0.149	0.010	0.733

Survey data	Employed	0.705	0.601	0.103	0.008***
	Unemployed	0.086	0.373	-0.274	0.000***
	Salary	19522	19558	-35	0.926
	Permanent contract	0.559	0.626	-0.068	0.171
	Better financial conditions	0.368	0.254	0.115	0.003***
	Better employment prospects	0.343	0.236	0.107	0.004***
	Search for job	0.238	0.312	-0.073	0.045**
	Intend to emigrate	0.159	0.047	0.112	0.000***

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.8.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: marital status, household size, the number of household members under 15, the number of unemployed household members and being very-long-term unemployed.

Table 9.8.2 Training for in-demand occupations (IN) 2019, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	0.0094523	0.0043137	0.028**
	Gender (1=male)	0.1369876	0.1192252	0.251
	Rural	0.2546401	0.1307864	0.052*
	Married	-0.4872222	0.1495507	0.001***
Household	Household size	-0.0127266	0.1042348	0.903
	Number of members under 15	-0.0569634	0.1073674	0.596
	Number of employed members	-0.0037004	0.1175777	0.975
	Number of unemployed members	-0.1279951	0.1186959	0.281
	Number of retired members	-0.0096071	0.118405	0.935
Human capital	Primary education	0.1903363	0.2461269	0.439
	Secondary education	0.1862323	0.2008531	0.354
	Higher education	0.0632702	0.2064582	0.759
	Previous work experience	-0.0085059	0.1220964	0.944
	Short-term unemployed (up to 1 year)	0.1820823	0.1156274	0.115

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.8.2, age, place of living and marital status have statistically significant impact on the probability to participate in the training for in-demand occupations. Namely, younger unemployed, those who live in rural areas and not married unemployment are more likely to be participants in this type of raining.

Table 9.8.3 Training for in-demand occupations (IN) 2019, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	0.103	0.020	0.039	0.053	2.65	0.37
Unemployed	-0.287	-0.212	0.032	0.049	-8.96	-4.35***
Salary	-35.569	-177.824	381.7	421.3	-0.09	-0.35
Permanent contract	-0.068	-0.004	0.049	0.057	-1.37	-0.06
Better financial conditions	0.115	0.127	0.038	0.049	3.01	2.57**
Better empl. prospects	0.107	0.134	0.037	0.048	2.88	2.78**
Search for job	-0.073	-0.036	0.037	0.051	-2.01	-0.70
Intend to emigrate	0.112	0.108	0.025	0.027	4.47	3.76***

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.8.3, participation in the training for in-demand occupations has statistically significant negative impact on unemployment, positive impact on the perception for better financial conditions and better employment prospects, as well as positive impact on intention to emigrate.

Table 9.8.4 Training for in-demand occupations (IN) 2019, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Unemployed	-0.204	-0.344	-0.309	-0.359	-0.320	-0.304	-0.295	-0.310	-0.194	-0.326
Better financial conditions	0.013	0.106	0.081	0.217	0.064	0.148	0.076	0.090	0.194	0.093
Better empl. prospects	-0.039	0.113	0.067	0.196	0.077	0.122	0.067	0.071	0.167	0.097
Intend to emigrate	0.195	0.089	0.126	0.098	0.128	0.102	0.162	0.105	0.139	0.122

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.8.4, we can draw the following conclusions with respect to the impact of training for in-demand occupations on disadvantaged groups:

- Youth are worse off than mature unemployed vis-à-vis probability of being unemployed, they express lower probability for better financial conditions and are worse off regarding the employment prospects; in addition they manifest higher probability to emigrate;
- Female are worse off than male unemployed vis-à-vis probability of being unemployed, they express lower probability for better financial conditions and are worse off regarding the employment prospects; in addition they manifest higher probability to emigrate;
- Unemployed from rural areas are slightly better off than those from urban areas vis-à-vis probability of being unemployed, they express higher probability for better financial conditions and are better off regarding the employment prospects; in addition they manifest higher probability to emigrate;
- Unemployed without work experience are slightly worse off than those with work experience vis-à-vis probability of being unemployed, they express lower probability for better financial conditions and are worse off regarding the employment prospects; in addition they manifest higher probability to emigrate;
- The very-long-term unemployed are worse off compared to those with shorter spells of unemployment , they express higher probability for better financial conditions and are better off regarding the employment prospects; in addition they manifest higher probability to emigrate;

The propensity score density functions and the quality of the matching are presented on Figure 9.8.1 and Figure 9.8.2 respectively.

Figure 9.8.1 Training for in-demand occupations (IN) 2019, Propens. score density functions

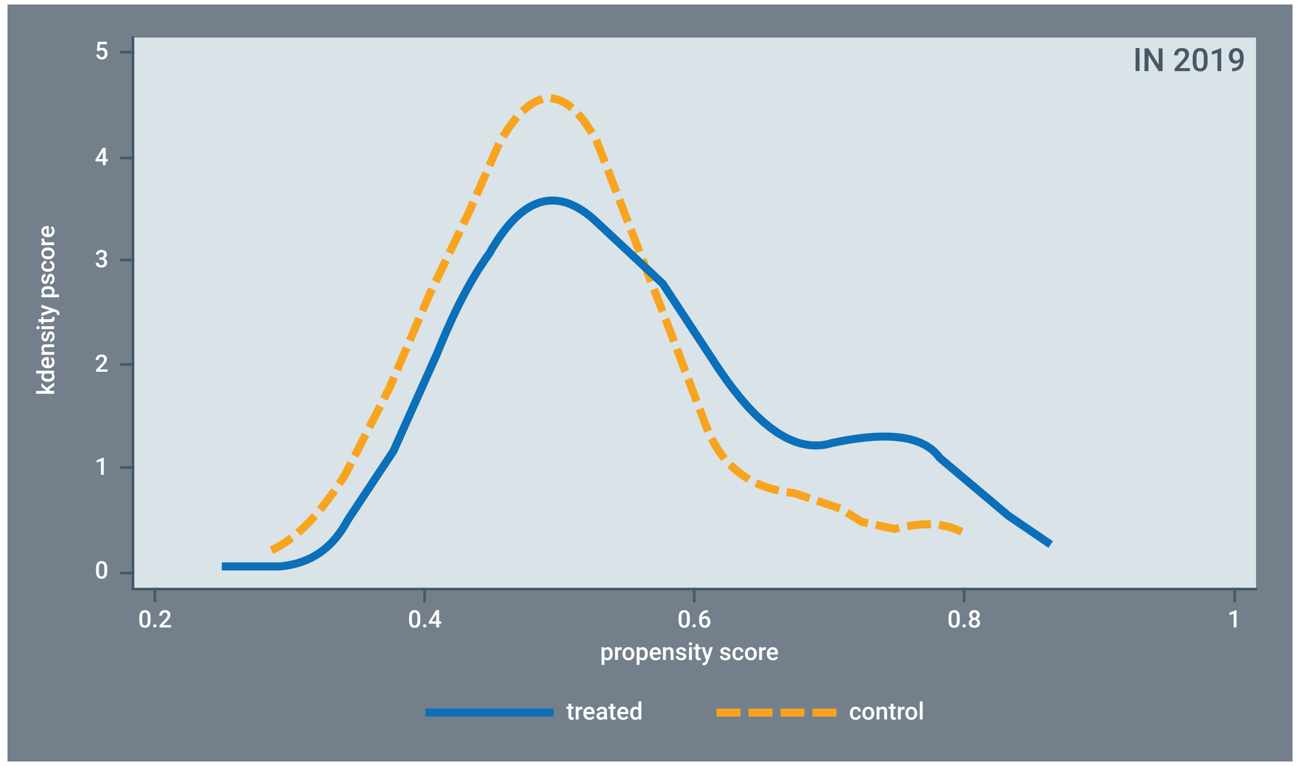
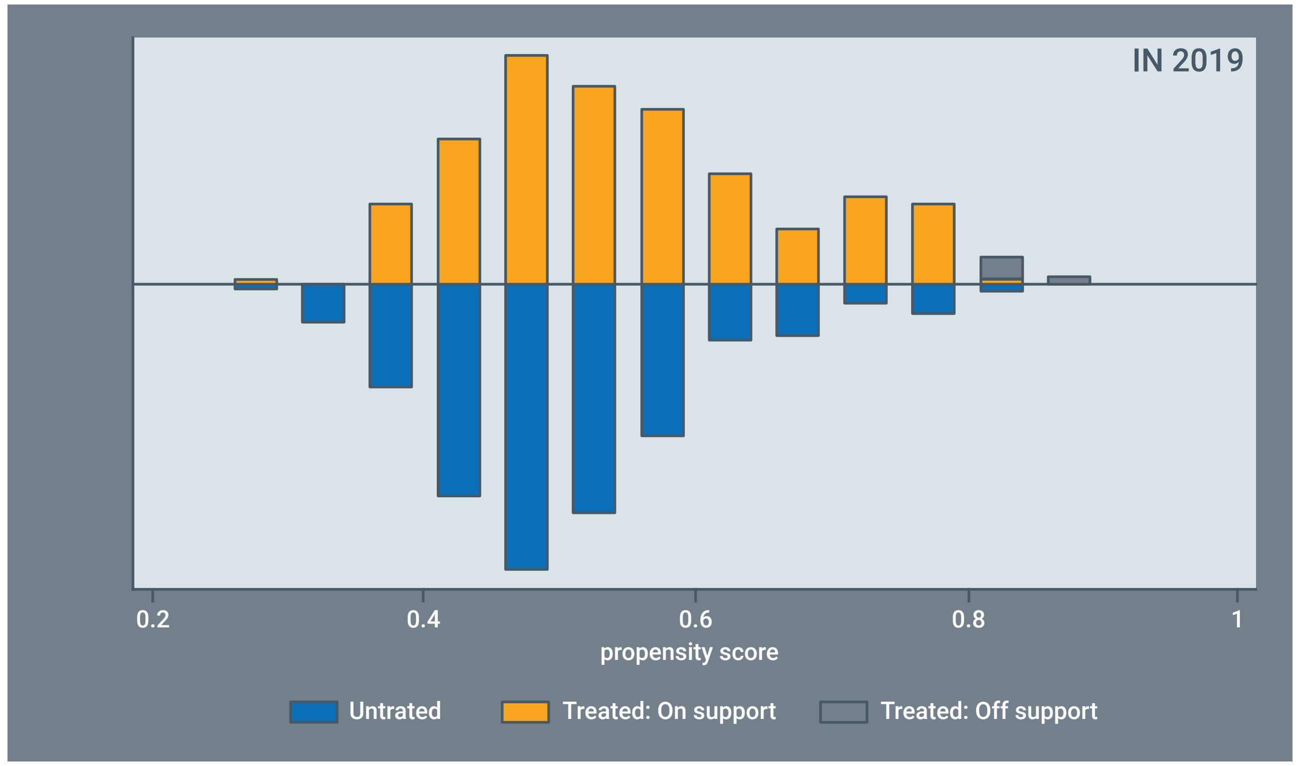


Figure 9.8.2 Training for in-demand occupations (IN) 2019, Matching quality



9.9 Wage subsidy program (WS) 2018

Table 9.9.1 Training for wage subsidies (WS) 2018, mean comparison

	Observables	Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	31.4	33.8	-2.4	0.089*
	Gender (1=male)	0.529	0.537	-0.008	0.878
	Rural	0.257	0.256	0.001	0.992
	Married	0.831	0.909	-0.078	0.043**
Household	Household size	3.70	3.91	-0.12	0.123
	Number of members under 15	0.80	1.17	-0.37	0.000***
	Number of employed members	1.83	2.03	-0.20	0.046**
	Number of unemployed members	0.742	0.488	0.254	0.010**
	Number of retired members	0.350	0.223	0.127	0.061*
Human capital	Primary education	0.337	0.215	0.122	0.015**
	Secondary education	0.486	0.488	-0.001	0.985
	Higher education	0.153	0.198	-0.045	0.273
	Previous work experience	0.602	0.645	-0.043	0.422
	Short-term unemployed (up to 1 year)	0.851	0.727	0.123	0.004***
Disadvantaged	Very-long-term unemployed (more than 4)	0.019	0.083	-0.063	0.003***
	Youth	0.483	0.322	0.160	0.003***
	Older	0.084	0.099	-0.015	0.636
	Disabled	0.011	0.016	-0.005	0.688
	Roma	0.038	0.058	0.020	0.390
	Outcome variables	**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.670	0.603	0.067	0.202
	Currently unemployed	0.115	0.157	-0.042	0.254
	Currently unknown	0.188	0.198	-0.011	0.807
Survey data	Employed	0.690	0.851	-0.162	0.001***
	Unemployed	0.091	0.000	0.091	0.001***
	Salary	19528	19556	-28	0.926
	Permanent contract	0.383	0.710	-0.327	0.000***
	Better financial conditions	0.150	0.140	0.100	0.808
	Better employment prospects	0.142	0.091	0.051	0.160
	Search for job	0.195	0.174	0.022	0.613
	Intend to emigrate	0.027	0.000	0.027	0.069*

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.9.1, statistically significant positive difference is observed with respect to the number of the unemployed household members, primary education and short-term unemployment, while negative difference is observed with respect to age, marital status, number of persons under 15 and number of employed in household.

Table 9.9.2 Training for wage subsidies (WS) 2018, propensity score coefficients (Probit model)

	Observables	Coefficient	Std. error	p-value
Socio-dem.	Age	-0.0133226	0.0066667	0.046**
	Gender (1=male)	-0.0364803	0.1462993	0.803
	Rural	-0.0730476	0.1650318	0.658
	Married	-0.2010786	0.2289442	0.380
Household	Household size	-0.2391221	0.7231031	0.741
	Number of members under 15	0.0007312	0.717749	0.999
	Number of employed members	0.0618584	0.7214297	0.932
	Number of unemployed members	0.334072	0.7218742	0.644
	Number of retired members	0.3714028	0.6981682	0.595

Human capital	Primary education	1.144861	0.3562483	0.001***
	Secondary education	0.7831719	0.3392132	0.021**
	Higher education	0.7213618	0.3631489	0.047**
	Previous work experience	-0.0748539	0.1603538	0.641
	Short-term unemployed (up to 1 year)	0.3157968	0.1857825	0.089*

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.9.2, age, education level and previous unemployment history have statistically significant impact on the probability to enjoy benefit from wage subsidies. Namely, younger unemployed, those with primary education and short-term unemployment are more likely to be wage subsidies beneficiary.

Table 9.9.3 Training for wage subsidies (WS) 2018, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	-0.163	-0.085	0.048	0.064	-3.42	-1.34
Unemployed	0.092	0.093	0.026	0.018	3.50	5.14**
Salary	-19.038	211.267	306.046	431.011	-0.06	0.49
Permanent contract	-0.325	-0.298	0.056	0.080	-5.77	-3.72**
Better financial conditions	0.009	0.016	0.039	0.058	0.24	0.27
Better empl. Prospects	0.051	0.039	0.037	0.049	1.41	0.80
Search for job	0.023	-0.008	0.043	0.067	0.52	-0.12
Intend to emigrate	0.027	0.020	0.015	0.008	1.82	2.25**

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.9.3, wage subsidies have statistically significant positive impact on unemployment and on intention to emigrate, while they have negative impact on the probability of having permanent contract.

Table 9.9.4 Training for wage subsidies (WS) 2018, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Unemployed	0.071	0.112	0.082	0.101	0.104	0.088	0.086	0.096	-	0.094
Permanent contract	-0.346	-0.337	-0.338	-0.239	-0.439	-0.233	-0.271	-0.348	-0.400	-0.308
Intend to emigrate	0.031	0.022	0.008	0.043	0.030	0.026	0.019	0.032	-	0.027

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.9.4, we can draw the following conclusions with respect to the impact of wage subsidies on disadvantaged groups:

- Youth are better off than mature unemployed vis-à-vis probability of being unemployed and having permanent employment contract, but express higher intention to emigrate;
- Female are better off than male unemployed vis-à-vis probability of being unemployed, worse off with respect of probability of having permanent employment contract, and express lower intention to emigrate;
- Unemployed from rural areas are worse off than those from urban areas vis-à-vis probability of being unemployed and having permanent employment and express slightly higher intention to emigrate;
- Unemployed without work experience are better off than those with work experience vis-à-vis probability of being unemployed and having permanent employment contract, and express lower intention to emigrate;
- The very-long-term unemployed are worse off compared to those with shorter spells of unemployment regarding the probability of having permanent contract.

The propensity score density functions and the quality of the matching are presented on Figure 9.9.1 and Figure 9.9.2 respectively.

Figure 9.9.1 Training for wage subsidies (WS) 2018, Propensity score density functions

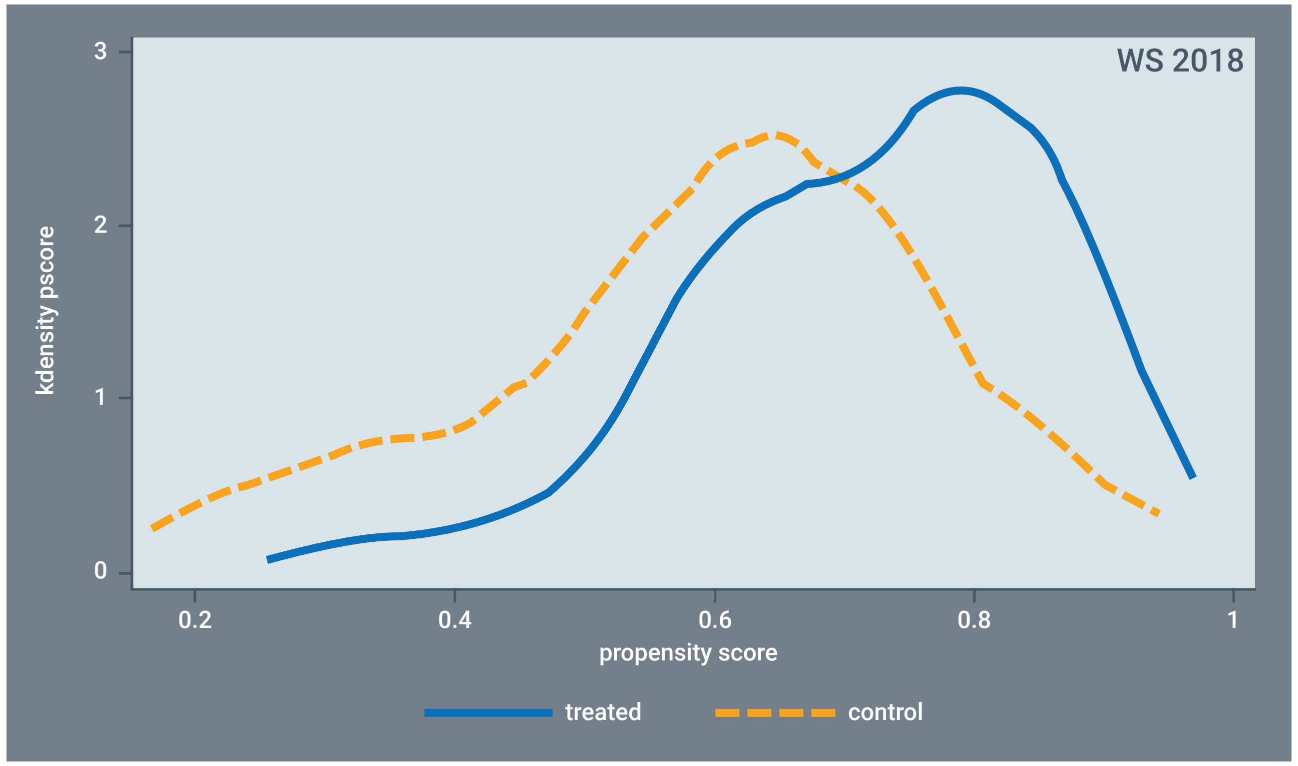
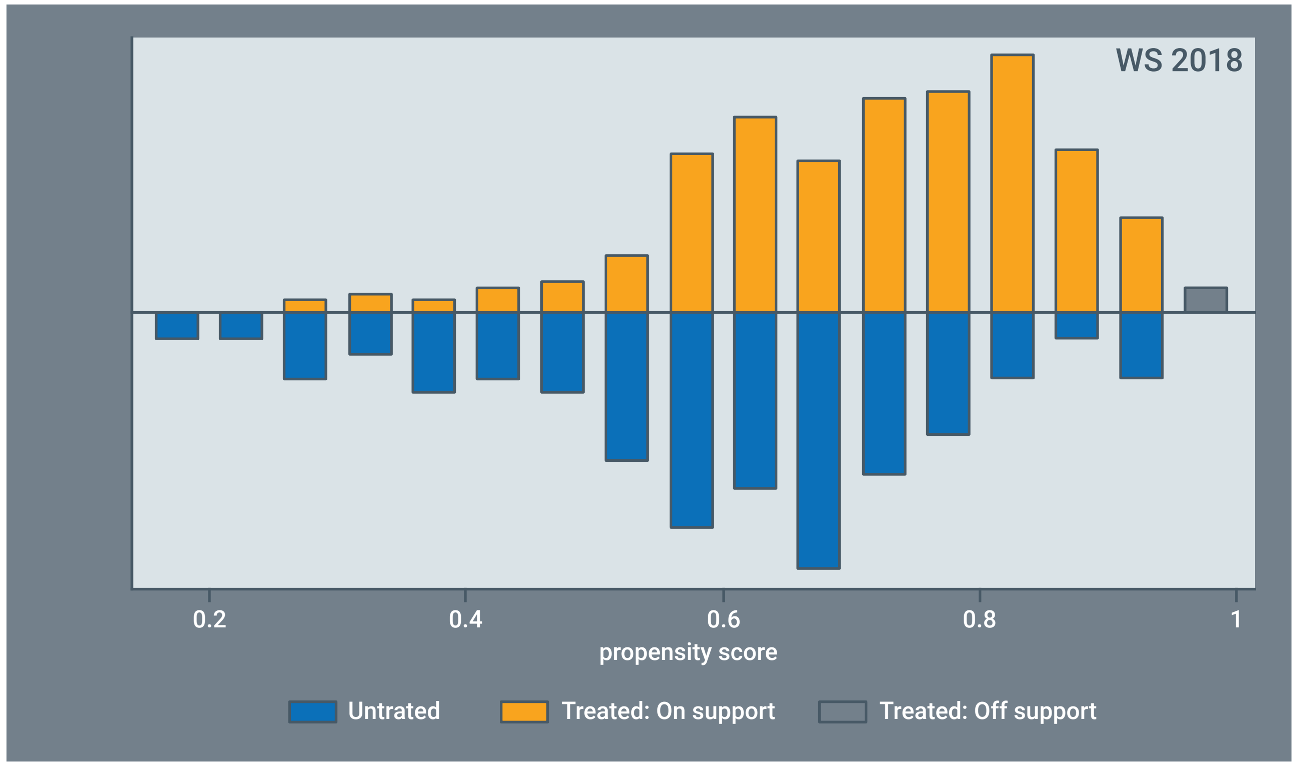


Figure 9.9.2 Training for wage subsidies (WS) 2018, Matching quality



9.10 Wage subsidy program (WS) 2019

Table 9.10.1 Training for wage subsidies (WS) 2019, mean comparison

	Observables	Mean treated	Mean control	Difference	p-value
Socio-dem.	Age	32.2	27.0	5.233	0.000***
	Gender (1=male)	0.423	0.549	-0.126	0.049**
	Rural	0.308	0.354	-0.046	0.444
	Married	0.820	0.793	0.027	0.590
Household	Household size	3.512	3.720	-0.207	0.133
	Number of members under 15	0.940	1.110	-0.170	0.128
	Number of employed members	1.885	1.866	0.019	0.870
	Number of unemployed members	0.607	0.598	0.009	0.928
	Number of retired members	0.171	0.146	0.025	0.675
Human capital	Primary education	0.295	0.268	0.027	0.649
	Secondary education	0.521	0.524	-0.003	0.963
	Higher education	0.141	0.195	-0.054	0.246
	Previous work experience	0.615	0.451	0.164	0.009***
	Short-term unemployed (up to 1 year)	0.829	0.805	0.024	0.623
Disadvantaged	Very-long-term unemployed (more than 4)	0.038	0.024	0.014	0.551
	Youth	0.393	0.500	-0.107	0.092*
	Older	0.094	0.000	0.094	0.004***
	Disabled	0.021	0.024	0.003	0.873
	Roma	0.026	0.049	-0.023	0.305
	Outcome variables	**Mean treated**	**Mean control**	**Difference**	**p-value**
Registry	Currently employed	0.756	0.561	0.195	0.001***
	Currently unemployed	0.094	0.213	-0.125	0.003
	Currently unknown	0.124	0.195	-0.071	0.113

Survey data	Employed	0.897	0.902	-0.005	0.889
	Unemployed	0.009	0.097	-0.089	0.000***
	Salary	21050	19792	1258	0.015**
	Permanent contract	0.258	0.324	-0.066	0.277
	Better financial conditions	0.090	0.012	0.077	0.018**
	Better employment prospects	0.094	0.037	0.057	0.098*
	Search for job	0.252	0.305	-0.053	0.354
	Intend to emigrate	0.278	0.561	-0.283	0.000***

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

From Table 9.10.1 we can observe that statistically significant difference between the treatment and control group is found for the following observables: age, gender and previous work experience.

Table 9.10.2 Training for wage subsidies (WS) 2019, propensity score coefficients (Probit model)

Observables		Coefficient	Std. error	p-value
Socio-dem.	Age	0.0269899	0.0100349	0.007***
	Gender (1=male)	-0.1998777	0.1659805	0.229
	Rural	0.0201982	0.1764942	0.909
	Married	0.2412135	0.256391	0.347
Household	Household size	-0.7162501	0.5964381	0.230
	Number of members under 15	0.5663615	0.6061233	0.350
	Number of employed members	0.796475	0.6167568	0.197
	Number of unemployed members	0.7551278	0.6161485	0.220
	Number of retired members	0.731589	0.6225828	0.240
Human capital	Primary education	-0.5897944	0.5882469	0.316
	Secondary education	-0.4735914	0.5795643	0.414
	Higher education	-0.6628186	0.5957272	0.266
	Previous work experience	0.2348546	0.173214	0.175
	Short-term unemployed (up to 1 year)	0.2097703	0.219059	0.338

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.10.2 only age appears to have statistically significant impact on the probability to enjoy benefit from wage subsidies. Namely, an additional year increases the probability to be wage subsidies beneficiary.

Table 9.10.3 Training for wage subsidies (WS) 2019, treatment effects on outcome variables

Outcome variables	Difference		Standard error		t-statistics	
	Unmatch.	ATT	Unmatch.	ATT	Unmatch.	ATT
Employed	-0.006	0.029	0.039	0.056	-0.15	0.52
Unemployed	-0.089	-0.121	0.022	0.051	-4.03	-2.37**
Salary	1314	1382	505.113	648.636	2.60	2.13**
Permanent contract	-0.065	-0.094	0.061	0.085	-1.07	-1.11
Better financial conditions	0.078	0.064	0.032	0.029	2.40	2.19**
Better empl. Prospects	0.058	0.040	0.035	0.040	1.67	1.00
Search for job	-0.052	-0.052	0.057	0.082	-0.91	-0.64
Intend to emigrate	-0.282	-0.260	0.059	0.086	-4.74	-3.03**

*Note: */**/*** indicate significance at 10/5/1 percent level respectively.*

According to Table 9.10.3, wage subsidies have statistically significant positive impact on salary and perception for better financial conditions, while negative impact on the probability of being unemployed and the intention to emigrate.

Table 9.10.4 Training for wage subsidies (WS) 2019, disaggregated ATT for disadvantaged categories

Outcome variables	Age		Gender		Place of living		Work experience		Unemployment	
	Youth	Mature	Female	Male	Rural	Urban	Without	With	Very-long	Short
Unemployed	-0.055	-0.206	-0.104	-0.010	-	-0.093	-0.045	-0.083	-	-0.072
Salary	886	1715	803	1989	885	1412	219	1534	-	1130
Better financial conditions	0.109	0.071	0.076	0.082	0.127	0.060	0.101	0.076	-	0.085
Intend to emigrate	-0.413	-0.339	-0.400	-0.495	-0.352	-0.430	-0.309	-0.514	-	-0.400

Note: Estimation based on nearest-neighbour matching only for statistically significant outcome variables.

According to Table 9.10.4, we can draw the following conclusions with respect to the impact of wage subsidies on disadvantaged groups:

- Youth are better off than mature unemployed vis-à-vis probability of being unemployed and expecting better financial condition but they have lower monthly salary and lower intention to emigrate;
- Female are better off than male unemployed vis-à-vis probability of being unemployed, they have similar expectations for the financial conditions and intention to emigrate, but they are worse of regarding the level of monthly salary;
- Unemployed from rural areas are worse off than those from urban areas vis-à-vis, they manifest lower intention to emigrate and they have lower level of monthly salary;
- Unemployed without work experience are worse off than those with work experience vis-à-vis probability of being unemployed, they have lower level of monthly salary and intention to emigrate, but they expect better financial conditions;
- The relative position of the very-long-term unemployed is not possible to be assessed because of their low representation among participants in the wage subsidy program.

The propensity score density functions and the quality of the matching are presented on Figure 9.10.1 and Figure 9.10.2 respectively.

Figure 9.10.1 Training for wage subsidies (WS) 2019, Propensity score density functions

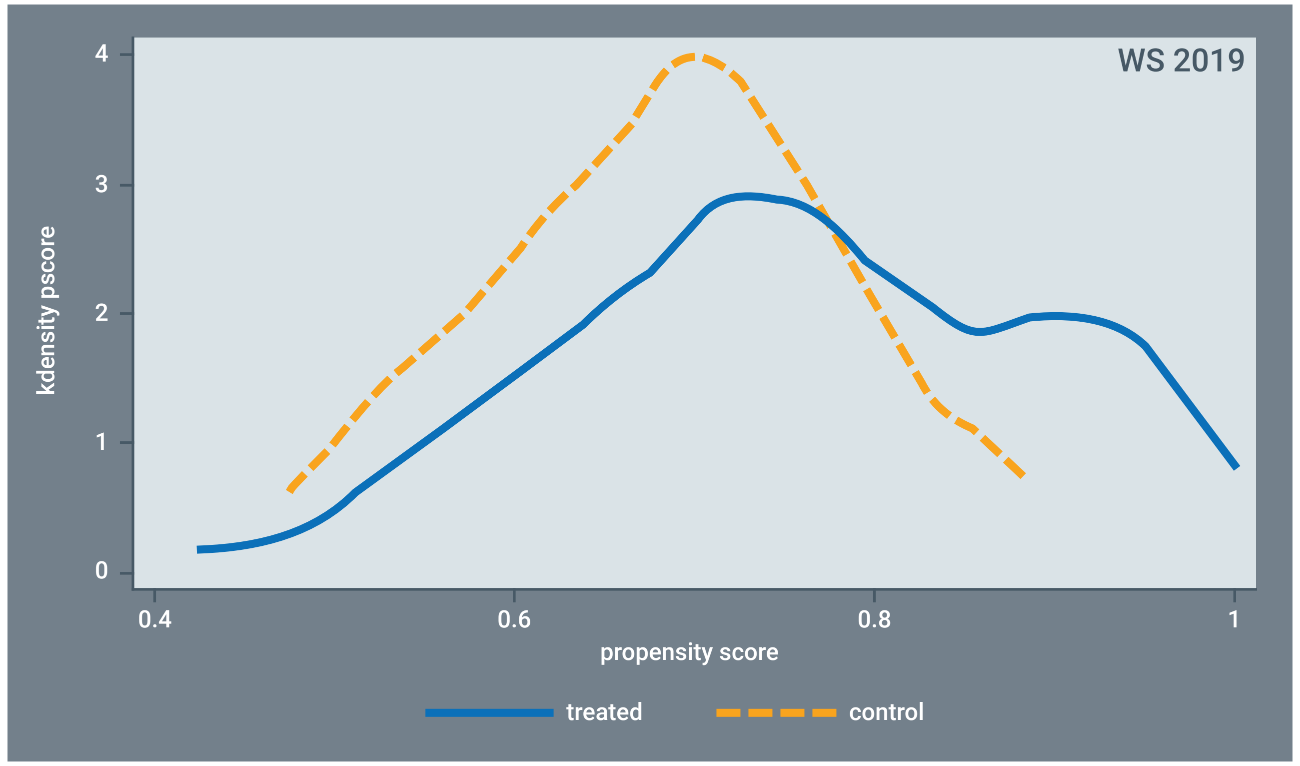


Figure 9.10.2 Training for wage subsidies (WS) 2019, Matching quality

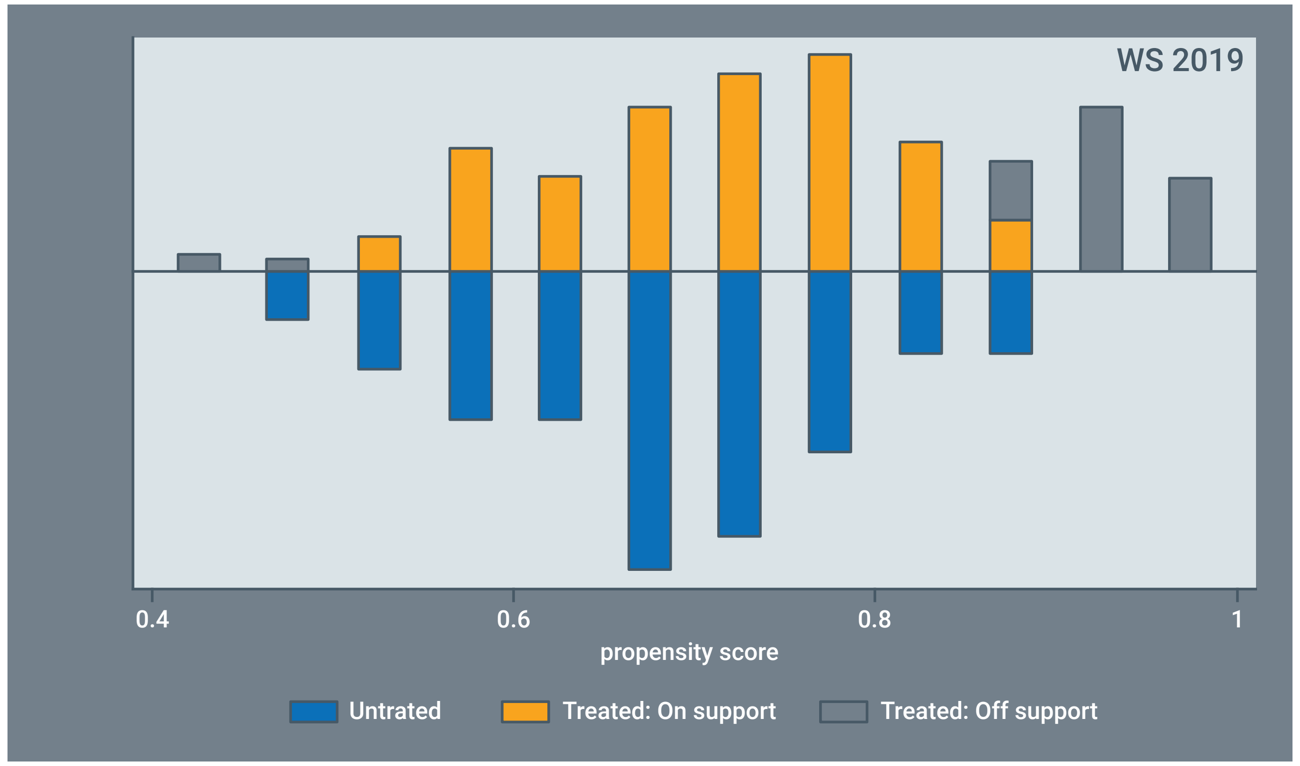


Table 9.11 Measures of matching quality

ALMM	Mean bias		% of reduct.	Pseudo R^2		Off common support	
	Un-match.	Matched		Un-match.	Matched	Number	% of total
DR 2016	34.8	18.0	48.3	0.195	0.184	10	9.5
DR 2020	30.3	9.9	67.3	0.235	0.061	3	2.5
TKE 2018	35.5	23.6	33.5	0.323	0.356	45	61.6
TKE 2019	31.2	23.8	23.7	0.626	0.313	55	70.5
IT 2017/18	21.9	9.2	58.0	0.111	0.028	3	1.8
IT 2019	19.0	13.4	29.5	0.131	0.072	3	2.1
IN 2018	14.2	7.3	48.6	0.099	0.036	5	2.0
IN 2019	10.9	5.2	52.3	0.039	0.009	9	1.5
WS 2018	18.0	10.3	42.8	0.099	0.038	4	1.0
WS 2019	14.5	6.3	56.6	0.078	0.017	59	18.7

Source: Author's calculations

From Table 9.11 it is obvious that for majority of the evaluated ALMMs there is a considerable reduction in the mean bias. The highest reduction is observed for the training for drivers, followed by the training for in-demand occupations and training for advanced IT skills. The lowest reduction is observed for the training for known employer which can be attributed to the small size of the control groups. As a consequence, the number of observations off common support for this program in 2018 and 2019 is considerably high amounting 61.6 and 70.5 percent of the total number of observations. On the other hand, the number of observations off common support for the remaining ALMMs is quite low and acceptable.

10. Self-assessed satisfaction

Besides the outcome variables, the success of a given ALMM depends on the satisfaction of the participants. In this context, the participants were asked about the gained knowledge and skills, the appropriateness of the applied training methods, the usefulness of the training materials and the appropriateness of the training environment. The results from the survey regarding the self-assessment of these issues are presented in Table 10.1, Table 10.2, Table 10.3 and Table 10.4 respectively.

Table 10.1 Satisfaction from the gained knowledge and skills (percent)

Active labour market measure	Not satisfied at all	Not satisfied	Do not have opinion	Satisfied to less extent	Satisfied to great extent
Training for drivers (DR) 2016	-	3.2	6.5	12.9	77.4
Training for drivers (DR) 2020	-	12.5	3.1	6.3	78.1
Training for known employer (TKE) 2018	-	11.5	1.6	4.9	82.0
Training for known employer (TKE) 2019	-	-	4.7	6.3	89.0
Training for advanced IT skills (IT) 2017/18	2.7	-	6.9	19.2	71.2
Training for advanced IT skills (IT) 2019	-	1.2	1.2	11.6	86.1
Training for in-demand occupations (IN) 2018	-	-	-	2.9	97.1
Training for in-demand occupations (IN) 2019	-	2.5	4.8	4.8	87.9

Source: Author's calculations

Table 10.2 Appropriateness of the applied training methods (percent)

Active labour market measure	Not appropriate at all	Not appropriate	Do not have opinion	Appropriate to less extent	Appropriate to great extent
Training for drivers (DR) 2016	-	6.5	6.5	12.9	74.2
Training for drivers (DR) 2020	-	6.3	6.3	12.5	75.0
Training for known employer (TKE) 2018	-	3.3	6.6	8.2	82.0
Training for known employer (TKE) 2019	-	-	4.7	6.3	89.0
Training for advanced IT skills (IT) 2017/18	2.7	2.7	5.5	8.2	80.8
Training for advanced IT skills (IT) 2019	-	-	5.8	9.3	84.9
Training for in-demand occupations (IN) 2018	-	-	1.9	1.9	96.2
Training for in-demand occupations (IN) 2019	-	3.2	3.5	5.7	87.6

Source: Author's calculations

Table 10.3 Usefulness of the training materials (percent)

Active labour market measure	Not useful at all	Not useful	Do not have opinion	Useful to less extent	Useful to great extent
Training for drivers (DR) 2016	-	12.9	-	9.7	77.4
Training for drivers (DR) 2020	-	3.1	15.6	-	81.3
Training for known employer (TKE) 2018	-	4.9	6.6	13.1	75.4
Training for known employer (TKE) 2019	-	-	3.1	4.7	92.2
Training for advanced IT skills (IT) 2017/18	2.7	2.7	4.1	11.0	79.5
Training for advanced IT skills (IT) 2019	-	-	2.3	9.3	88.4
Training for in-demand occupations (IN) 2018	-	-	1.0	3.0	96.0
Training for in-demand occupations (IN) 2019	-	1.9	4.2	4.4	89.5

Source: Author's calculations

Table 10.4 Appropriateness of the training environment (percent)

Active labour market measure	Not appropriate at all	Not appropriate	Do not have opinion	Appropriate to less extent	Appropriate to great extent
Training for drivers (DR) 2016	-	6.5	9.7	9.7	74.2
Training for drivers (DR) 2020	-	9.4	6.3	6.3	78.1
Training for known employer (TKE) 2018	1.6	-	8.2	6.6	83.6
Training for known employer (TKE) 2019	-	-	6.3	1.6	92.2
Training for advanced IT skills (IT) 2017/18	4.1	-	2.7	11.0	82.2
Training for advanced IT skills (IT) 2019	-	-	3.5	9.3	87.2
Training for in-demand occupations (IN) 2018	-	-	1.0	1.9	97.1
Training for in-demand occupations (IN) 2019	-	0.9	3.5	2.9	92.7

Source: Author's calculations

From Table 10.1 to Table 10.4 we can conclude that majority of the participants where generally satisfied with the provided trainings. Although the differences among training programmes are small, the most satisfied are participants in the training for in-demand occupations in 2018 and participants in the training for known employer in 2019. On the other hand, the least satisfied are participants in the training for drivers in 2016 and 2020.

In the case of wage subsidies, the satisfaction is assessed with respect to the job, salary, on-the-job training and superiors.

Table 10.5 Satisfaction from the job (percent)

Active labour market measure	Not satisfied at all	Not satisfied	Do not have opinion	Satisfied to less extent	Satisfied to great extent
Wage subsidy program (WS) 2018	-	0.5	1.4	32.7	65.5
Wage subsidy program (WS) 2019	5.3	1.0	0.5	2.4	90.8

Source: Author's calculations

Table 10.6 Satisfaction from the salary (percent)

Active labour market measure	Not satisfied at all	Not satisfied	Do not have opinion	Satisfied to less extent	Satisfied to great extent
Wage subsidy program (WS) 2018	5.4	19.9	3.2	40.7	30.8
Wage subsidy program (WS) 2019	19.8	11.1	4.4	9.7	55.1

Source: Author's calculations

Table 10.7 Satisfaction from the on-the-job training (percent)

Active labour market measure	Not satisfied at all	Not satisfied	Do not have opinion	Satisfied to less extent	Satisfied to great extent
Wage subsidy program (WS) 2018	-	0.5	1.8	16.8	80.9
Wage subsidy program (WS) 2019	15.5	3.9	3.9	8.7	68.1

Source: Author's calculations

Table 10.8 Satisfaction from the superiors (percent)

Active labour market measure	Not satisfied at all	Not satisfied	Do not have opinion	Satisfied to less extent	Satisfied to great extent
Wage subsidy program (WS) 2018	-	1.4	1.4	21.4	75.9
Wage subsidy program (WS) 2019	3.4	2.9	2.9	5.3	85.5

Source: Author's calculations

From Table 10.5 to Table 10.8 we can conclude that majority of the wage subsidy beneficiaries where generally satisfied from the job, the on-the-job training and the superiors. However, lower satisfaction can be observed regarding the level of monthly salary.

Table 10.9 Willingness to apply for another ALMM (percent)

ALMM	No		Yes		Do not have opinion	
	Treatment	Control	Treatment	Control	Treatment	Control
DR 2016	22.6	24.3	61.3	66.2	16.1	9.5
DR 2020	21.9	20.7	65.6	51.7	12.5	27.6
TKE 2018	37.7	25.0	42.6	58.3	19.7	16.7
TKE 2019	25.0	7.1	50.0	85.7	25.0	7.1
IT 2017/18	13.7	25.8	76.7	68.8	9.6	5.4
IT 2019	11.6	55.0	69.8	33.3	18.6	11.7
IN 2018	17.5	34.0	68.9	38.7	13.6	27.3
IN 2019	26.0	43.8	60.3	54.7	13.7	1.5
WS 2018	37.9	45.5	45.6	46.3	16.5	8.3
WS 2019	46.6	37.8	33.8	29.3	19.7	32.9

Source: Author's calculations

From Table 10.9 we can conclude that the participants, the training for advanced IT skills in 2019 and in the training for in-demand occupations in 2018 express the highest willingness to apply for another ALMM. In contrast, among the control group applicants, those applying for the training for known employer in 2019 manifest the highest willingness to apply for another ALMM.

11. The impact of Covid-19

The last Covid-19 crisis exerted devastating effects on the world economy as well as the functioning of the labour markets. When the pandemic spread out around the world, the governments reacted swiftly with wide-ranging containment measures. The negative impact of this crisis is manifested as structural distortions among a number of industries and professions that will have long lasting economic consequences.

The Covid-19 crisis has stimulated many activities in the digital gig economy[4]. The demand for gigs in many sectors and the expected ascension of several new forms of job calls for the employment of a comprehensive gig economy framework. Following the Covid-19 outbreak, many sectors in the economy are under pressure including home rental, design and crafting, simple tasks and renting. Others, such as software-based services, banking and investment services are expected to remain at the same level or even increase, while vital sectors such as service delivery are expected to rise considerably (Dhaini et al., 2020).

Notwithstanding, it is expected that the recovery from the Covid-19 will last longer and will need more substantial restructuring of the economy. In this context, the most affected are the vulnerable population segments such as: women, older people, immigrants and the workers with lower levels of education and they are less likely to be reached by the mitigation and job retention measures that have been adopted in response to the Covid-19 pandemic. According to the World Bank estimates, recent poverty reduction gains in a number of economies will likely be lost because of the pandemics as firms resort to labour shedding in the most affected sectors. In addition, the mobility limitations engendered from the pandemics has considerably restricted the possibilities for circular migration and had significant adverse effects on the emigrants welfare.

Digital technologies nowadays represent a significant generator of changes in the domain of employment. In this context, the internet has opened up a wide range of opportunities for employment through providing easier access to the global labour market and developing new forms of employment. The recent studies in this domain indicate that online platforms provide job opportunities for those otherwise excluded through geographic borders, gender, or ability. Although ICTs have implied many positive effects on employment, certain studies indicate negative impacts that mainly arise from process optimization and capital-labour substitution in traditional industries. According to these insights the internet induces specific changes on the job market, such as: the end of job stability, and the rise of freelancing, self-employment and odd-jobs. However, it should be noted that arguments about net positive effects prevail indicating that new technologies generate new types of employment.

4 A gig worker is someone who is employed on a freelance basis, carrying out short-term jobs or contracts to one or more employers.

Table 11.1 The extent to which Covid-19 pandemic imposed a need for new skills (percent)

Active labour market measure	Did not impose at all		Did not impose		Do not have opinion		Imposed to less extent		Imposed to great extent	
	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.	Control
Training for drivers (DR) 2016	9.7	-	32.3	90.5	25.8	4.1	9.7	-	22.6	5.4
Training for drivers (DR) 2020	-	4.6	53.1	85.2	18.8	2.3	6.3	2.3	21.9	5.7
Training for known employer (TKE) 2018	3.3	-	60.7	83.3	13.1	-	8.2	-	14.8	16.7
Training for known employer (TKE) 2019	-	-	67.2	42.9	25.0	7.1	1.6	-	6.3	50.0
Training for advanced IT skills (IT) 2017/18	6.9	8.6	41.1	41.9	12.3	2.2	13.7	24.7	26.0	22.6
Training for advanced IT skills (IT) 2019	1.2	1.7	60.5	58.3	24.4	3.3	3.5	-	10.5	36.7
Training for in-demand occupations (IN) 2018	1.0	13.3	98.1	28.7	1.9	14.0	-	2.0	-	42.0
Training for in-demand occupations (IN) 2019	3.8	2.5	26.0	33.0	13.7	7.6	24.4	28.3	32.1	28.6
Wage subsidy program (WS) 2018	1.9	0.8	31.2	27.3	1.2	0.8	30.0	31.4	35.8	39.7
Wage subsidy program (WS) 2019	25.6	19.5	3.0	-	15.8	25.6	-	-	55.6	54.9

Source: Author's calculations

According to Table 11.1, the pandemic of Covid-19 imposed a need for new skills to less extent among participants in training for drivers and training for known employer. In contrast, a higher need for new skills due to the pandemic is observed among participants in the training for advanced IT skills and training for in-demand occupations.

Table 11.2 Increased demand for skills due to Covid-19 pandemic (percent)

Active labour market measure	Foreign languages		Basic IT skills		Advanced IT skills		E-commerce		E-banking		Other	
	Trea.	Cont.	Trea.	Cont.	Trea.	Cont.	Trea.	Cont.	Trea.	Cont.	Trea.	Cont.
Training for drivers (DR) 2016	45.5	-	-	-	36.4	60.0	9.1	20.0	-	20.0	9.1	-
Training for drivers (DR) 2020	-	-	-	-	55.6	100	33.3	-	11.1	-	-	-
Training for known employer (TKE) 2018	14.3	-	-	-	57.1	-	14.3	50.0	14.3	50.0	-	-
Training for known employer (TKE) 2019	20.0	14.3	-	-	-	85.7	-	-	60.0	-	20.0	-
Training for advanced IT skills (IT) 2017/18	-	1.4	50.0	58.1	21.7	16.2	-	-	6.5	1.4	21.7	23.0
Training for advanced IT skills (IT) 2019	7.7	18.2	15.4	-	69.2	72.7	-	-	7.7	9.1	-	-
Training for in-demand occupations (IN) 2018	-	48.5	-	4.6	-	33.3	-	7.6	-	6.1	-	-
Training for in-demand occupations (IN) 2019	8.0	1.8	30.8	34.8	8.9	3.3	1.9	0.7	1.0	2.5	49.5	56.9
Wage subsidy program (WS) 2018	2.7	-	36.2	41.3	5.4	5.0	2.3	-	0.4	1.7	53.1	52.1
Wage subsidy program (WS) 2019	39.8	31.1	1.6	-	39.1	42.2	7.0	15.6	12.5	11.1	-	-

Source: Author's calculations

From Table 11.2 we can notice that the majority of the respondents emphasised the increased demand for advanced IT skills due to the pandemic of Covid-19. The high shares of the category 'Other' for some ALMM such as the training for in-demand occupations in 2019, the training for advanced IT skills in 2017/18 and the wage subsidies in 2018 suggest a need for more detailed inspections. In particular, some other skills engendered from the social and physical distancing may have not been anticipated. The EU experience shows that the burden of the Covid-19 social distancing falls disproportionately on vulnerable workforce groups, such as: women, older employees, the lower-educated and those employed in small enterprises. As a consequence there is an urgent need for immediate and targeted policy responses to prevent ongoing job losses and widening of labour market and social inequalities due to the pandemic.[5]

5 Based on the Covid-19 social distancing risk index (COV19R), CEDEFOP.

12. Cost effectiveness

The cost effectiveness analysis serves as a tool to calculate the cost of producing of one unite of outcome. In order to carry out a cost effectiveness analysis the outcomes from the ALMMs must be quantifiable and completely attributable to the intervention. In addition, cost effectiveness analysis obviously require accurate measure of the cost of the intervention. Finally, this analysis requires the comparison of at least two interventions, one of which can be the current intervention or status quo. The costs typically include the direct costs of the ALMM or the income support costs while clients received interventions, and these usually come from administrative records.

Two issues are fundamental to the measurement of the cost effectiveness analysis of ALMMs: first, what is the outcome? and second, when should one measure the outcome: immediately after the training or over some time period? Outcomes of interest in labour market programs typically relate to some form of employment and might include increases in earnings, increases in hours worked, or change in job status from part-time to full-time. Other more indirect measures include reduction in social assistance or employment insurance use. In addition, time presents an important challenge. A follow-up survey after a year may be sufficient to establish return to work in stable employment. Hence, choosing where to position a cost effectiveness analysis along the outcomes is an important decision for the evaluator.

The total cost and cost per participant for the ALMMs under consideration are presented in Table 12.1.

Table 12.1 Average cost per participant

ALMM	Total cost	Number of participants	Cost per participant (denars)
DR 2016	1678670	65	25826
DR 2020	1311100	52	25213
TKE 2018	3142551	210	14965
TKE 2019	3366720	199	16918
IT 2017/18	16800000	200	84000
IT 2019	23959920	218	109908
IN 2018	19175238	588	32611
IN 2019	35321669	805	43878
WS 2018	165186000	1206	136970
WS 2019	307344000	1945	158017

Source: Author's calculations

From Table 12.1 we can conclude that the lowest cost per participant are observed for the training for known employer (around 16000 denars), followed by the training for drivers (around 25500 denars), training for in-demand occupations (around 38000 denars) and training for advanced IT skills (around 97000 denars). The wage subsidies should be considered separately since their purpose and administration differ from those of the training programs. Namely, the average cost of wage subsidies per participant is 147500 denars, but the period for which the subsidies are granted should be taken into consideration.

Although the calculation of the net cost of activities and outputs is a very useful role for cost effectiveness analysis in program management, its most common application in the training literature calculates the cost of producing a unit of net outcome. The term 'net' indicates that the evaluator has controlled the external influences on outcomes and estimated the exact relationship between the ALMMs and the change in employment of participants. In this context, we can calculate the cost per employed participant. The results are presented in Table 12.2.

Table 12.2 Average cost effectiveness ratio (ACER)

ALMM	Total cost	Number of participants	Probability of employed participant	Cost per employed participant
DR 2016	1678670	65	0.667	38719
DR 2020	1311100	52	0.517	48769
TKE 2018	3142551	210	0.438	34166
TKE 2019	3366720	199	0.667	25365
IT 2017/18	16800000	200	0.875	96000
IT 2019	23959920	218	0.390	281815
IN 2018	19175238	588	0.357	91347
IN 2019	35321669	805	0.699	62772
WS 2018	165186000	1206	0.695	198507
WS 2019	307344000	1945	0.873	181005

Source: Author's calculations

From Table 12.2 it is obvious that cost per employed participant for each ALMM is higher than the cost per participant due to the fact that only a fraction of participants are currently employed. This measure is also known as average cost effectiveness ratio (ACER).

In order to assess whether the particular ALMM change its effectiveness in the course of time, we can calculate the so-called incremental cost effectiveness ratio (ICER). An incremental cost-effectiveness ratio is a summary measure representing the economic value of an intervention, compared with an alternative (comparator). It is usually the main output or result of an economic evaluation. An ICER is calculated by dividing the difference in total costs (incremental cost) by the difference in the chosen measure of treatment outcome (incremental outcome) to provide a ratio of 'extra cost per extra unit of outcome'. In other words, we can use the following formula:

$$ICER = \frac{(Cost_1 - Cost_0)}{Outcome_1 - Outcome_0}$$

As outcome measures we can use the number of currently employed participants. Hence, the ICER is calculated as a change in total cost divided by the change in the number of employed participants according to the following formula:

$$ICER = \frac{(Cost_1 - Cost_0)}{(\text{No.employed participants}_1 - \text{No.employed participants}_0)}$$

The results for the ALMMs under consideration are presented in Table 12.3.

Table 12.3 Incremental cost effectiveness ratio (ICER)

ALMM	Total cost	Number of participants	Probability of employed participant	ICER per employed participant
DR 2016	1678670	65	0.667	ICER2020/2016 22316
DR 2020	1311100	52	0.517	
TKE 2018	3142551	210	0.438	ICER2019/2018 5501
TKE 2019	3366720	199	0.667	
IT 2017/18	16800000	200	0.875	ICER2019/2018 -79572
IT 2019	23959920	218	0.390	
IN 2018	19175238	588	0.357	ICER2019/2018 45769
IN 2019	35321669	805	0.699	
WS 2018	165186000	1206	0.695	ICER2019/2018 165336
WS 2019	307344000	1945	0.873	

Source: Author's calculations

From Table 12.4 we can notice that ICER per participant has the lowest value for the training for drivers, followed by the training for in-demand occupation. The extra cost for an additional employed participant in the training for drivers in 2020 vis-à-vis 2016 was 22316 denars. This is lower than the observed average cost per employed participant in 2016 (38719 denars), which means that the cost effectiveness of this ALMM over the period 2016/2020 increased. Similarly, the extra cost for an additional employed participant in the training for in-demand occupations in 2019 vis-à-vis 2018 was 45769 denars. This is twice as lower as the observed average cost per employed participant in 2018 (91347 denars), which means that the cost effectiveness of this

ALMM for the period 2018/2019 increased as well. The highest increase in the cost effectiveness is observed for the training for known employer since the ICER is 5501 denars, which is about six times lower than the average cost per employed participant in 2018 (34166 denars). On the other hand the negative value of ICER for the training for advanced IT skills means that their cost effectiveness in 2019 deteriorated compared to 2017/18. This can be used as a signal for possible amendments in the design and targeting of this ALMM. The ICER for wage subsidies is 165336 which is lower compared to the average cost per employed participant in 2018 (198507). Therefore, we can conclude that the cost effectiveness of wage subsidies in 2019 increased compared to 2018.

Furthermore, the cost effectiveness analysis can be extended by evaluating the cost and benefits for each ALMM known as Cost-benefit analysis (CBA). CBA provides a powerful conceptual framework for assessing a program in terms of the difference between its costs and benefits; if the discounted value of benefits exceeds the discounted value of the costs, the program is unambiguously beneficial. CBA faces some important challenges, not the least of which is estimating the money value of every benefit and cost that might arise due to the program. Translating benefits into financial equivalents represents one of the core challenges for CBA. A similar challenge exists for estimating the financial equivalence for costs, such as the cost of wages in high unemployment areas or whether we should count the wages as the full cost of a program if people are unemployed. Enumerating the range of benefits and costs also challenges CBA. For example, the benefits of a training program for disadvantaged persons would typically include the increased wages enjoyed by the trainees upon re-employment. Other benefits could include reduced unemployment and increased taxes to government from having more of the population employed.

Within the typical CBA framework for estimating the impacts of a given program on the long-run, time plays a crucial role. Namely, time alters the financial estimates of costs and benefits. A cost incurred now is valued more than a cost that will only be incurred in several years. Similarly, a benefit that arises in the future has less value than one received now. Assuming that one can translate all benefits and costs into present day financial values, a CBA provides a very convenient way of summarizing the value for money of projects. If the discounted present value of benefits exceeds the discounted present value of costs, the program should proceed.

In our case, the time perspective for evaluation is quite short, and therefore the standard CBA with discounting costs and benefits is not feasible. Notwithstanding, we can make an attempt to simplify the CBA by summing up the monetary costs and benefits for each training program under consideration for a period of one year. The total cost per participant consists of the direct cost per participant (as calculated in Table 12.1) and opportunity cost of lost income during the training. The opportunity cost is calculated as an average duration of a training program multiplied by the average salary of the control group adjusted by the probability of employed control group applicant. On the other hand, the total benefit per participant consist of the yearly average salary of the participant adjusted by its probability of employment.

The fact that outcomes and costs are all expressed in money terms allows the analysts to create a benefit-cost ratio. Comparisons among training programs by using the same model provide some basis for assessing relative program worth. Even if we examine only one program, when benefits exceed cost, a case can be made for maintaining the program. The cost-benefit analysis and calculated cost-benefit ratios for the training programs under consideration is presented in Table 12.4.

Table 12.4 Cost-benefit analysis

ALMM	Cost per participant (denars)	Average salary (participants)	Average salary (control group)	Average duration of training (months)	Probability of employed (participant)	Probability of employed (control group)	Opportunity cost (participant)	Total cost	Total benefit (yearly basis)	Benefit-cost ratio
	1	2	3	4	5	6	7 (3*4*6)	8 (1+7)	9 (2*5*12)	10
DR 2016	25826	23055	18958	1.0	0.667	0.095	1801	27627	184532	6.68
DR 2020	25213	20588	20000	3.0	0.517	0.207	12420	37633	127728	3.39
TKE 2018	14965	17337	17500	5.7	0.438	0.375	37406	52371	91123	1.74
TKE 2019	16918	17988	22500	6.4	0.667	1.000	144000	160918	143976	0.89
IT 2017/18	84000	22386	22283	3.2	0.875	0.722	51483	135483	235053	1.73
IT 2019	109908	25300	22608	4.0	0.390	0.585	52903	162811	118404	0.73
IN 2018	32611	22580	20714	3.0	0.357	0.306	19015	51626	96733	1.87
IN 2019	43878	19522	19558	3.7	0.699	0.680	49208	93086	163751	1.76

Source: Author's calculations

From Table 12.4 we can notice that six out of eight training programmes have positive benefit-cost ratio. In this context, the most beneficial is the training for drivers which cost-benefit ratio for 2016 is 6.68, while for 2020 is 3.39. In addition, a positive net benefit is observed for the training for in-demand occupations in 2018 and 2019. In contrast, the CBA for the remaining two training programmes shows mixed results. Namely, the training for known employer and the training for advanced IT skills have positive net benefit in 2018, but negative in 2019. This is an additional reason why these training programs have to be analyzed in details in order to detect the causes for their low effectiveness.

13. Conclusions

This report presents the findings of the impact evaluation carried out on selected active labour market measures implemented by the Employment Service Agency. In this context, we evaluated the following ALMMs: The training for drivers for C, D and E category (2016 and 2020), the training for known employer (2018 and 2019), the training for advanced IT skills (2017/18 and 2019), the training for in-demand occupations (2018 and 2019) and wage subsidy program (2018 and 2019). The choice of the years was based on the intention to assess the short-term effectiveness of the programs in the circumstances of changing environment due to the Covid-19 pandemic. The key research question was whether participation in the active labour market programs increased the probability of participants to find and retain gainful employment. However, in addition to this main outcome, we included other outcome variables such as: inactivity, unemployment, salaries, changes in the financial situation and employment prospects after the program, search for job and intention to emigrate.

Ideally, policy makers should assess effectiveness of programs by first implementing and evaluating pilot projects. In this case a design should assume one group participating in a program and a similar group of non-participants. Comparing the performance of the two groups over time would reveal the effectiveness of the program. Based on these evaluations, policy makers can design and target programs more effectively. In addition, evaluations can enable policy makers to make informed decisions about which target groups benefit most from a particular program, resulting in targeted programs and enhanced program performance. Finally, some programs are ineffective and should be eliminated or changed, hence rigorous evaluations help policy makers to identify them and allow resources to be redirected to programs that are more cost-effective.

Data for evaluation were gathered through telephone survey that was carried out during September 2021, covering the participants (treatment group) and non-participants (control group). The total sample size was 2.230 respondents, of which 1.260 participants, and 970 control group applicants.

In order to answer the research question, we employed a post-program quasi-experimental evaluation method with an aim of achieving unbiased results. By using the propensity score matching technique the 'net' effects of programs on the outcome variables were estimated. In addition to estimating the general effect, we disaggregated the average treatment effect on treated participants by various attributes in order to identify the particular impact of each ALMM on the vulnerable labour market segments. Finally, we conducted cost effectiveness and simplified cost-benefit analyses with an aim to explore whether the devoted funds for the ALMMs are worth with respect to the expected benefits from their implementation. The results from the analyses with regarding the statistically significant estimations and the targeting are briefly summarised in Table 13.1.

Table 13.1 Summary of the ALMMs impact (statistically significant estimations)

ALMM	Employed	Unemployed	Salary	Permanent contract	Better financial condition	Better employment prospects	Search for job	Intention to emigrate
DR 2016	Positive impact Poorly targeted: rural and long-term unempl.	Negative impact Poorly targeted: long-term unemployed		Positive impact Less likely: youth and long-term unempl.		Positive impact Less likely: rural		
DR 2020	Positive impact Poorly targeted: rural and long-term unempl.	Negative impact Poorly targeted: Youth, rural and without exp.			Positive impact Less likely: older and long-term unempl.	Positive impact Less likely: older and long-term unempl.		
TKE 2018					Positive impact Less likely: rural and without work experience	Positive impact Less likely: rural		
TKE 2019		Negative impact Poorly targeted: youth, female and long-term unemployed			Positive impact Less likely: male and long-term unemployed	Positive impact Less likely: male and long-term unemployed		
IT 2017/ 2018					Positive impact Less likely: older and long-term unempl.	Positive impact Less likely: older and long-term unempl.		

IMPACT ASSESSMENT OF THE ACTIVE LABOUR MARKET MEASURES IN NORTH MACEDONIA

ALMM	Employed	Unemployed	Salary	Permanent contract	Better financial condition	Better employment prospects	Search for job	Intention to emigrate
IT 2019							Positive impact Less likely: rural and without work exp.	
IN 2018					Positive impact Less likely: youth and male	Positive impact Less likely: youth and male	Negative impact Less likely: youth	
IN 2019		Negative impact Poorly targeted: long-term unemployed			Positive impact Less likely: female and rural	Positive impact Less likely: youth and female		Positive impact Less likely: youth and female
WS 2018		Positive impact Poorly targeted: long-term unemployed		Negative impact Less likely: male and urban				Positive impact More likely: Male and with work exp.
WS 2019		Negative impact Poorly targeted: youth and without work experience	Positive impact More likely: older, male, urban, with work exp.		Positive impact Less likely: long-term unemployed			Negative impact Less likely: Male and short-term unempl.

14. Policy implications

The reforms of the active labour market measures should be delivered by applying integrated and partnership-based approach and should be combined with sufficient management and implementation capacity. In addition, the reforms of active labour market policies should account for the possible complementarities with the unemployment compensation system and the existing social assistance programs. The assessment results for each particular intervention have to be used to inform policy makers whether the program has achieved the objectives and to provide information regarding the potential continuation, re-design or termination of the program. The possibility of combining different programs such as wage subsidies and trainings may bring good synergies and can strengthen their individual impact.

The reforms of active labour market policies in North Macedonia have to take into account the specific socio-economic context due to the Covid-19 pandemics, as well as the ESA capacities. This study demonstrated that ALMMs do not work equally well for different individuals and further improvements of their targeting is required. Since one of the main objectives of active labour market measures is to assist the unemployed to get back into work, they require a reasonably buoyant supply of job vacancies in order to be effective. If economy of North Macedonia is generating few vacancies as a consequence of the Covid-19 crisis, one should not be surprised if active measures show to be relatively ineffective.

Having in mind the above analyses, in what follows we provide short assessment of the ALMMs under consideration and attempt to formulate some policy recommendations that should guide the future actions of the policy makers.

Training for drivers for C, D and E category (DR)

This ALMM provide strong positive results for the participants and it is run by well established providers. Although it has been undertaken on a small scale, the estimation results show some deficiencies with regard to its targeting. Particularly poorly targeted are unemployed from rural areas and the long-term unemployed. In addition, this program is highly cost effective and beneficial for the participants, leading to the conclusion that it has to be retained in the future.

Training for known employer (TKE)

Although delivered for specific employers, this training program provides rather uncertain results. Namely, we only identified diminishing impact on the unemployment in 2019 and positive impact on the subjective perceptions for better financial conditions and employment prospects. In this context, some disadvantaged segments such as: rural and workers without work experience in 2018, and male and long-term unemployed in 2019 are less likely to enjoy these perceptions. Moreover, we should be cautious with drawing conclusions regarding this training program because of the small sample size of the control groups. Although it is reasonably cost effective, we found diminishing beneficial effects in 2019.

Training for advanced IT skills (IT)

The advanced IT skills have been particularly praised by the respondents in the light of the newly created circumstances due to the Covid-19 pandemic. However, in our analysis we only identified a significant effects on the subjective perception of participants in 2017/18 and on the intensity to search for job in 2019. In addition, the negative incremental cost effectiveness and diminishing beneficial effects suggest that this program becomes increasingly more expensive. Hence, we recommend its redesign by taking into consideration the changing needs for specific IT skills.

Training for in-demand occupations (IN)

Although, the aim of this ALMM is to satisfy the increased demand for particular skills in the labour market, the analyses revealed only a diminishing impact on unemployment in 2019. Moreover, the training for in-demand occupation has generally covered short-term unemployed who face higher level of employment probability thus, indicating a possibility for substantial deadweight loss. This training program has positive impact on the subjective perceptions for better financial situation and employment prospects. In addition, we found out negative impact on the job search effort in 2018, while positive impact on intention to emigrate in 2019. By having in mind the increasing cost effectiveness and fairly good beneficial effects relative to other training program, we recommend continuation of this program in the future. However, the information about the actual needs for skills on the labour market should be up to date according to the results from the ESA Survey on demanded occupations (employers' interviews).

Wage subsidy program (WS)

The evaluation of the outcomes from the wage subsidy program reveals it improvement in 2019 relative to 2018. Namely, wage subsidies in 2018 exerted increasing unemployment associated with increasing intention to emigrate. This can be attributed to the possible job closures after the expiration of the period for receiving wage subsidy. However, in 2019 we find out that wage subsidies exert diminishing impact on unemployment associated with positive impact on salary and negative impact on the intention to emigrate. Although, the incremental cost effectiveness ration demonstrates improving effectiveness in 2019 vis-à-vis 2018, this ALMM is still considered as one of the most expensive measures. The cost-effectiveness analysis of the wage subsidy program needs to be accompanied by cost-benefit analysis in order to assess its beneficial effects relative to the costs. In this context, we recommend redesign of this measure by improving its targeting and conditions for retaining the subsidised jobs.

References and bibliography

1. Atanassov, A. and Trifonova, S. (2020) "Assessment of the net effect of the active labour market policy in Bulgaria", *Journal of Contemporary Management Issues,* Vol.25, No.2, pp.263-290;

2. Blache, G. (2011) "Active Labour Market Policies in Denmark: A Comparative Analysis of Post-Program Effect", *CES Working Papers*, 2011:71;

3. Boone, J. and van Ours, J. (2004) "Effective Active Labour Market Policies, IZA Discussion Paper, No.1335;

4. Borra, C., Palma, L., Gonzalez, C. and Aguado, L. (2012) "Evaluation of an Active Labour Market Programme in a Context of High Unemployment", *Revista Desarrollo y Sociedad, II semestre;*

5. Brown, A. and Koettl, J. (2015) "Active labour market programs – employment gain or fiscal drain?", *IZA Journal of Labour Economics* (2015) 4:12;

6. Caliendo, M. and Hujer, R. (2005) "The Microeconometric Estimation of Treatment Effects – An Overview", *IZA Discussion Paper,* No.1653;

7. Corbanese, V. and Rosas, G. (2009) "Guide to the design, monitoring and evaluation of innovative active labour market programmes targeting individuals at risk of labour market exclusion", *International Labour Organization;*

8. Crato, N. and Paruolo, P. (2019) *"Data-Driven Policy Impact Evaluation, How Access to Microdata is Transforming Policy Design"*, Springer;

9. Crepon, B. and van den Berg, G. (2016) "Active labour market policies", *IFAU – Office of Labour Market Policy Evaluation, Working paper* 2016:17;

10. Dar, A. and Tzannatos, Z. (1999) "Active labour market programs: A review of the evidence from evaluations", *World Bank Social Policy Discussion Paper* No.9901;

11. Dhaini, A., Bouchnak, C. and Dreiza, T. (2020) "Covid-19 as accelerator for digital transformation and the rise of the gig economy", KPMG;

12. Eichhorst, W. and Konle-Seidl, R. (2016) "Evaluating Labour Market Policy", *IZA Discussion Paper,* No.9966;

13. Employment Service Agency of North Macedonia, Operational Plans 2007-2021 https://av.gov.mk/operativen-plan.nspx;

14. Escudero, V. (2018) "Are active labour market policies effective in activating and integrating low-skilled individuals? An international comparison", *IZA Journal of Labour Policy 7:4;*

15. European Commission (2015) "Upskilling unemployed adults (aged 25 to 64): The organization, profiling and targeting of training provision", *European Employment Policy Observatory Review;*

16. European Commission (2018) *"Labour market policy statistics methodology 2018"*, Directorate-General for Employment Social Affairs and Inclusion;

17. European Commission (2019) "Index on quality of Active Labour Market Policy (ALMP) implementation", *European Network of Public Employment Services;*

18. Fay, R. (1996) "Enhancing the Effectiveness of Active Labour Market Policies: Evidence from Programme Evaluation in OECD Countries", *OECD Labour Market and Social Policy Occasional Paper, No.18;*

19. FREN (2015) "Impact Evaluation of Active Labour Market Programmes targeting disadvantaged youth in Serbia", *FREN and ILO;*

20. Gaëlle, P. (1999) "A framework for active labour market policy evaluation", *International Labour Office, Employment and training papers,* No.49;

21. Gertler, P., Martinez, S., Premand, P., Rawlings, R. and Vermeersch, C. (2016) *"Impact Evaluation in Practice",* Second edition, World Bank Group;

22. Guijarro, F. (2018) "Economic Recovery and Effectiveness of Active Labour Market Initiatives for the Unemployed in Spain: A Gender Perspective of a Valencian Region", *Sustainability*, 10, 3623;

23. Hujer, R. and Caliendo, M. (2000) "Evaluation of Active Labour Market Policy: Methodological Concepts and Empirical Estimates", *IZA Discussion Paper,* No.236;

24. ILO (2016) "What works, Active labour market policies in Latin America and Caribbean", *International Labour Organization;*

25. Kluve, J. (2006) "The Effectiveness of European Active Labor Market Policy", *IZA Discussion Paper,* No.2018;

26. Kluve, J. (2016) "A review of the effectiveness of Active Labour Market Programmes with a focus on Latin America and Caribbean", *International Labour Office, Research department Working Paper* No.9;

27. Krstevska, A. and Ilievska, M. (2018) "Developments in major labour market indicators and active labour market measures in dealing with unemployment: Evidence from Macedonia", *BIS Working Party on Monetary Policy,* Zagreb;

28. Lammers, M. and Kok, L. (2021) "Are active labour market policies (cost-) effective in the long run? Evidence from the Netherlands", *Empirical Economics* (2021) 60: 1719-1746;

29. Lance, P., Guilkey, D., Hattori, A. and Angels, G. (2014) "How do we know if a program made a difference? A guide to statistical methods for program impact evaluation", Chapel Hill, North Carolina: MEASURE Evaluation;

30. Lauringson, A., Vilsaar, K., Tammik, L. and Luhavee, T. (2011) "Impact Evaluation of Labour Market Training", *Estonian Unemployment Insurance Fund;*

31. Loi, M. and Rodrigues, M. (2012) "A note on the impact evaluation of public policies: the counterfactual analysis", *Joint Research Center Scientific and Policy Reports;*

32. Martin, J. (2000) "What Works Among Active Labour Market Policies: Evidence from OECD Countries' Experiences", OECD *Economic Studies* No.30, 2000/I;

33. Martin, J. and Grubb, D. (2001) "What works and for whom: a review of OECD countries' experiences with active labour market policies", *IFAU – Office of Labour Market Policy Evaluation, Working paper* 2001:14;

34. Mason, G. and Tereraho, M. (2007) "Value-for-money Analysis of Active Labour Market Programs", *The Canadian Journal of Program Evaluation,* Vol.22, No.1, pp.1-29;

35. McKenzie, D. (2017) "How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence", *World Bank Group, Policy Research Working Paper,* No.8011;

36. Mojsoska-Blazevski, N. and Petreski, M. (2015) "Impact evaluation of active labour market programs in FYR Macedonia: Key findings", *International Labour Organization;*

37. OECD (2020) "Impact Evaluation Framework for the Spanish Ministry of Labour and Social Economy and Ministry of Inclusion, Social Security and Migrations", November, 2020;

38. Pierre, G. (1999) "A framework for active labour market policy evaluation", *Employment and training department, International Labour Office;*

39. Rodriguez-Planas, N. and Benus, J. (2006) "Evaluating Active Labour Programs in Romania", *IZA Discussion Paper,* No.2464;

40. Sahnoun, M. and Abdennadher, C. (2018) "The assessment of active labour market policies: Evidence from OECD countries", *Econ Polit,* February 2018;

41. Sekhon, J. (2007) "The Neyman-Rubin Model of Causal Inference and Estimation via Matching Methods", *The Oxford Handbook of Political Methodology;*

42. Smith, J. (2000) "A Critical Survey of Empirical Methods for Evaluating Active Labor Market Policies", NBER;

43. White, H. and Raitzer, D. (2017) *"Impact Evaluation of Development Interventions"*, Asian Development Bank;

44. Zubović, J. and Domazet, I. (2012) "On the Methodology of Cost-Benefit Analysis of ALMP – The Case of Serbia", *New Challenges in Changing Labor Market, Institute of Economic Sciences, Belgrade.*

Appendix 1a: Questionnaire for individual participants

Application ID _____________

1. The main motive for application

   (1) Employment

   (2) Higher wage

   (3) Additional skills

   (4) Change profession

   (5) Emigration

   (6) Other ____________________________

2. Current employment status

   (1) Employer

   (2) Employed

   (3) Self-employed

   (4) Unpaid family worker

   (5) Employed at program end, but currently not employed

   (6) Inactive - has not searched for a job at least four weeks (go to 6)

   (7) Not employed at any time after participation (go to 6)

3. Type of contract (if employed or last employment)

   (1) Permanent (open-end)

   (2) Temporary (close-end)

   (3) Seasonal

   (4) No contract

4. Type of ownership of the company (if employed or last employment)

   (1) Public

   (2) Private – registered

   (3) Private – unregistered

   (4) Other

5. Monthly wage at current job (if employed or last employment)

   (1) 0

   (2) 0 – 9.999

   (3) 10.000 – 14.499

   (4) 15.000 – 19.999

   (5) 20.000 – 24.999

   (6) 25.000 – 29.999

   (7) 30.000 – 34.999

   (8) 35.000 – 39.999

   (9) 40.000 and above

6. Current marital status

   (1) Single

   (2) Married

   (3) Divorced

   (4) Widowed

7. No. of members ____

8. No. of members under 15 ____

9. No. of employed members ____

10. No. of unemployed members ____

11. No. of retired persons ____

12. To what extent do you search for (new) job?

    (1) Do not search at all

    (2) Do not search

    (3) Do not have opinion

    (4) Search to less extent

    (5) Search to great extent

13. To what extent do you plan to emigrate in search for job?

    (1) Do not plan at all

    (2) Do not plan

    (3) Do not have opinion

    (4) Plan to less extent

    (5) Plan to great extent

14. Change in financial conditions (after program participation)

    (1) Better

    (2) Same

    (3) Worse

15. Change in employment prospects (after program participation)

    (1) Better

    (2) Same

    (3) Worse

16. Does the Covid-19 pandemic imposed for you a need for new skills?

    (1) Did not impose at all

    (2) Did not impose

    (3) Do not have opinion

    (4) Imposed to less extent

    (5) Imposed to great extent

17. The demand for which of the following skills do you think increased due to the Covid-19 pandemic?

    (1) Foreign languages

    (2) Basic IT skills

    (3) Advanced IT skills

    (4) E-commerce

    (5) E-banking

    (69 Other ____________________________

Self-reported satisfaction from the training

18. To what extent are you satisfied from the gained knowledge and skills?

    (1) Not satisfied at all

    (2) Not satisfied

    (3) Do not have opinion

    (4) Satisfied to less extent

    (5) Satisfied to great extent

19. To what extent were appropriate the applied training methods?

    (1) Not appropriate at all

    (2) Not appropriate

    (3) Do not have opinion

    (4) Appropriate to less extent

    (5) Appropriate to great extent

20. To what extent were useful the training materials?

    (1) Not useful at all

    (2) Not useful

    (3) Do not have opinion

    (4) Useful to less extent

    (5) Useful to great extent

21. To what extent was appropriate the training environment?

    (1) Not appropriate at all

    (2) Not appropriate

    (3) Do not have opinion

    (4) Appropriate to less extent

    (5) Appropriate to great extent

22. Would you apply for another ALMM?

    (1) No

    (2) Yes

    (3) Do not have opinion

Appendix 1b: Questionnaire for individual non-participants

Application ID ____________

1. The main motive for application

   (1) Employment

   (2) Higher wage

   (3) Additional skills

   (4) Change profession

   (5) Emigration

   (6) Other __________________________

2. Current employment status

   (1) Employer

   (2) Employed

   (3) Self-employed

   (4) Unpaid family worker

   (5) Employed at program end, but currently not employed

   (6) Inactive - has not searched for a job at least four weeks (go to 6)

   (7) Not employed at any time after application (go to 6)

3. Type of contract (if employed or last employment)

   (1) Permanent (open-end)

   (2) Temporary (close-end)

   (3) Seasonal

   (4) No contract

4. Type of ownership of the company (if employed or last employment)

   (1) Public

   (2) Private – registered

   (3) Private – unregistered

   (4) Other

5. Monthly wage at current job (if employed or last employment)

   (1) 0

   (2) 0 – 9.999

   (3) 10.000 – 14.499

   (4) 15.000 – 19.999

   (5) 20.000 – 24.999

   (6) 25.000 – 29.999

   (7) 30.000 – 34.999

   (8) 35.000 – 39.999

   (9) 40.000 and above

6. Current marital status

   (1) Single

   (2) Married

   (3) Divorced

   (4) Widowed

7. No. of members ____

8. No. of members under 15 ____

9. No. of employed members ____

10. No. of unemployed members ____

11. No. of retired persons ____

12. To what extent do you search for (new) job?

    (1) Do not search at all

    (2) Do not search

    (3) Do not have opinion

    (4) Search to less extent

    (5) Search to great extent

13. To what extent do you plan to emigrate in search for job?

    (1) Do not plan at all

    (2) Do not plan

    (3) Do not have opinion

    (4) Plan to less extent

    (5) Plan to great extent

14. Change in financial conditions (after program participation)

    (1) Better

    (2) Same

    (3) Worse

15. Change in employment prospects (after program participation)

    (1) Better

    (2) Same

    (3) Worse

16. Does the Covid-19 pandemic imposed for you a need for new skills?

    (1) Did not impose at all

    (2) Did not impose

    (3) Do not have opinion

    (4) Imposed to less extent

    (5) Imposed to great extent

17. The demand for which of the following skills do you think increased due to the Covid-19 pandemic?

(1) Foreign languages

(2) Basic IT skills

(3) Advanced IT skills

(4) E-commerce

(5) E-banking

(6) Other ___________________________

18. Would you apply for another ALMM?

(1) No

(2) Yes

(3) Do not have opinion

good.better.regional.

Employment and Social Affairs
Platform 2 Project (#ESAP2)
www.esap.online

@rccint

RegionalCooperationCouncil

RCCSec

regionalcooperationcouncil_rcc

Regional Cooperation Council

Powered by RCC.int

Regional Cooperation Council

This project is funded by the European Union