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Counterfactual Impact Evaluation (CIE) of Estonian Adult Vocational Training Activity

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Authors:

Reelika Leetmaa Email: Reelika.Leetmaa@praxis.ee Address: Praxis Center for Policy Studies, Tornimäe 5, Tallinn, Estonia

Andres Võrk Email: Andres.Vork@praxis.ee Address: Praxis Center for Policy Studies, Tornimäe 5, Tallinn, Estonia

Miko Kupts Email: Miko.Kupts@praxis.ee Address: Praxis Center for Policy Studies, Tornimäe 5, Tallinn, Estonia

Laura Kirss Email: Laura.Kirss@praxis.ee Address: Praxis Center for Policy Studies, Tornimäe 5, Tallinn, Estonia

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RAHANDUSMINISTEERIUM

Praxis Center for Policy Studies
Tornimäe 5
10145 Tallinn, Estonia
Tel: +372 640 8000
www.praxis.ee
praxis@praxis.ee

European Commission
DG Employment, Social Affairs and Inclusion
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Executive summary

Objective of the project

The general objective of the project "Counterfactual Impact Evaluation of Estonian Adult Vocational Training Activity" was to promote the use of counterfactual impact evaluation (CIE) of ESF interventions in the domains of the Estonian Ministry of Education and Research (MoER). The specific objectives of the project were following:

a) to provide evidence on the effects of the ESF programme "Work-related training and development of adult education" implemented by the MoER;

b) to enhance the capacity of the MoER to effectively implement evaluations through the development of the description of the data needs for evaluations and data collection system for future evaluations;

c) to raise awareness on CIE through the general and special training courses.

As a result of the project the database on participants of adult vocational education and non-participants from PIAAC data was created from the scratch by Praxis Center for Policy Studies and Statistics Estonia. This allowed the partners (Ministry of Finance, Ministry of Education and Research) to learn what kind of data is needed for conducting impact evaluations, how it should be collected and handled to ensure the conformity with the EU data protection rules. Secondly, in the framework of the project the options for monitoring and evaluation ESF projects for 2014-2020 period were analysed in depth. The process scheme for collecting the data in the new programming period was worked out by project partners. One of the long lasting effect of the project is that the data on ESF projects is now collected centrally into single database and by the most competent institution in the field (Statistics Estonia). Thirdly, introductory and in-depth training courses on impact evaluations were prepared based on the experience of the project. In total 58 civil servants participated in introductory training course on impact evaluations and 20 took part in in-depth training. Finally, this evaluation report on the impacts of work-related training programmes has been prepared both in English and in Estonian as a result of this project. The evaluated intervention is relatively new policy instrument in Estonia (adult vocational training courses are financed by the state only from 2007) and it was one of the largest ESF programmes both in terms of participants and expenditure. However, there was no robust and credible evidence on the impact of adult training courses available in Estonia and this is the first attempt to evaluate these impacts.

Results of the evaluation

In the evaluation analysis we used propensity score matching combined with difference-in-differences analysis and regression models to estimate the effect of adult vocational training in 2010–2011 on later labour market outcomes. We combined data from several sources. Treatment group data was received from training centres and for a comparison group we used PIAAC survey data. Both data were merged with individual tax records from the Estonian Tax and Customs Board from 2008–2013. We analysed the effect of training on later employment probability, number of months worked, annual earnings and average monthly wage.

Analysis suggests that adult vocational training has a positive modest effect on later labour market outcomes, but the size and statistical significance of the results are sensitive to which comparison group and matching technique to use. As we combine totally different datasets, a risk remains that we are not able to fully make the treated and comparison group comparable in terms of unobservable characteristics. Propensity score matching combined with difference-in-difference approach, which compares the difference in labour market outcomes of treated and matched comparison groups before and after the training, suggests that the effects of training are small, often statistically insignificant for employment rates or months of employment. The estimated average effect of training on monthly wages is about 30-40 euros per months one or two years after the training, which corresponds to 5-6% increase compared to pre-treatment wages. Analysis using propensity score matching techniques suggests that the effects of training are larger for those who were already employed at the time when applying to the courses. These results are in accordance with earlier feedback surveys of participants that the effect of training is missing for unemployed participants, as the training courses might be too short to be useful for the unemployed. The results also suggest higher effects of training on later employment probability for people with lower education (up to basic education), younger (20–29) and older people (50+). The effect is smaller for people with university education. We did not find any significant difference by main language or by gender. Better background data on participants and comparison group together with follow-up of the participants might be needed to ascertain the results, especially the long-run impacts.

Improving the intervention logic and targeting

Defining a clearer intervention logic and target group as well as choosing an adequate approach to reach the target group could strengthen the impacts of the programme and make impact evaluations easier. In our case, the programme documents were unclear whether the change in participants' post-programme labour market outcome was seen as an ultimate aim of the programme, or was the creation of additional study places a priority. Programme documents also mentioned that priority should be given to participants with low qualifications and adults whose qualification has become outdated, but in reality, a large share of participants had a higher education.

Improving data collections

In order to improve the capability to evaluate the impact of training, data on applicants, both successful and non-successful, should be electronically collected. In case the number of non-applicants is too small to create a comparison group, a separate comparison group, e.g. from available survey data, must be constructed. The data on participants and non-participants can be merged with various registry data to get information on past and future labour market variables, active labour market services and social benefits. While initially it was planned that the Managing Authorities will be responsible for collecting the relevant data for ESF projects for 2014-2020, as a result of our analyses it was decided to delegate this task to Statistics Estonia.

Increase the awareness of civil servants responsible for evaluations in general and for ESF evaluations in particular

As a part of this project both introductory and in-depth training courses on impact evaluations were conducted. Introductory training courses were two-day events and the in-depth training course was a five-day event. In both courses we highlighted what kind of data and statistical tools are needed for a counterfactual impact evaluation. While the civil servants working in analysis departments have a broad understanding of the nature of impact evaluations, the authorities dealing with ESF management often lack the knowledge of how to plan, collect relevant data and conduct the CIEs. Both the vagueness of the intervention logic as well as the lack of data, which were serious hindrances in the case of the current evaluation as well as the feedback from the training sessions support that conclusion. Hence, capacity building on the CIE approach within public authorities is still needed.

1. Introduction

Demographic challenges and need to respond to changing economic conditions have led to the increased importance of adult education and lifelong learning policies in most of the European countries. In Estonia, work-related training and retraining provided as courses were generally not free for learners until 2007, with the exception of courses provided to unemployed and certain specific groups of employees (e.g. teachers, and officials). Since then, the opportunities to participate in work-related training and retraining have been considerably widened with the help of the European Social Fund (ESF).

This study evaluates the impact of the programme “Work-related training and development of adult education” (WRT) programme, which was one of the largest ESF supported programmes in Estonia during the previous ESF financing period (2007–-2013). The programme was implemented by the Ministry of Education and Research (MoER), which is one of the three institutions responsible for the development and financing of adult education in Estonia. While the Ministry of Education and Research (MoER) targets employed adults, the Ministry of Social Affairs together with the Estonian Unemployment Insurance Fund are responsible for providing labour market training to the unemployed and the Ministry of Economic Affairs and Communication targets employed adults by supporting the creation of training opportunities through companies.

The programme was implemented between January 2009 and June 2014 and it aimed to provide short- term vocational and general training courses to a minimum of 33,000 adults. As the programme is relatively new, it’s impact has not been previously evaluated, hence providing robust evidence on the net effects of the intervention allows us to fill this gap in the existing knowledge. Furthermore, according to Schwerdt et al. (2011) also international evidence on the effectiveness of government supported short- term professional training programmes targeting employed adults rather than the unemployed is also limited. Hence, our study also supplements also international knowledge on designing public policies to improve the skills of employed adults.

In the course of preparations for the evaluation proposal, we discovered that no individual level data on participants was centrally collected and stored. To evaluate the impact of the programme we had to collect the application forms from each training institution and enter the data manually into a single database, which enabled us to construct a database on participants. To keep this task manageable we decided to concentrate on a certain time period (July 2010 to June 2011) and focus only on the courses in priority areas. The data on the comparison group was constructed based on the Estonian Survey of Adult Skills (PIAAC) data. Both data sources were merged with individual tax records from the Estonian Tax and Customs Board from 2008–2013. In total, we received information on 2,586 participants and 7,613 of non-participants.

This exercise convinced us that even if we will not have the ideal dataset for evaluation, raising awareness on the nature and importance of the counterfactual impact evaluations through learning from the experiences of this pilot project is of the utmost importance for improving the knowledge-based policy making in the future. Therefore, in addition to evaluation report the project contained also other components, namely a feasibility study on the ESF data collection and validation requirements for 2014–-2020 and training courses targeted to civil servants. As a result, one of the outcomes of this project is that the data collection of ESF projects was delegated to Statistics Estonia instead of the managing authority as initially planned. Hence, it is likely that for future ESF evaluations the relevant data is properly collected.

The following sections of the current evaluation report provide a detailed overview of the WRT programme being evaluated (chapter 2), data collection mechanisms and evaluation technique (chapter 3). The results based on propensity score matching combined with difference-in-differences analysis and regression models are discussed in chapter 4. These suggest that adult vocational training has a positive effect on later labour market outcomes on (employment probability, number of months worked, annual earnings and average monthly wage), but the results are sensitive to which comparison group and matching technique to use. As we combine totally different datasets, a risk remains that we are not fully able to fully make the treated and comparison group comparable in terms of unobservable characteristics. Our conclusions and recommendations for policy making in future are presented in the final chapter.

2. Description of the intervention being evaluated

2.1. Description of the programme

The programme "**Work-related training and development of adult education" (WRT)** is a part of adult education and training policy in Estonia. The overall framework for adult education and training policy in Estonia is set by the Adult Education Act[1], which provides the basis for adult education and training as well as legal guarantees for adult learners in Estonia. The WRT programme is a tool to support professional education and training, which is one category of adult education as defined by the Act[2]. Although the Adult Education Act describing professional work-related training as a part of general adult education was adopted in 1993, work-related training and retraining courses were generally not free for learners until 2007 (the state funded only the training of registered unemployed and certain specific groups such as teachers and certain officials). However, in the period 2008–2014 three programmes supporting participation in adult education were implemented in Estonia with the co-financing of the European Social Fund. In addition to the WRT programme, which was the largest programme in terms of financing (8.6 million euros), these included also a training programme in popular adult education institutions (4 million euros) and a PR programme for adult education (1 million euros)[3]. Hence, in broad terms the WRT programme was the first intervention subsidising work-related adult training in Estonia, which makes the evaluation of this intervention and learning from the results even more important.

The **aim of the WRT programme** was to facilitate increased participation in lifelong learning and contribute to the labour market competitiveness of the adult population across all Estonian regions by supporting vocational training programmes in vocational education and professional higher education institutions. The programme aimed to train and educate a minimum of 33,000 adults between January 2009 and June 2014, and it had a budget of 8.6 million euros. Hence, it has been one of the largest ESF interventions both in terms of participants and expenditures during the observed period in Estonia. In addition to training adults, the programme was directed at improving and developing the quality of training programmes and the field in general. As can be seen from Table 1, work-related training courses had more than 41,000 participants over the course of the programme. However, the number of participants as a share of the workforce (aged 20–64) in each year has been below 2% and during the whole period below 5%, which indicates that it is likely that the impact of participation at macro level is marginal.

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[1] Adult Education Act. https://www.riigiteataja.ee/en/eli/ee/517122014002/consolide Accessed 28.05.2015. According to the Act employees are entitled to study leave for up to thirty calendar days per year to participate in professional education. Out of this, employers are obliged to maintain the average wages for twenty calendar days. Hence, the legal framework supports participation in professional training by compensating the loss of wages related to participation, which is among the major obstacles to participation in adult training according to many studies. However, there is no empirical evidence available on how effective these provisions are in supporting the participation in professional education and training in Estonia.

[2] The other two categories defined by the Adult Education Act are formal education and informal education.

[3] Ministry of Education and Research. Adult education programmes. https://www.hm.ee/en/activities/structural-funds/adult-education-programmes Accessed 28.05.2015.

TABLE 1. NUMBER OF PARTICIPANTS AND THE BUDGET OF THE WORK-RELATED TRAINING COURSES BY PROGRAMME YEAR

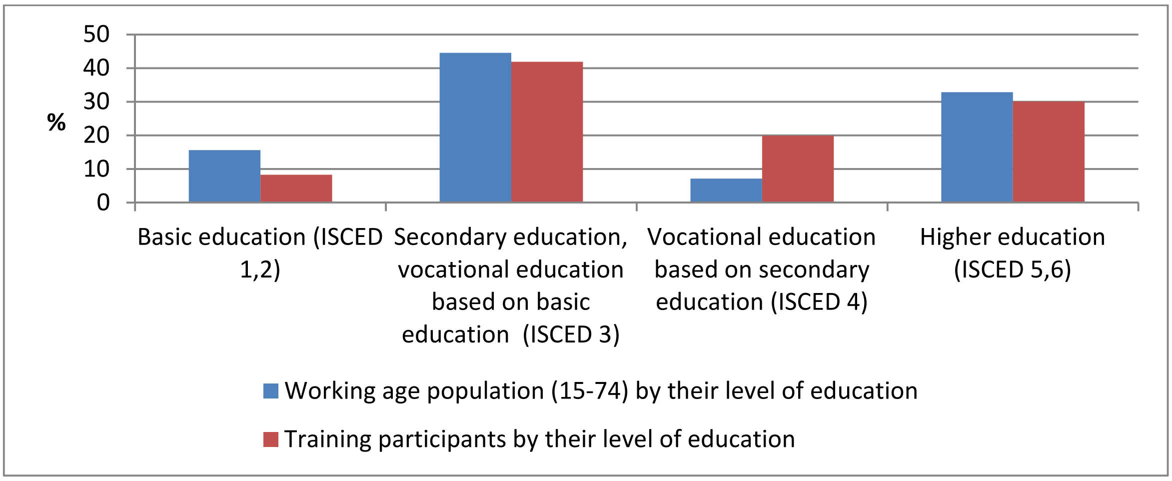
Year	Budget	Participants	Participants as a share of working age population aged 15-74
2009	1 080 000 €	4 900	0,47%
2010	2 520 000 €	11 900	1,16%
2011	1 710 000 €	8 600	0,84%
2012	1 008 000 €	4 900	0,48%
2013	500 000 €	2 600	0,26%
2014	1 460 000 €	7 700	0,78%
2015	295 000 €	1 700	
Total	**8 573 000 €**	**42 300**	**4,27%**

Source: Ministry of Education and Research (data as of 26.08.2015); Statistics Estonia, author's calculations (last column)

The **target population** of the work-related training courses was the **working age adult population across the whole territory of Estonia** who are not subject to compulsory education any more (having acquired basic education and being over 17 years old). Over the course of the programme the main target group has been changing. Initially in 2009 unemployed people could not participate but since 1 July 2010, applicants can also be registered unemployed (registered at the Estonian Unemployment Insurance Fund). It was also added that applicants cannot be studying at any vocational, professional or higher education institution at a state-commissioned study place. From 2011 the programme started to prioritise participants with low qualification and/or those adult whose qualification has become outdated. As a large share of participants had a higher education background (see Figure 2), it was then decided that they could be included in the programme in case there were vacancies available. The main reason behind these changes in the target group was the economic situation – initially the aim of the programme was just to increase participation in lifelong learning in general, although in the times of economic crisis it became more important to increase and to support people's labour market competitiveness and stability[4].

[4] Haaristo, H-S., Nestor, M. (2014). Review and expert opinion on the process of state funding of work-related trainings for adults. Praxis Center for Policy Studies.

FIGURE 1. WORKING AGE POPULATION (15-74) AND PARTICIPANTS OF WORK-RELATED TRAINING COURSES BY THEIR LEVEL OF EDUCATION (2009-2015) AS A SHARE OF TOTAL WORKING AGE POPULATION/TOTAL NUMBER OF PARTICIPANTS



Source: Ministry of Education and Research (data as of 26.08.2015); author's calculations based on Estonian Labour Force Survey data

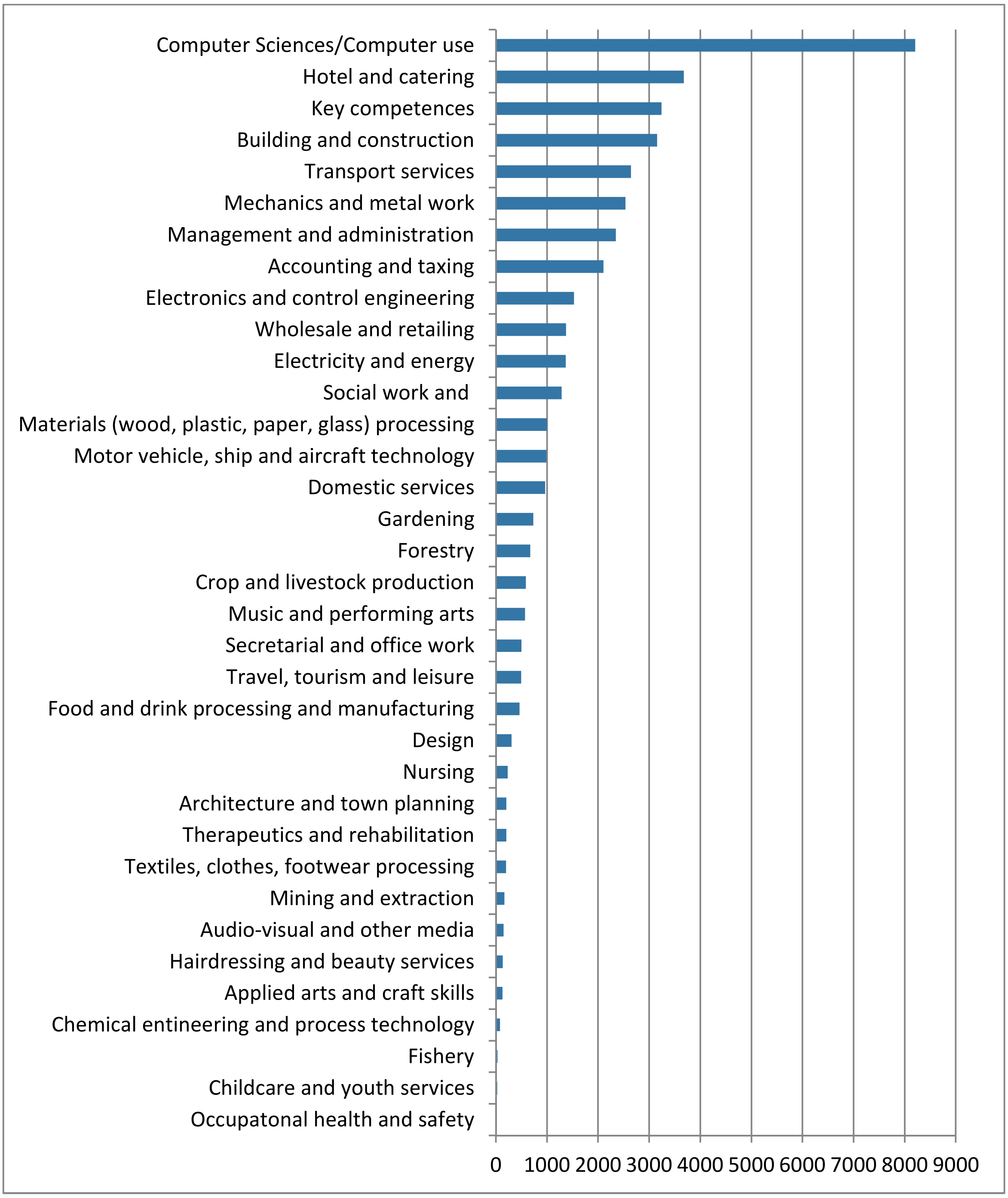
In our study we focus on evaluating the impact of participation in the courses which took place from the second half of 2010 until the second half of 2011. During this period the main target group as defined by the Ministry of Education and Research (MoER) were working age adults who had the compulsory education and were not studying at any vocational, professional or higher education institution at state-commissioned study places. Furthermore, the courses could not be ordered by companies for their employees. Since January 2011, it was also explicitly spelled out in the selection criteria that priority should be given to low skilled adults (Ministry of Education and Research, 2010 & 2011).

The current study will focus on analysing the impact of participation in the priority areas defined by the MoER in the second half of 2010 and first half of 2011. The main reasons behind this selection are as follows:

- firstly, no individual level data was centrally collected and stored; hence we had to construct the database of the participants from scratch by entering the data on participants manually from the paper application forms. This also meant that we had to keep the sample size manageable for that task.
- secondly, to increase the homogeneity of the intervention, we decided to focus on the so-called priority areas defined by the MoER in the second half of the 2010 and first half of 2011. The priority areas defined for that period included ICT skills, accommodation and catering, mechanics and metal work, trade and retail, material processing, electronics and automatics, energy and electrical engineering. While the total numbers of participants in the second half of 2010 and first half of 2011 were 5,758 and 5,254 respectively, in the priority areas the respective numbers were 2,553 and 2,386. In addition to the priority areas, the MoER required the category "building and construction" to be included into our analysis, because of the high number of participants in this area.
- thirdly, the main arguments behind the selection of the time period were: 1) the period to evaluate the post-participation effects is sufficiently long, 2) the

programme was at its "peak" during this time frame, the number of participants decreased remarkably from the second half of 2011, 3) since the second half of 2010 the registered unemployed were granted access to participate in the training courses (previously the access was denied for individuals registered as unemployed in the Estonian Unemployment Insurance Fund), 4) the comparison group will be composed based on the data from the Estonian Survey of Adult Skills (PIAAC), which was conducted in 2011 and retrospective part covered 12 months, hence we are able to observe the treatment and comparison groups during the same time period.

FIGURE 2. NUMBER OF PARTICIPANTS IN ADULT WORK-RELATED TRAINING COURSES BY CURRICULUM GROUPS, 2009–2015



Source: Ministry of Education and Research (data as of 25.08.2015)

2.2. Previous studies

Despite the fact that the observed intervention was one of the largest ESF projects both in terms of expenditures and participants, its impact has not been evaluated using counterfactual evaluation methods. Furthermore, there are no such evaluation studies available on adult education programmes provided under the jurisdiction of the MoER. Hence, conducting an evaluation study in the domain of MoER clearly has the largest added value in terms of awareness raising and data development.

In addition, international evidence on the effectiveness of government supported adult professional training programmes targeting the entire working age population is limited. As discussed in Schwerdt *et al*. (2011), the existing literature focuses either on analysing the labour market returns to private on-the-job-training within firms (e.g. Bassanini *et al.*, 2005; Frazis and Loewenstein, 2005; Booth and Bryan, 2005; Leuven and Oosterbek, 2008), labour market effects on formal education for adults (e.g. Albrecht *et al.* 2004; Stenberg, 2002, 2003,2005,2011; Bergemann and van den Berg, 2008; de Luna, Stenberg and Westerlund, 2011) or on estimating the impact of labour market training programmes targeted at the unemployed (see, for example, meta-analyses by Card, Kluve and Weber, 2010). In addition to these studies, Schwerdt *et al.* (2011) conducted an experimental study to analyse the Swiss untargeted voucher programme for adult education courses targeted at the entire population, but the design of this programme was different from our case.

The trend that seems to emerge from this literature is that participation in adult education courses targeted at the entire population has no or limited effects on employment probability or earnings of the participants (Schwerdt *et al.* (2011)). In addition, the impact of participation in formal training is smaller compared to vocational labour market training courses targeted at the unemployed (see Stenberg, 2002, 2003, 2005). Hence, the evidence seems to suggest that we can expect only limited positive impact on participants' future employment and prospective earnings and these should be lower than the training programmes targeted at the unemployed.

There are three impact evaluations available on the effects of labour market training targeted at the registered unemployed in Estonia (Leetmaa *et al.* (2003); Lauringson *et al.* (2011) and Anspal *et al.* (2012)). The earliest study by Leetmaa *et al.* (2003) was based on micro-level data from a follow-up survey and administrative records from the National Labour Market Board, which was a predecessor of the current Estonian Unemployment Insurance Fund. The study focused on analysing the impact of labour market training on employment and wages of the participants in Estonia during 2000–2002. The authors used propensity score matching and linear regression models and found a positive and statistically significant impact on employment probability of the participants one to two years after participation.

The more recent studies (Lauringson *et al.* (2011) and Anspal *et al.* (2012)) are based on linked administrative microdata from the Estonian Unemployment Insurance Fund and Tax and Custom Board. Both studies were based on matching methods and the results of these studies show that participation in labour market training in 2009–2010 increases the probability of being employed. However, as the official policy of the Estonian Unemployment Insurance Fund during this period was to offer training to the unemployed who were likely to find a job due to participation and there is no information on the selection process to training available in these studies, the positive results may be at least partly also associated with cream-skimming effects.

The recent impact evaluations of ALMPs in Estonia have been implemented by the Estonian Unemployment Insurance Fund with the exception of the study by Anspal *et al.* 2011. The lack of evaluation studies by academics is mainly due to the strict privacy protection rules, which make it difficult for researchers outside the EUIF to access the microdata.

However, over the course of the programme several analyses and studies have been carried out related to work-related training courses. There have been regular feedback surveys among the participants of the programme as well as few wider studies on participation in adult education and organisation of the work-related trainings.

Feedback surveys have been carried out annually since 2010[5] and in general the participants of the work-related training courses have been positively satisfied with the courses. Participants mainly emphasise the widening of their overall knowledge and horizon, gaining skills and knowledge that can be used outside of their everyday job and finding new acquaintances. On the other hand, the impact of the courses on people's work-related skills and opportunities has been perceived less. The strongest positive effect on their labour market competitiveness was realised by participants with lower educational levels, youth, men, non-Estonian speakers, people from the North-Eastern parts of Estonia, blue-collars, craftsmen, specialists and workers from the service sector. Conversely, unemployed participants did not describe any positive effect on their competitiveness in their feedback. **One of the main sources of discontent with the work-related training courses has been its short duration**. At the same time, no major conclusions can be drawn based on these feedback surveys as one of the major problems that has emerged when training activities are offered, is reaching the preferred target group – the unemployed and low qualifications groups – that have hence also been underrepresented in the feedback surveys.

In 2012 a study was implemented on the **participation of low educated adults in lifelong learning**[6]. The aim of the study was to describe the characteristics of the target group and factors that influence their participation in lifelong learning. It concluded that the main obstacles for participation were the price of the training, availability of courses, non-accordance with the work-schedule, age, health problems and family obligations. In 2013–2013 a study was carried out on **how to support the return of adults with a low education background (without basic or general education) to formal education**[7]. The aim of the study was to gather information about the barriers and preconditions for adults wishing to obtain secondary education in Estonia and, in the light of these, to analyse the current education organisation, study organisation and support measures regarding adult learners in adult gymnasiums and vocational schools. It concluded that the most prominent barriers to returning are financial and attitudinal barriers and that the most common motivators for adults to return to school are better career opportunities, wish to enter tertiary education or internal motivation to improve one's knowledge.

In 2014 an analysis was carried out to give an **overview of the planning process of the state-commissioned funding of work-related training courses**, to assess the relevance and effectiveness thereof, and to make recommendations for improvements in the future programmes[8]. The study pointed out that the objective of work-related training activities for adults is very broad (simultaneously increasing participation in lifelong learning as well as raising competitiveness), lacks

[5] Available at: http://ttka.hm.ee/uuringud-ja-analuusid/

[6] Järve, J., Räis, M.L., Seppo, I. (2012). Participation of low educated adults in lifelong learning. Centar.

[7] Räis, M.L., Kallaste, E., Kaska, M., Järve, J., Anspal, S. (2014). Supporting adults without basic or secondary education to return to formal education. Centar.

[8] Haaristo, H-S., Nestor, M. (2014). Review and expert opinion on the process of state funding of work-related trainings for adults. Praxis Center for Policy Studies.

clarity and leaves room for interpretation to various partners in the development process and therefore it has been more difficult to make relevant decisions regarding priority setting, course planning or funding of the courses. It also concluded that so far the development process of state-commissioned study places has not relied on sufficient and relevant input, including taking into consideration regional requirements, the needs of businesses and target groups and special circumstances. In addition, the target group has been very diverse as the employed and/or people with higher qualifications have different needs compared to the unemployed and/or lower qualification groups regarding raising their competitiveness. In the development process on state-commissioned study places no significant options existed that allowed for distinguishing between different target groups and taking their differing needs into consideration.

In 2014 an **analysis of the priority target groups of adult education by different Estonian counties**[9] was also carried out. Until now, the work-related training courses have been planned and funded based on the general target group and labour market needs throughout Estonia as a whole, but this has not been efficient enough as people's educational background, labour market competitiveness as well as the needs of the local labour market can differ greatly from one county to another. The study identified the most important target groups being people with low educational background, poor language skills, inactive elderly, those employed in low-salary jobs and non-ethnic Estonians. Although the shares of these groups vary among the counties it can still be seen that these are the groups with the lowest labour market competitiveness in Estonia.

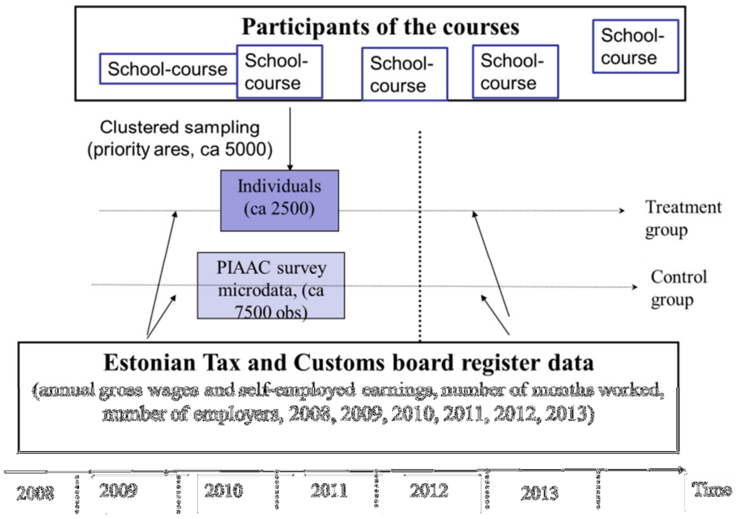
[9] Tõnurist, A. (2014). Priority target groups of adult education by counties. Estonian Statistical Office.

3. Data and evaluation technique

3.1. General approach

To evaluate the impact of the training programme, individual data from different sources were merged. First, a sample of individual level data of participants from the programme "Adult Vocational Training and Development Activities" from the second half of 2010 to the first half of 2011 were collected. Second, individual level data from the Estonian Survey of Adult Skills (national version of the Programme for the International Assessment of Adult Competencies (PIAAC)) were obtained to create a comparison group. PIAAC data was chosen to construct comparison groups as it includes people with a similar age, gender, education, language, and labour market status as the participants. The PIAAC survey was conducted in 2011–2012, and the retrospective part covered the previous 12 months, hence the same period as the treatment group. In addition, the PIAAC data has information on participation on short-term training courses, allowing us to exclude those people from the comparison group.

FIGURE 3. OVERVIEW OF THE DATA COLLECTION



Both data from the "Adult Vocational Training and Development Activities" programme and the Estonian PIAAC data were individually linked to tax records of the Estonian Tax and Customs Board. The information on tax data allowed us to receive information on (legally) working and labour earnings from 2008 until 2013, thus covering two years before and after the training period. Matching combined with difference-in-differences analysis was used to improve the match on observable characteristics between the treatment group and comparison group.

3.2. Sampling of the treatment group

The population for our study consists of training courses that began between 1 July 2010 and 31 June 2011. In total we had 871 courses with the background information of about 11,000 participants[10], such as proportion of males, disabled people, distribution of age groups, education levels, labour market status, languages of the courses, and share of people who completed courses. As individual level data on the population of the participants were not available we drew a stratified random sample of courses from priority subject areas (see Table 2) and then collected individual level data of all participants who finished the course from each course that was in the sample. The total number of courses in priority areas (including building and construction) was 461. From these courses we selected randomly 214 training courses in 31 different training centres with approximately 2,600 participants. The training centres sent scanned individual applications of all those participants who graduated the course to Statistics Estonia. From these scanned individual applications the main socio-economic characteristics of participants were entered into a computer database. Each observation received an individual unique ID number, which was later used to merge the database with different public registers. The variables used are described in Annex 7.

TABLE 2. SAMPLING OF COURSES

Subject area	Number of courses in total	Randomly sampled courses	% of sampled courses	Individuals according to the registry of courses in the sample	Individual records received on graduates
Computer sciences	171	41	24	529	527
Building and construction	55	33	60	385	370
Electronics	41	24	59	321	309
Electricity and energy	26	19	73	232	233
Wholesale and retailing	27	16	59	201	193
Hotel and catering	69	34	49	451	438
Materials processing	22	16	73	173	159
Mechanics and metal work	52	31	60	367	357
Total	**463**	**214**	**46**	**2,659**	**2,586**

Source: Ministry of Education and Research, own calculations

In total we received information on 2,586 participants, of which 4 people did not graduate (although data on graduates were asked) and were dropped from later analysis. The merging of individual applications allowed the analysis of the distribution of participants by courses taken, which had never been done before because of missing individual level register data. It revealed that the remaining 2,582 participants consisted of 2,331 different persons. While the majority of people (91.2%) had

[10] The maximum number of participants reported in various reports to the Ministry of Education and Research was 11,495. The number varied by different distributions (e.g. for age distribution the number was 10,220, for education structure the number was 10,218, etc.).

participated in only one of the courses (that was covered by our sample of courses), there were 7.5% of people who had taken two courses, and some people (1.4%) who had taken more than two courses.

TABLE 3. NUMBER OF DIFFERENT INDIVIDUALS IN THE TREATMENT GROUP

Courses	People	Proportion (%)
1	2,125	91.2
2	174	7.5
3	26	1.1
4	4	0.2
5	1	0.0
10	1	0.0
Total	**2,331**	**100**

Source: own calculations. Note: unweighted data.

Of those 2,331 people, 10 died (with 13 occurrences of training) before the end of our observation period (December 2013). As the number is so small we have dropped them from our analysis.

The main socio-economic characteristics of participants by the subject are presented in the following table. We have a large variation between courses. There is clear segregation by gender, males dominate in most of the courses: construction, electronics, electrotechnics and energy, materials, mechanics and metal work; females dominate in accommodation and wholesale and retail sale. On average, 66% of the people had courses in Estonian, 65% of participants were employed before the start of the courses, 24% were unemployed and 11% were inactive. The mean age was 39.5 years.

TABLE 4. CHARACTERISTICS OF THE TREATMENT GROUP

Course	Males	Course in Estonian language	Employed	Unemployed	Inactive	Mean age
Computer sciences	0.38	0.61	0.65	0.23	0.12	43.6
Building and construction	0.88	0.82	0.59	0.27	0.14	39.1
Electronics	0.89	0.60	0.84	0.10	0.07	36.9
Electricity and energy	0.98	0.45	0.61	0.26	0.13	41.4
Wholesale and retailing	0.22	0.83	0.49	0.35	0.16	35.9
Hotel and catering	0.06	0.71	0.68	0.24	0.08	40.9
Materials processing	0.94	0.84	0.70	0.22	0.08	38.9
Mechanics and metal work	0.99	0.48	0.64	0.26	0.10	35.1
Total	**0.62**	**0.66**	**0.65**	**0.24**	**0.11**	**39.5**

Source: own calculations. Note: unweighted data. Labour market status is self-assessed by participants

The employment and labour earnings based on registry data are presented in section 4.

The duration of courses, measured by contact hours and by the number of days the courses spanned, are described in Annex 5. Typically, the courses had duration of 40, 60 or 80 hours and they spanned over 1–2 months. The courses are short term and often distributed over longer period, over many weeks. The average duration of courses is also shorter than courses provided for the unemployed by the Estonian Unemployment Insurance Fund. (The average duration of courses provided by the EUIF was 129 hours in 2012, while the average duration was ca 50 hours in our population data.)

Our analysis of course subject areas and participants' occupation suggests that the participation in courses seems to be related to a person's occupation and the choice of courses is not driven by the need for a leisure activity (see Annex 4). For example, the biggest share of employed people taking construction courses is made up by building and related trades' workers. For electronics related courses, the biggest share of participants are electrical and electronic trades' workers. A similar trend also holds true for the rest of the courses. Hence, although in the feedback surveys participants emphasised the importance of widening of their overall knowledge and horizon, gaining skills and knowledge that can be used outside of their everyday job and finding new acquaintances (see previous section), our analysis shows that most of the courses are filled with participants who have a relevant occupation.

3.3. Selection of the comparison group

The comparison group was drawn from the Estonian PIAAC data set. Compared to the public user file[11], we received a few additional variables, such as detailed education levels, main language, county of residence, and occupation from the Ministry of Education and Research. The total sample size of the PIAAC data was 7,632 observations, of which 19 observations were also in the treatment group, resulting in 7,613 potential candidates for the comparison group. PIAAC data were also merged with information from tax records.

The PIAAC data included a question whether the person had participated in any kind of formal education during the survey or 12 months before the survey, i.e. depending on the interview date during the period August 2010–May 2012[12]. These people are excluded from the comparison group as the "Adult Vocational Training and Development Activities" programme is targeted at people who are not studying at any vocational, professional or higher education institution.

The PIAAC data also included a question whether the person had participated in any non-formal training during the previous 12 months before the interview[13]. Based on that indicator we have three possible comparison groups: a) those who did not participate in the non-formal training (our preferred comparison group); b) those who participated in the non-formal training; c) both previous groups. In all cases a comparison group is matched with participants based on main socio-economic variables and past labour market history.

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[11] Public dataset on Estonia "prgestp1.csv" is available at http://vs-web-fs-1.oecd.org/piaac/puf-data. We used the data version as of 6 December 2013.

[12] Question B_Q02a "Are you currently studying for any kind of formal qualification?" Question B_Q04a "During the last 12 months … have you studied for any formal qualification, either full-time or part-time?"

[13] Question B_Q12a_T "Courses outside the programme of studies in last 12 months (Trend-IALS/ALL), Yes (1) / No (2)"", in Estonian "Kas inimene on uuringule eelnenud 12 kuu jooksul osalenud väljaspool formaalhariduse omandamist täienduskoolitustel ?"

3.4. Evaluation strategy

3.4.1. Main technique

We use propensity score matching combined with difference-in-differences approach as our primary evaluation methodology. Propensity score matching is a flexible approach to estimate the effects of training on the labour market performance of participants. It allows taking into account rich background data and past labour market experience to make participants and non-participants comparable with each other.

We use two approaches. In the first approach we match labour market history (average monthly earnings, working months, number of employers before training) and socio-demographic variables (gender, age, mother tongue, education, region, occupation) and compare the difference in labour market variables of matched groups one or two years after training. In addition to propensity score matching, we employ simple regression adjustment technique on matched samples to discover potential heterogeneous effects of duration of schooling. In the second approach we match socio-demographic variables and calculate the difference-in-differences estimator on the matched sample, assuming a common trend in outcome variables. In both cases our main outcome variables are annual and monthly labour market earnings, average number of months employed and being employed at least in one month. For a brief overview of the propensity score matching and difference-in-difference techniques, see Loi and Rodrigues (2012)[14].

We compare the labour market status and earnings of those who participated in training with those who did not. Given that the two groups of people are similar with respect to all other characteristics, we can assign the difference in their labour market outcomes to training programmes. Next, we briefly present this formally, drawing closely on Sianesi (2001) and Heckman, Lalonde and Smith (1998).

We are interested in the effect of a labour market programme on an outcome *Y* of all employed and unemployed people, who constitute our population, compared to the absence of the programme. In our case, the population is all adult people who did not study in any formal training programmes and thus were eligible for the vocational work-related training in 2010–2011.

We use the following notation:

Y_1 – potential result when a person participates in the programme,

Y_0 – potential result when a person does not participate in the programme,

D=1, person participates in the programme,

D=0, person does not participate in the programme

X – personal characteristics that affect the labour market outcome and potentially participation in labour market programmes, but which are not influenced by the programme itself (for example, gender, ethnicity, general education, place of living, etc.).

Using the notation above, we can write the observed outcome for an individual *i*:

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[14] Massimo Loi and Margarida Rodrigues "A note on the impact evaluation of public policies: the counterfactual analysis", 2012, https://ec.europa.eu/jrc/sites/default/files/lbna25519enn.pdf.

$$Y_i = (1 - D_i)Y_{0i} + D_i Y_{1i} = Y_{0i} + D_i(Y_{1i} - Y_{0i}) \quad (1)$$

The effect of the active labour market programmes or treatment effect for an individual *i* is defined as the difference of the potential results $Y_{1i} - Y_{0i}$. As we cannot observe a person in two states, we aim only to estimate the average treatment effect on the treated (ATET):

$$ATET = E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1) \quad (2)$$

ATET shows the effect of the programme for those people who actually participated. As we cannot observe the last term of the equation (2) $E(Y_0 \mid D = 1)$ – the average outcome of those people who participated in the programme if they had not participated – we have to construct it.

First, we may use the non-participants actual outcome as the counterfactual:

$$E(Y_0 \mid D = 1) = E(Y_0 \mid D = 0) \quad (3)$$

We know that because of both observed and potentially unobserved differences in the characteristics of the participants and non-participants we cannot rely on the equality (3). We use the conditional independence assumption (CIA), which states that given the observed characteristics *X,* the outcome of participants if they had not participated is equal to the actual outcome of non-participants:

$$E(Y_0 \mid D = 1, X) = E(Y_0 \mid D = 0, X) \quad (4)$$

To find the ATET we have to find the average over *X* based on the distribution of *X* among participants.

$$\begin{aligned} ATET &= E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1) = \\ &= E_X\left[\{E(Y_1 \mid D = 1, X) - E(Y_0 \mid D = 1, X)\} \middle| D = 1\right] \\ &\overset{CIA}{=} E_X\left[\{E(Y_1 \mid D = 1, X) - E(Y_0 \mid D = 0, X)\} \middle| D = 1\right] \\ &= E_X\left[\{E(Y \mid D = 1, X) - E(Y \mid D = 0, X)\} \middle| D = 1\right] \end{aligned} \quad (5)$$

Whether the CIA is satisfied in our case is open to discussion. In theory, all relevant variables must be included in a set of X, but that is complicated in practice. We discuss this in the next section.

Due to the possible dimensionality problem, we estimate the effect of training using propensity score matching. This means that instead of conditioning on *X*, we condition on the probability to participate in the programme, which is the function of *X*:

$$E(Y_0 \mid D = 1, \Pr(D = 1 \mid X)) = E(Y_0 \mid D = 0, \Pr(D = 1 \mid X)) \quad (6)$$

The matching was based on the propensity score that was estimated using a probit model including various socio-economic variables and past labour market information. We imposed a common support by dropping treatment observations whose estimated propensity score was higher than the maximum or less than the minimum estimated propensity score of the comparisons. We impose a caliper (0.01) and we use different matching strategies: 1, 3 and 5 nearest neighbours, radius matching and kernel matching. Our explanatory variables *X* are labour market history (average monthly earnings, working months) and socio-demographic variables (gender, age, mother tongue, region, and occupation for employed people). Our main outcome variables *Y* are annual and average monthly labour market earnings, average number of months employed and being employed at least in one month. The effect of training is estimated for outcome variables in 2012 and 2013.

We also report point estimates and approximate standard errors to take into account unequal sampling probabilities, finite size of the population and clustering of participants into courses.

After matching we employ a weighted linear regression model on the matched sample to adjust for possible remaining differences in covariates or adding additional treatment indicators, such as duration of courses.

$$Y_{2013,2014} = \beta_0 + \beta_1 \times Duration_1 + \beta_2 \times Duration_2 + \beta_3 \times Y_{2008,2009} + \sum_k \alpha_k \times X_k + u \qquad \textit{with weights} \qquad (7)$$

We also use a difference-in-differences estimator on matched samples to check the sensitivity of our results. When using the difference-in-differences approach we match only on socio-economic variables and not on past labour market variables, which are used in differenced form as a dependent variable.

$$Y_{2013,2014} - Y_{2008,2009} = \beta_0 + \beta_1 \times D + \sum_k \beta_k \times X_k + u \qquad \textit{with weights} \qquad (8)$$

All estimation is done using Stata. Matching is done with the psmatch2 command written for Stata[15]. Estimation details are available from the authors.

3.4.2. Limitations of the analysis

The validity of our results relies on various assumptions and it is affected by several limitations.

First we have data limitations as we needed to combine two totally different data sources to have a treatment and a comparison group. Although we merge administrative data on the labour market history to our survey data sets, we still do not have detailed information on the past occupations of the people. Furthermore, for a control group that is derived from the PIAAC data, we observe detailed occupation variable only for employed people at the time of the survey of the PIAAC, i.e. between August 2011 and May 2012. When using occupation variable in the matching of employed treatment and comparison groups we will most likely underestimate the effect of the training as the comparison group must have been employed approximately a year after the training took place to have occupation variable in the data. (That is we do not allow people from the comparison group to become unemployed 2011-2012.)

Second, using matching to find treatment effects relies on two strong assumptions – the stable unit treatment value (SUTVA) and conditional independence assumption (CIA). The SUTVA assumption is relevant to all partial equilibrium analyses. General equilibrium effects may occur, for example, when participants take the jobs which would otherwise have gone to non-participants, or the so-called substitution and displacement effects. However, small programmes are unlikely to produce noticeable general equilibrium effects (Bryson *et al.* 2002, p. 5). As the share of participants in training

[15] E. Leuven and B. Sianesi. (2003). “PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing”. http://ideas.repec.org/c/boc/bocode/s432001.html, version 4.0.11 from 22 October 2014.

programmes has been below 2% of the labour force (20–64) during the observation period (see Table 1), we believe that there are no general equilibrium effects associated with these programmes.

For identifying the impact of training programmes we explicitly rely on CIA, which states that if all the characteristics that jointly influence the outcomes as well as the selection for the treatments are taken into account, the outcome of non-participants can be used as a counterfactual for participants. The plausibility of CIA depends on the richness of the available dataset as well as selection process into training. We think that past employment history, such as monthly wage, annual earnings, number of employers, number of months employed one and two years before the training, together with main demographic variables should capture personal characteristics that influence the participation decision in a training programme. When using propensity score matching we check the balance of these covariates to ensure that matching results in a similar comparison group.

As mentioned previously, there were some general administrative rules broadly defining the target population of the programme (see section 2.1). However, the selection process for the training consisted mainly of filling in an application, being accepted into the programme and starting the training course. Hence, as individuals self-select themselves into training, unobserved factors may affect participation decisions.

To get a greater in-depth overview on how the information on courses was shared and the participants were selected we interviewed training managers of the vocational training institutions. Out of 31 schools represented in our sample we received information from 28 training managers[16]. However, the results should be taken with some caution due to possible recalling errors as the interviews took place more than four years after the selection process was actually carried out[17].

The information about the courses was published in the public media, advertised on the website of programme as well as on the training institutions and also directly to local employers. The selection of participants into training courses was mainly based on the criteria established by the MoER and the requirements set out in the curricula for respective courses. The evidence from the interviews suggests that the number of participants equalled to available study places in 14 schools and exceeded only slightly the number of available study places in 5 schools. This was explained by the fact that most of the training courses were very specific (e.g. the use of the Sibelius music graphics program; preparatory courses for professional examination of electricians) and participation required specific knowledge and experience. However, in 9 schools the number of candidates exceeded remarkably the number of available study places. In these cases the selection of participants was based either on the first registered first served basis or additional screening of candidates (e.g. by requiring motivation letters, interviewing potential candidates, prioritising previous experience). Hence, in these 9 cases cream skimming effects might be present. We also tested whether the impact estimates were higher in schools where the competition for study places was tougher, but we found no effect.

In sum, given the available data, we cannot entirely justify the CIA. To avoid such problems in future, more detailed data on both participants as well as selection process including the number of candidates should be collected.

[16] We interviewed 30 training managers, but in 2 cases there was no information available on the required time period.

[17] Interviews took place in February–March 2015, while the participants were selected between the second half of 2010 and first half of 2011.

Third assumption that we use, is the assumption of common trends in outcome variables. That is to overcome the selection bias due to the possibility of unobservables we also use the difference-in-difference approach in combination with the propensity score matching. This means that instead of relying fully on CIA we invoke the assumption of common trend in outcome variables. It means that we assume that in the absence of the training programme, we assume that employment rate, earnings level, and number of months employed would have developed with the same trend both for the treatment and the control group. In Section 4.1 we will see that the participants and relevant comparison group seem to follow a common trend in the main labour market variables before the training, i.e. in 2008-2010.

Finally, our standard errors might be imprecise as a result of mixture of various statistical and econometric procedures when estimating the treatment effects. Our standard errors are affected by stratified random sampling of finite number of courses, potential clusters of participants within courses, and estimation of the propensity score. To test the sensitivity of our standard errors with respect to sampling procedure, we calculate also standard errors taking into account full sampling design.

4. Results

4.1. Comparison of treatment and unmatched comparison group

Before matching, the treatment and comparison group have different socio-economic characteristics (see Table 5 for details of the treatment group and various subsamples of PIAAC data). Our default comparison group consists of those observations from PIAAC that had neither formal nor non-formal training during the last 12 months before the survey (column *d* in Table 5).

TABLE 5. SOCIO-DEMOGRAPHIC STRUCTURE OF THE TREATMENT AND UNMATCHED COMPARISON GROUP

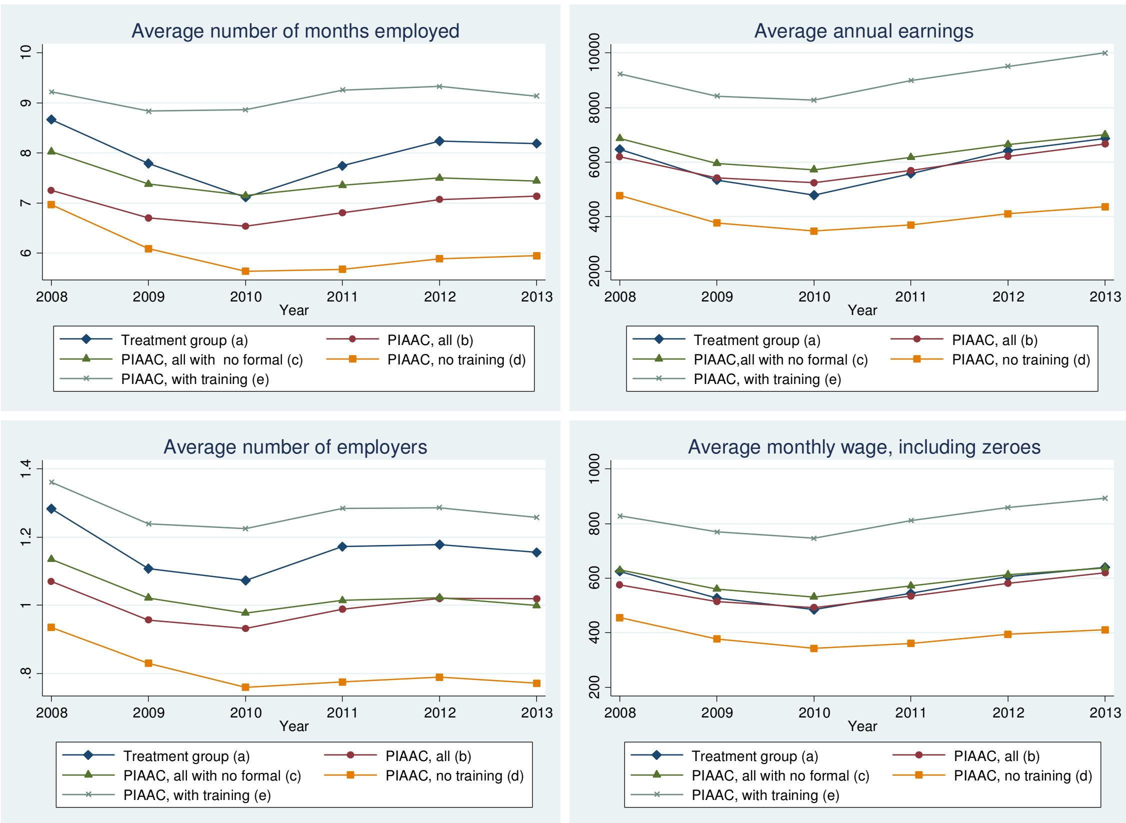
	(a)	(b)	(c)	(d)	(e)
	Treatment group	PIAAC			
		All observations	of which without formal training during last 12 months	and without non-formal training during last 12 months	with non-formal training during last 12 months
Gender (%)					
Female	39.6	54.6	54.3	50.4	58.8
Male	60.4	45.4	45.7	49.6	41.2
Age groups (%)					
16–19	0.9	7.7	1.8	1.7	2.0
20–29	24.9	20.2	16.4	14.4	18.6
30–39	25.4	20.5	21.7	17.6	26.2
40–49	25.7	20.9	24.1	22.8	25.5
50–59	19.6	21.2	24.9	27.1	22.3
60+	3.6	9.4	11.2	16.2	5.4
Education structure (%)					
Up to basic education	10.7	16.5	12.1	17.4	6.2
Secondary education	20.0	21.9	19.6	23.4	15.3
Vocational education after basic education	28.6	20.1	23.3	28.1	17.9
Vocational education after secondary education	18.6	15.5	17.4	16.2	18.8
University education	22.2	26.1	27.6	14.9	41.8
Main language (%)					
Estonian	64.7	71.4	69.5	64.2	75.5
Other	35.3	28.6	30.5	35.8	24.5
Number of people	2321	7613	6240	3315	2925

Source: own calculations, national PIAAC data. Note: unweighted data

Our treatment group (column *a*) includes more men (60.4% vs 49.6%), more people from age groups 20–49, and more people with university education. Analysis of PIAAC data shows that those people who had no non-formal training during the last 12 months before the survey (column (d)) compared to those who did (column (e)) were older, with lower education, included less Estonians and less men. We use propensity score matching to make treatment group and comparison groups similar with respect to socio-economic variables.

We merged both the treatment group and comparison group with tax records from 2008–2013. Figure 4 illustrates the average number of months people received earnings, number of employers, average annual earnings and monthly average earnings in treatment and (unmatched) comparison groups. The groups are the same as in Table 5. The people in the treatment group (group *a*) have a better labour market history than those in the PIAAC survey who did not take part in any training courses (group *d*), but worse than those in the PIAAC survey who also participated in some kind of informal training (group *e*).

FIGURE 4. DYNAMICS OF THE LABOUR MARKET OUTCOME IN TREATMENT AND UNMATCHED COMPARISON GROUP



Note: unweighted data; letters in the legend refer to the groups in Table 5.

The graphs show that the labour market outcome of the treatment group (*a*) and the PIAAC group without non-formal training (*e*) follow a similar trend before the treatment (in 2008–2009), which suggests that the common trend assumption of the treated and comparison group can be satisfied and the difference-in-difference approach used. We also use PIAAC group (c), which include both those who received and those who did not receive non-formal training, as a comparison group in several cases. Figure 4 suggests that in that comparison our treatment group experienced a steeper decline in all labour market indicators, suggesting that when applying the difference-in difference approach to this comparison group, most likely we might underestimate the effect of the treatment.

In what follows we drop all persons from comparison group that had formal training, because these people could not participate in the programme according to the programme rules. (That is we do not use comparison group (*b*) in our analysis anymore, but only a subset of it.) We match treated observations with two comparison groups from Table 5: 1) group (*c*), which we call "all PIAAC", 2) group (d), which we call "PIAAC with no non-formal training". We match on socio-economic variables and labour market history. We present mainly results with the first comparison group (observations from PIAAC who do not have non-formal training). Other results are available from authors.

4.2. Matching

The matching was based on propensity score, i.e. the probability to be in the treatment group. The probability depended on age, gender, education, main language and 2008–2009 labour market information, such as average monthly wage, employed or not, and number of different employers in a year when employed. The treatment probability was estimated using a probit model. When using difference-in-difference analysis we match only on socio-demographic variables and difference initial labour market discrepancies away.

The results of the probit models are presented in Table 6. Comparing our treated and all PIAAC sample (column (1)) or subset of PIAAC sample with no non-formal training (column (2)), we see that most of the explanatory variables are statistically significant. We have also estimated a model to compare those who were trained in our treatment group and those trained in the PIAAC sample (column (3)), although the latter group is not used as a comparison group.

TABLE 6. PROBIT MODEL RESULTS: TREATED VS COMPARISON GROUP

	(1)	(2)	(3)
	Treated vs PIAAC Table 5: (a) vs (c)	Treated vs PIAAC with no non-formal training Table 5: (a) vs (d)	Treated vs PIAAC with non-formal training Table 5: (a) vs (e)
Age group 16–19	0.275* (0.151)	0.815*** (0.175)	-0.664*** (0.184)
Age group 20–29	0.849*** (0.071)	1.213*** (0.079)	0.264*** (0.096)
Age group 30–39	0.716*** (0.070)	1.037*** (0.078)	0.240** (0.095)
Age group 40–49	0.645*** (0.069)	0.870*** (0.076)	0.285*** (0.094)
Age group 50–59	0.461*** (0.070)	0.601*** (0.076)	0.207** (0.096)
Male	0.364*** (0.032)	0.256*** (0.038)	0.480*** (0.039)
Estonian language	-0.111*** (0.032)	0.019 (0.038)	-0.247*** (0.040)
Secondary education	0.130** (0.057)	0.229*** (0.063)	-0.077 (0.077)

	(1)	(2)	(3)
	Treated vs PIAAC Table 5: (a) vs (c)	Treated vs PIAAC with no non-formal training Table 5: (a) vs (d)	Treated vs PIAAC with non-formal training Table 5: (a) vs (e)
Vocational education after basic education	0.198*** (0.055)	0.272*** (0.060)	0.007 (0.074)
Vocational education after secondary education	0.186*** (0.059)	0.417*** (0.067)	-0.218*** (0.077)
University education	0.056 (0.058)	0.539*** (0.067)	-0.465*** (0.075)
Number of months employed in 2008	0.005 (0.006)	0.000 (0.008)	0.006 (0.008)
Number of employers in 2008 is 1	0.229*** (0.071)	0.295*** (0.080)	0.111 (0.091)
Number of employers in 2008 is 2	0.340*** (0.078)	0.457*** (0.090)	0.190* (0.098)
Number of employers in 2008 is 3 or more	0.389*** (0.094)	0.607*** (0.113)	0.195* (0.115)
Monthly wages in 2008	-0.041 (0.046)	-0.008 (0.053)	-0.076 (0.055)
Number of months employed in 2009	-0.006 (0.006)	0.003 (0.006)	-0.019*** (0.007)
Number of employers in 2009 is 1	0.250*** (0.065)	0.171** (0.074)	0.252*** (0.083)
Number of employers in 2009 is 2	0.294*** (0.076)	0.173* (0.089)	0.330*** (0.096)
Number of employers in 2009 is 3 or more	0.329*** (0.097)	0.325*** (0.118)	0.338*** (0.117)
Monthly wages in 2009	-0.272*** (0.054)	-0.016 (0.065)	-0.416*** (0.064)
Constant	-1.713*** (0.087)	-1.933*** (0.095)	-0.172 (0.124)
Observations treated comparison LR test, chi2 (p-value) Pseudo R^2	8448 2290 6158 553.4 (p=0.000) 0.056	5544 2290 3254 726.1 (p=0.000) 0.097	5194 2290 2904 662.4 (p=0.000) 0.093

*** – p<0.01, ** – p<0.05, * – p<0.10, standard errors in parenthesis; no sample weights were used.

Notes: The age group 60+ and number of employers equal to zero were used as reference categories. Treatment group included only those who participated in the training courses in these schools that were included in the sample. Comparison groups never include those observations from PIAAC who participated in formal training either at the time of the survey or during the previous 12 months. In addition, in model (2) comparison group included only those observations that did not participate in non-formal training and in model (3) only those who did participate. See also Annex 7 for detailed description of variables.

TABLE 7. PROBIT MODEL RESULTS: TREATED VS COMPARISON GROUP FOR DIFFERENCE-DIFFERENCE ANALYSIS

	(1)	(2)	(3)
	Treated vs PIAAC Table 5: (a) vs (c)	Treated vs PIAAC with no non-formal training Table 5: (a) vs (d)	Treated vs PIAAC with non-formal training Table 5: (a) vs (e)
Age group 16–19	0.149 (0.149)	0.594*** (0.172)	-0.602*** (0.180)
Age group 20–29	0.873*** (0.070)	1.259*** (0.077)	0.298*** (0.094)
Age group 30–39	0.725*** (0.069)	1.120*** (0.076)	0.176* (0.093)
Age group 40–49	0.666*** (0.068)	0.947*** (0.074)	0.237** (0.093)
Age group 50–59	0.492*** (0.069)	0.668*** (0.075)	0.179* (0.094)
Male	0.311*** (0.030)	0.267*** (0.036)	0.377*** (0.037)
Estonian language	-0.136*** (0.032)	0.021 (0.037)	-0.308*** (0.040)
Secondary education	0.133** (0.056)	0.282*** (0.062)	-0.137* (0.076)
Vocational education after basic education	0.212*** (0.054)	0.335*** (0.059)	-0.038 (0.073)
Vocational education after secondary education	0.186*** (0.058)	0.500*** (0.065)	-0.298*** (0.076)
University education	0.015 (0.055)	0.666*** (0.064)	-0.664*** (0.072)
Constant	-1.425*** (0.080)	-1.636*** (0.087)	-0.021 (0.113)
Observations treated comparison LR test, chi2 (p-value) Pseudo R^2	8448 2290 6158 412.4 (p=0.000) 0.042	5544 2290 3254 563.7 (p=0.000) 0.075	5194 2290 2904 491.2 (p=0.000) 0.069

*** – p<0.01, ** – p<0.05, * – p<0.10, standard errors in parenthesis; no sample weights were used. Notes: see previous table

The resulting distribution of the propensity scores are presented in Annex 9. The figures show that for a few observations from the treatment group there is a problem to find similar observations from a comparison group and they may drop out from our analysis, although the overall number remained less than 10. We use different matching techniques to find similar people from the comparison groups, the main criteria being that resulting average characteristics were similar in the treatment group and comparison group.

4.3. Treatment effects

4.3.1. Propensity score matching

We apply radius matching and kernel matching to balance our treatment and comparison group in terms of both socio-demographic variables and previous labour market variables[18]. The means of unmatched and matched variables are presented in Annex 10 and 11. The matching procedure yielded similar treatment and comparison groups where none of the socio-economic variables or pre-treatment labour market characteristics was significantly different. We use two groups from where we drew comparisons: a) those observations from PIAAC that did not have any formal and non-formal education during last twelve months (Table 8); b) all PIAAC observations that did not have any formal education (Table 9).

The results suggest that the estimated average treatment effects on the proportion of employed are about 6 per cent in 2012 and 2013, and number of months employed is 0.5–0.7 months higher. Annual earnings are about 400–600 euros higher and monthly wages about 40–50 euros higher.

We also apply sampling design to take into account that people had unequal probabilities to be in the sample and that the total number of courses was not infinite, but only twice as large as our sample. The resulting point estimates are slightly higher and standard errors, which still take into account only sampling variance and not estimation of the propensity score, slightly smaller.

TABLE 8. ESTIMATED AVERAGE TREATMENT EFFECTS ON TREATED, COMPARISON GROUP WITHOUT NON-FORMAL TRAINING

	Participated in training	Matched comparison group	Difference	Standard error[a]	Weighted difference	Standard error[b]
Employed (not long-term unemployed)						
Radius matching						
2012	0.817	0.757	0.060	0.013	0.066	0.009
2013	0.808	0.745	0.064	0.014	0.072	0.009
Kernel matching						
2012	0.817	0.751	0.067	0.013		
2013	0.808	0.740	0.068	0.013		
Number of months employed						
Radius matching						
2012	8.240	7.584	0.656	0.158	0.797	0.111
2013	8.191	7.717	0.475	0.159	0.615	0.118
Kernel matching						
2012	8.240	7.500	0.740	0.155		
2013	8.191	7.634	0.557	0.157		
Annual earnings						
Radius matching						
2012	6415.8	5932.7	483.0	176.1	522.0	151.5
2013	6855.2	6430.4	424.8	189.9	462.8	158.3

[18] Nearest neighbour matching methods (we tried 1:1, 1:3 and 1:5) did not balance before treatment labour market variables.

	Participated in training	Matched comparison group	Difference	Standard error[a]	Weighted difference	Standard error[b]
Kernel matching						
2012	6415.8	5839.1	576.7	173.7		
2013	6855.2	6325.6	529.6	187.5		
Monthly wage						
Radius matching						
2012	604.4	561.1	43.3	15.0	43.0	12.3
2013	639.2	593.6	45.6	16.1	44.1	13.0
Kernel matching						
2012	604.4	553.7	50.8	14.8		
2013	639.2	585.3	53.9	15.9		

Note:
(a) standard errors do not take into account that propensity scores are estimated.
(b) standard errors based on reweighting of matched observations with Stata's survey command that takes into account sampling weights, clusters (courses), strata (subject areas) and finite population correction (total number of courses in each strata, where sample was taken).

When comparing our treatment group with the comparison group from all PIAAC data, consisting both of those who participated in any non-formal training and those who did not, the treatment effects are smaller, as expected, being insignificant for monthly wages and annual earnings and smaller for employment (about 3–4 percentage points) and months of employed (about 0.2–0.3 months).

TABLE 9. ESTIMATED AVERAGE TREATMENT EFFECTS ON TREATED, COMPARISON GROUP FROM ALL PIAAC

	Participated in training	Matched comparison group	Difference	Standard error[a]
Employed (not long-term unemployed)				
Radius matching				
2012	0.818	0.782	0.036	0.010
2013	0.808	0.768	0.040	0.011
Kernel matching				
2012	0.818	0.783	0.035	0.010
2013	0.808	0.768	0.040	0.011
Number of months employed				
Radius matching				
2012	8.248	7.978	0.270	0.129
2013	8.194	7.973	0.221	0.130
Kernel matching				
2012	8.248	8.006	0.242	0.128
2013	8.194	7.988	0.206	0.129
Annual earnings				
Radius matching				
2012	6431.1	6507.4	-76.3	171.6
2013	6872.4	6973.3	-100.9	186.3
Kernel matching				
2012	6431.1	6505.9	-74.8	170.3
2013	6872.4	6965.8	-93.4	184.9
Monthly wage				
Radius matching				
2012	605.6	606.7	-1.1	14.7
2013	640.5	642.9	-2.4	15.7
Kernel matching				
2012	605.6	605.3	0.3	14.6
2013	640.5	641.0	-0.5	15.6

Note: (a) standard errors do not take into account that propensity scores are estimated.

We also test whether there is any effect of the duration of the training courses (in lecture hours) on employment probabilities (Table 10). Of those who participated in a single course, about 13% of people had courses lasting less than 40 hours, 29% lasting 40–59 hours, 16% lasting 60–79 hours, and 33% lasting 80–119 hours. Those people who participated in more than one course also had accumulated training with more than 80 hours.

TABLE 10. DISTRIBUTION OF PARTICIPANTS ACCORDING TO DURATION OF COURSES ATTENDED

	One course	More than one course	Total
up to 40 hours	309 14.6%	0 0.0%	309 13.3%
40–59 hours	660 31.2%	5 2.5%	665 28.7%
60–79 hours	370 17.5%	7 3.4%	377 16.2%
80–119 hours	778 36.8%	50 24.5%	828 35.7%
more than 120 hours		142 69.61%	142 6.1%
Total	2,117 100.0%	204 100.0%	2,321 100.0%

Note: unweighted data

We add indicators of the duration of the first course (valid for more than 91% of people) to the regression model on the matched sample (with radius matching) of treated and comparison groups. For those who participated in more than one course, we have an additional indicator of participating in multiple courses in the regression model. Comparison group with zero duration of training serves as a reference category.

The results suggest that the effect of duration on the employment and future earnings is the highest when training courses lasted 40–59 hours (Table 11 and 12 include extracts from full models, see Annex 12 for the details of the estimation results.). Participation in more than one course in 2010–2011 did not have any significant positive effect. Surprisingly, participation in longer courses suggests a negative relationship with future earnings if we draw a comparison group from all PIAAC data, which is difficult to explain.

TABLE 11. ESTIMATED EFFECTS OF DURATION OF TRAINING ON LABOUR MARKET OUTCOME, COMPARISON GROUP WITHOUT NON-FORMAL TRAINING

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
up to 40 hours	0.066*** (0.021)	0.057*** (0.022)	0.849*** (0.255)	0.564** (0.263)	725.9** (290.6)	567.3* (333.1)	67.5*** (24.3)	49.7* (27.8)
40–59 hours	0.085*** (0.015)	0.105*** (0.015)	1.263*** (0.185)	1.065*** (0.181)	937.7*** (195.2)	970.7*** (215.9)	68.5*** (15.9)	83.6*** (17.8)
60–79 hours	0.050*** (0.019)	0.061*** (0.021)	0.429* (0.240)	0.284 (0.247)	597.4** (270.5)	532.2* (307.6)	49.4** (22.1)	65.4*** (25.3)
80 hours	0.054*** (0.015)	0.056*** (0.016)	0.401** (0.185)	0.302 (0.189)	73.8 (203.3)	-1.515 (227.4)	15.0 (16.9)	15.3 (19.1)
Participated in more than 1 course	-0.001 (0.027)	-0.052* (0.031)	-0.237 (0.329)	-0.393 (0.364)	80.4 (391.9)	64.2 (459.8)	22.9 (32.4)	-8.5 (39.4)

Notes: See Annex 12 for full models. The parameters are from a weighted linear regression model on matched sample, robust standard errors in parentheses. The model also includes age, gender, language, education, wage, number of months, and number of employers in 2008 and 2009. The same indicators are used in radius matching. The model includes only course duration of the first course if multiple courses have been participated.

TABLE 12. ESTIMATED EFFECTS OF DURATION OF TRAINING ON LABOUR MARKET OUTCOME, COMPARISON GROUP FROM ALL PIAAC

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
up to 40 hours	0.035* (0.020)	0.029 (0.021)	0.363 (0.242)	0.229 (0.251)	13.0 (270.3)	-90.1 (313.7)	10.1 (22.8)	-9.3 (26.4)
40–59	0.052*** (0.013)	0.075*** (0.013)	0.760*** (0.168)	0.709*** (0.165)	271.5 (173.3)	338.5* (194.8)	16.3 (14.2)	28.4* (16.1)
60–79	0.020 (0.018)	0.034* (0.020)	-0.028 (0.226)	-0.034 (0.234)	-46.5 (249.4)	-60.3 (286.0)	-2.4 (20.4)	11.9 (23.5)
80	0.027* (0.014)	0.030** (0.015)	-0.015 (0.171)	-0.014 (0.176)	-512.5*** (183.7)	-578.3*** (206.2)	-30.6** (15.3)	-36.0** (17.3)
Participated in more than 1 course	0.001 (0.027)	-0.058* (0.031)	-0.218 (0.325)	-0.434 (0.363)	136.0 (390.3)	62.1 (457.0)	27.7 (32.2)	-9.6 (39.3)

Notes: See Annex 12 for full models. The parameters are from a weighted linear regression model on matched sample, robust standard errors in parentheses. The model includes also age, gender, language, education, wage, number of months, and number of employers in 2008 and 2009. The same indicators are used in radius matching. The model includes only course duration of the first course if people have participated in multiple courses.

Analysis of the effects by labour market status suggests that the effects of training are larger for those who were already employed at the time when applying to the courses. For those who were unemployed or inactive, the effects were missing in most cases, and in a few cases even negative, which is hard to explain. The results that effects are larger for employed people and smaller or missing for unemployed people are in accordance with previous feedback surveys of participants (see Section 2.2), which found that the effect of training is missing for unemployed participants, as the training courses might be too short to be useful for the unemployed.

For employed people, the effect of training on later employment probability is 5–9 percentage points, depending on the comparison group and year of the outcome variable. Note that the average employment rate, which is measured as working at least one month in a year, was about 90% one year after the training among those who were employed before the training. The effect of the training on the number of months employed (that is the number of months earnings received) in a year varies between 0.55–1.35. The average number of months employed of the treatment group was 9.3–9.6. The effect on monthly earnings varies from 30–80 EUR, which is about 4-10% increase.

When we match also on occupation (ISCO first-level code) then the effect of training for employed people is smaller, often insignificant. However, these estimates most likely underestimate the true effect, as in order to have an ISCO code, people from the comparison group had to be employed at the time of the PIAAC survey, which was up to 12 months later than when the training took place (August 2011–April 2012). Hence, comparison group people must have been employed in the interim period between the treatment period (June 2010–July 2011) and outcome measurement period (2013).

TABLE 13. ESTIMATED AVERAGE TREATMENT EFFECTS ON TREATED BY LABOUR MARKET STATUS BEFORE TREATMENT, COMPARISON GROUP WITHOUT NON-FORMAL TRAINING

	Employed 2012	Employed 2013	Months employed 2012	Months employed 2013	Annual earnings 2012	Annual earnings 2013	Monthly wage 2012	Monthly wage 2013
Employed	0.093 (0.014)	0.075 (0.015)	1.35 (0.171)	0.885 (0.177)	1074.6 (209.2)	800.5 (227.9)	83.9 (17.7)	67.4 (19.2)
Employed (matched also on occupation)	0.028 (0.013)	0.023 (0.014)	0.400 (0.171)	0.220 (0.18)	696.3 (238.1)	563.7 (258.8)	60.7 (20.0)	50.1 (21.6)
Inactive	0.028 (0.034)	0.073 (0.034)	-0.177 (0.355)	0.124 (0.363)	-277.4 (322.0)	-236.4 (346.6)	-6.2 (29.6)	8.9 (31.9)
Unemployed	0.007 (0.023)	0.039 (0.022)	-0.662 (0.251)	-0.292 (0.254)	-1100.0 (217.2)	-732.9 (254.3)	-74.4 (19.4)	-36.0 (22.1)

Notes: The parameters are from a propensity score matching with radius matching. Standard errors in parentheses. The matching model includes age, gender, language, education, wage, number of months, and number of employers in 2008 and 2009. Treatment group observations are restricted to have self-assessed labour market status when applying for training courses. Point estimates and standard errors do not take into account sampling weights. Standard errors do not take into account that propensity scores were estimated. After propensity score matching treated and comparison group did not have remaining significant difference in pre-treatment variables.

TABLE 14. ESTIMATED AVERAGE TREATMENT EFFECTS ON TREATED BY LABOUR MARKET STATUS BEFORE TREATMENT, COMPARISON GROUP FROM ALL PIAAC

	Employed 2012	Employed 2013	Months employed 2012	Months employed 2013	Annual earnings 2012	Annual earnings 2013	Monthly wage 2012	Monthly wage 2013
Employed	0.061	0.050	0.860	0.552	571.0	371.8	44.9	30.1
	(0.011)	(0.011)	(0.135)	(0.142)	(200.2)	(219.6)	(17.)	(18.3)
Employed (matched also on occupation)	0.008	0.003	0.097	0.031	491.4	393.7	42.7	31.3
	(0.010)	(0.011)	(0.136)	(0.145)	(226.5)	(248.5)	(19.4)	(20.8)
Inactive	-0.006	0.037	-0.842	-0.315	-930.1	-748.8	-47.6	-35.8
	(0.033)	(0.032)	(0.337)	(0.345)	(321.9)	(347.5)	(29.7)	(31.9)
Unemployed	-0.017	0.016	-1.014	-0.582	-1546.4	-1211.7	-103.8	-77.7
	(0.021)	(0.021)	(0.238)	(0.241)	(225.1)	(260.7)	(20.1)	(22.5)

Notes: see previous table

We also estimated the effects of training on employment probability for different demographic groups by stratifying all analysis by the groups (see Table 15). The results suggest higher effects of training on later employment probability for people with lower education (up to basic education), younger (20–29) and older people (50+).

TABLE 15. ESTIMATED AVERAGE TREATMENT EFFECTS ON TREATED BY DEMOGRAPHIC GROUPS

	Comparison group: without non-formal training				Comparison group: all			
	Employed in 2012		Employed in 2013		Employed in 2012		Employed in 2013	
	Point estimate	St. error	Point estimate	St. error	Point estimate	St. error	Point estimate	St. error
Female	0.069	0.020	0.070	0.020	0.025	0.015	0.035	0.015
Male	0.059	0.019	0.063	0.019	0.035	0.014	0.031	0.015
Up to basic education	0.103	0.043	0.096	0.044	0.068	0.037	0.060	0.037
Secondary education	0.068	0.032	0.082	0.032	0.015	0.026	0.030	0.026
Vocational education after basic education	0.061	0.025	0.062	0.025	0.024	0.021	0.037	0.021
Vocational education after secondary education	0.061	0.033	0.082	0.033	0.032	0.024	0.043	0.024
University education	0.058	0.029	0.046	0.030	0.009	0.019	0.005	0.021
Non-Estonian	0.048	0.025	0.066	0.025	0.038	0.019	0.046	0.019
Estonian	0.061	0.017	0.056	0.017	0.028	0.013	0.032	0.013
Age 20–29	0.109	0.031	0.080	0.032	0.063	0.022	0.047	0.023
Age 30–39	0.046	0.027	0.057	0.027	0.009	0.020	0.009	0.020
Age 40–49	0.031	0.024	0.050	0.025	0.018	0.020	0.024	0.020
Age 50–59	0.074	0.029	0.093	0.029	0.033	0.023	0.047	0.023
Age 60–69	0.133	0.070	0.148	0.070	0.044	0.062	0.031	0.062

Notes: see previous table

4.3.2. Difference-in-difference analysis after propensity score matching

In the difference-in-difference analysis we compare the 2012 and 2013 labour market outcome of matched treated and comparisons with their 2008 and 2009 outcomes (Table 13). The results depend on the matching methods used. While one-to-one, one-to-three and one-to-five nearest neighbour matching methods did not always show significant results, radius matching and kernel matching suggests that treatment had some significant effect on annual earnings, average monthly wage and months employed. In all cases treated and comparison groups did not have any remaining significant differences in socio-economic variables after matching[19].

[19] Details are available from the authors.

The results of difference-in-differences analysis suggest that the effect of training is smaller compared to simple matching (Table 8 earlier). The point estimates of the effect of training on employment is about 2 percentage points (compared to matching estimates about 6–7 percentage points), but the effects are statistically insignificant in majority of cases. The point estimate of the effect of training on months in employment is about 0.3 months (matching estimates were about 0.5–0.7 months).

TABLE 16. TREATMENT EFFECTS OF DIFFERENCE-IN-DIFFERENCES ANALYSIS, COMPARISON GROUP WITHOUT NON-FORMAL TRAINING

	2013 vs 2008	2013 vs 2009	2012 vs 2008	2012 vs 2009
Employed (at least one months during a year)				
1:1	0.020	0.015	0.020	0.015
1:3	0.019	0.016	0.020	0.016
1:5	0.019	0.016	0.020	0.017
Radius matching	0.017	0.016	0.018	0.016
Kernel matching	0.019	0.017	0.023*	0.021
Number of months employed in a year				
1:1	0.157	0.160	0.309**	0.312**
1:3	0.167	0.166	0.314**	0.313**
1:5	0.157	0.133	0.311**	0.287*
Radius matching	0.056	0.096	0.238	0.279*
Kernel matching	0.079	0.126	0.306**	0.352**
Annual earnings				
1:1	469.629***	364.630**	466.332***	361.333**
1:3	510.045***	364.781***	514.965***	369.701***
1:5	521.634**	335.296**	532.327***	345.989**
Radius matching	430.488**	329.941**	448.967**	348.420**
Kernel matching	467.749***	405.028***	509.614***	446.893***
Average monthly wage (including zeroes)				
1:1	33.199*	33.941**	28.745*	29.487**
1:3	36.662**	34.683***	31.657**	29.678**
1:5	40.251**	35.016**	35.069*	29.834**
Radius matching	35.872*	34.558**	30.329*	29.014**
Kernel matching	37.001**	38.400***	35.042**	36.440***

Notes: *** p<0.01, ** p<0.05, * p<0.10, point estimates and standard errors do not take into account that propensity scores were estimated and there were different sampling weights. Matching was based on socio-economic variables using propensity score matching and requiring the common support. Adding sample weights to difference-in-difference regression models change the point estimates very little[20].

The estimated effects of training on annual earnings are 300–400 euros (matching estimates were 400–500 euros) and these are also statistically significant. The impact of training on average monthly

[20] Details are available from the authors.

wages, which includes zeroes for non-workers, are about 30–40 euros or 5-6% increase compared to pre-treatment wages. Overall, the difference-in-differences analysis shows that our results are sensitive to methods used, the difference-in-difference estimator giving smaller estimates compared to propensity score matching.

5. Conclusions and recommendations

Summary of results

In this analysis we used propensity score matching combined with difference-in-differences analysis and regression models to estimate the effect of adult vocational training in 2010–2011 on later labour market outcomes. We combined data from several sources. Treatment group data was received from training centres and for a comparison group we used PIAAC survey data. Both data were merged with individual tax records from the Estonian Tax and Customs Board from 2008–2013. We analysed the effect of training on later employment probability, number of months worked, annual earnings and average monthly wage.

Analysis suggests that adult vocational training has a positive effect on later labour market outcomes, but the size and statistical significance of the results are very sensitive to which comparison group and matching technique to use. As we combine totally different datasets, a risk remains that we are not able to fully make the treated and comparison group comparable in terms of unobservable characteristics.

When we use propensity score matching (PSM) technique, which assumes that there are no unobservable characteristics that would simultaneously affect participation in the programme and the outcome, the results are statistically and economically more significant, compared to the combined PSM and difference-in-differences approach, which assumes that there is a common trend in outcome variables.

When using more PSM technique our results indicate that the average effect of vocational training on later employment probability, which is equal to reduction in long-term unemployment in our case, is about 6–7 percentage points. The effect on the number of months employed in a year is about 0.5–0.6 months, which is similarly about 6–7 percentage increase from the average 7.7 months for the baseline case. We also see an average effect on monthly wage of about 40 euros per months. Analysis showed that the effect of duration of courses on the employment and future earnings is the highest when training courses were between 40–59 hours. Longer courses surprisingly did not have any larger effects. Analysis of the effects by labour market status suggests that the effects of training are larger for those who were already employed at the time when applying to the courses. The results are in accordance with feedback surveys of participants that the effect of training is missing for unemployed participants, as the training courses might be too short to be useful for the unemployed. We also estimated effects of training on employment probability for different demographic groups. The results suggest higher effects of training on later employment probability for people with lower education (up to basic education), younger (20–29) and older people (50+). The effect is smaller for people with university education and even insignificant when the comparison group is drawn from all PIAAC. We did not find any significant difference by main language or by gender.

On the other hand, our sensitivity analysis using difference-in-difference approach, which compares the difference in labour market outcomes of treated and matched comparison groups before and after the training, suggests that the effects of training are smaller, often statistically insignificant for employment rates or months of employment. We find that the average effect of training on employment is about 2 percentage points and on months in employment per year about 0.3 months, which is more than two times smaller than in the case of simple propensity score matching. The estimated effects of training on average annual earnings or average monthly wages are not so much affected by different estimation methods being around 300–400 euros per year or 30-40 euros per months (or 5-6% increase compared to pre-treatment wages), and these are also statistically significant. Overall, this is consistent with the conclusion by Schwerdt *et al.* (2011) that participation in adult education courses targeted at the entire population has no or limited effects on employment probability or earnings of the participants.

Our results show also that the effects of the adult vocational courses on employment are smaller than the impact of labour market training programmes arranged by the Estonian Unemployment Insurance Fund for unemployed people (Lauringson *et al.* (2011), Anspal *et al.* (2012)). This is to be expected as courses organized by the MoER are shorter and there is more variation in the labour market orientation of the courses.

As our results are sensitive to estimation method and comparison group used better background data on participants and comparison group together with follow-up of the participants is needed to ascertain the results, especially the long-run impacts.

Recommendations

Improving the intervention logic and targeting

One precondition for conducting counterfactual impact evaluation is clear intervention logic. There should be a clear causal mechanism, which links inputs and activities to outputs, results and impact. If the causal mechanism of the intervention is not clear, it is unlikely that the intervention can lead to measurable impacts. Well-designed intervention logic can be used for defining which results should be measured by counterfactual impact evaluations, what is the expected magnitude of the impact, who is the intended target group, when should the impact be measured and what data should be collected to measure the impacts. (European Commission, 2012)

In our case, the programme theory was only vaguely articulated in the documents. As a result, it was not clear whether the change in participants' post-programme employment status or income was seen as an impact of the programme. Instead, it seemed that creating additional study places for adult learners was emphasised as a priority. In evaluation literature the latter (number of courses offered in different subject areas) is usually treated as output of the programme, while the impact of the programme could be the change in employment status, occupation or income compared to non-participation.

Vaguely defined programme impact theory also led to a poor definition of the target group. In programme documents it was mentioned that priority should be given to participants with low qualifications and/or those adults whose qualification has become outdated. To participate in training courses the individuals had to show their own initiative and apply for the courses, which lead to the situation where a large share of participants had a higher education. The existing evidence also suggests that poorly qualified adults are less likely to participate in training measures and assuming that those people would pick up lifelong learning measures is a fallacy (Rubenson 2011). To reach the target group, the selection criteria were changed several times over the life-cycle of the programme, that is, between 2009 and 2013. For example, the unemployed were initially not entitled to participate; in later stages of the programme the courses could also be designed to the employees of the sole firm, which might reduce the incentives for firms to invest to training courses that increase firm-specific skills. The target group was stable during the evaluation period of the current study, but was changed before and after that, which means that the results are not directly transferrable to other time periods.

Hence, defining a clear intervention logic and target group (individuals or firms) as well as choosing an adequate approach to reach the target group is an important precondition for a programme to produce impacts of sufficient magnitude as well as for conducting impact evaluations. This conclusion is also supported by the analysis of Haaristo and Nestor (2014), who conducted process evaluation of the programme "Work-related training and development of adult education". They also found that the aim of providing adult training courses was not clear and the target group was poorly defined.

Collecting appropriate data electronically and improving access to microdata for researchers

As the individual level data was not centrally collected and stored for adult vocational training, we had to construct the database of the participants from the scratch. The relevant data was entered manually from the paperback application forms and the resulting dataset was thereafter merged with relevant registry data. This process was very time consuming and could have been avoided had the appropriate data collection mechanism been in place. Furthermore, we lacked some important variables for the evaluation that were not possible to collect later with reasonable cost.

In order to raise the awareness of the ESF Managing Authorities, the data collection process and database construction were properly documented. The types of data needed are summarised in Annex 1 and briefly discussed below.

In order to improve the capability to evaluate the impact of training, data on applicants, both successful and non-successful, should be collected. Currently, data on non-successful applicants are not stored. In case the number of non-applicants is too small to create a comparison group, a separate comparison group, e.g. from the Labour Force Survey, must be constructed.

The data on participants and non-participants should be merged with data from the Estonian Tax and Custom's board to get information on past and future labour market variables (e.g. earnings and number of employers). In addition, merging the data with the Estonian Unemployment Insurance Fund's register data would enable to get more accurate information about the participants and non-participants who are or who have been also registered as unemployed and received services and benefits by the EUIF (e.g. data on the length of unemployment spell, receipt of unemployment benefits, participation in training or other active labour market measures). The participants and non-participants data can be merged with data from the register of the Estonian National Social Insurance Board (*Sotsiaalkindlustusamet*) to get information on early retirement pensions and disability pensions.

To make the treatment and comparison groups more comparable, data about their current occupation, or previous occupation in case of the unemployed, should be asked in the application forms (currently, only the occupation of the employed people is known). In the future, the relevant information can be retrieved from the register of employees. Finally, participants might be asked in the applications in an adequate way whether they are going to use the gained knowledge in their work or rather in their personal life, in order to gain more insight if people are treating the courses as leisure or work-related activity.

In our case, the data was made available for analysts over a secure VPN connection in accordance with the "Procedure for dissemination of confidential data for scientific purposes" adopted by Statistics Estonia at the end of 2011. This procedure regulates the dissemination of all confidential data at the disposal of Statistics Estonia for scientific purposes, regardless of the source from which they were collected. Hence, this procedure allows Statistics Estonia to ensure that the data is handled according to the rules and we recommend using this option more widely for conducting impact evaluations.

In addition, we analysed the options for implementing the ESF Support Centre Guidance document "Monitoring and Evaluation of European Cohesion Policy. European Social Fund. Guidance Document

Annex D – Practical guidance on data collection and validation" for 2014-2020. We analysed in detail which indicators are available in the registries and which need to be additionally collected. While initially it was planned that the Managing Authorities will be responsible for collecting the relevant data, as a result of this analyses it was decided to delegate this task to Statistics Estonia. The process scheme for collecting data according to the requirements of those foreseen in the ESF guidance document can be found in Annex 2. Statistics Estonia has also developed a detailed description of the data collection process for ESF monitoring and guidance, but this is already out of the scope of the current project.

Both the detailed overview of the indicators required for evaluation of the impact of training programmes and the ESF data collection process can be used for building up an adult learning module in the Estonian Education Registry (EHIS).

Increase the awareness of civil servants responsible for evaluations in general and for ESF evaluations in particular

While the civil servants working in analysis departments have a broad understanding of the nature of impact evaluations, the authorities dealing with ESF management often lack the knowledge of how to plan, collect relevant data and conduct the CIEs. Both the vagueness of the intervention logic as well as the lack of data, which were serious hindrances in the case of the current evaluation as well as the feedback from the training sessions support that conclusion. Hence, capacity building (including training, different guidance materials, etc.) on the CIE approach within public authorities is still needed. As a part of this project both introductory and in-depth training courses on impact evaluations were conducted. (See Annex 13 for details).

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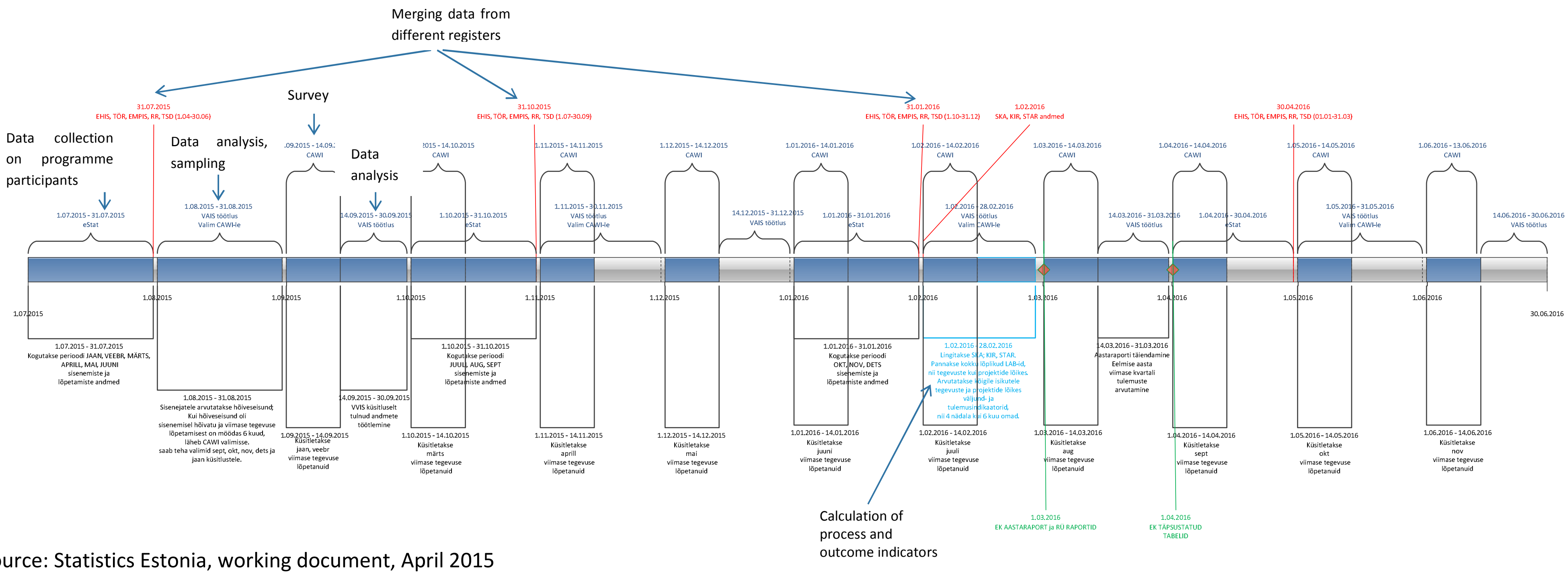
Annex 1. Data types and sources required for evaluating the impact of training

Variable	Treatment group	Comparison group 1 (non-successful applicants)	Comparison group 2 (other survey data, e.g. Labour Force Survey)
Unique personal identifier (*isikukood*)	From personal applications		Statistics Estonia has access
Gender and date of birth	From personal applications		From survey data
Educational attainment	From personal application; for younger people merge from education information system (EHIS)		From survey data; for younger people merge from education information system (EHIS)
Employment status when entering training, including information on self-employment, reasons of inactivity, duration of unemployment	From personal applications		From survey data
Occupation when entering training (last occupation if unemployed or inactive)	From personal applications		From survey data
Start and end date of the training	From personal applications	Cross-check that they have not participated	
Contact hours of training	From personal applications		
County of residence	From personal applications (was missing in our survey)		From survey data
Past and future labour market variables, monthly	Merge from Estonian Tax and Custom Board register data		
Past and future benefit recipiency (depending on specific programme and participants)	Merge from Estonian Unemployment Insurance Fund (*Töötukassa*) register (unemployment benefits, participation in active labour market programmes) Merge from Estonian National Social Insurance Board (*Sotsiaalkindlustusamet*) register (pensions, including early retirement pensions and disability pensions)		

Annex 2. Proposed data collection process for implementing the ESF monitoring and Guidance rules



Source: Statistics Estonia, working document, April 2015

Notes:

eStat - electronic data collection environment by Statistics Estonia,

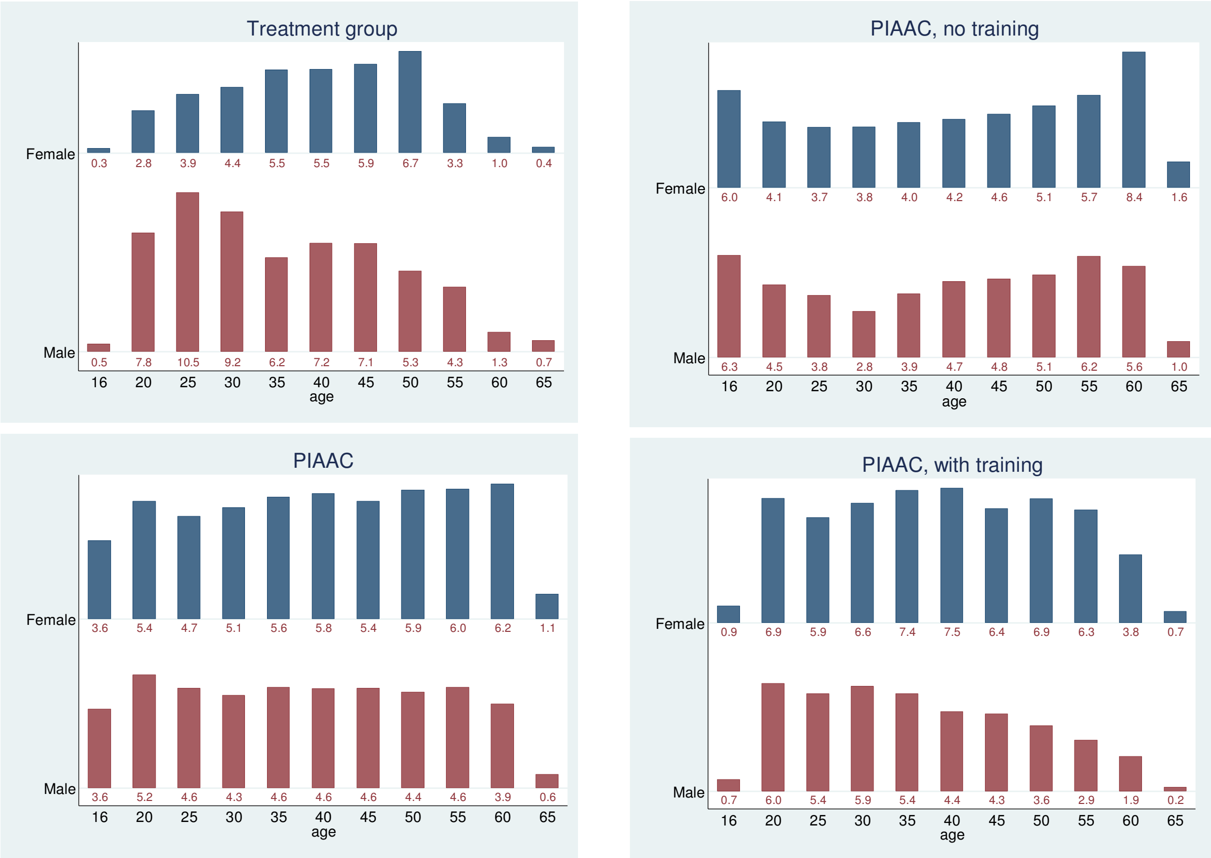
CAWI – computer assisted web interview,

VAIS – information system for data analysis by Statistics Estonia (*vaatluste andmetöötluse infosüsteem*),

EHIS,TÖR, EMPIS, RR, TSD, SKA, KIR, STAR – abbreviations of various Estonian registers.

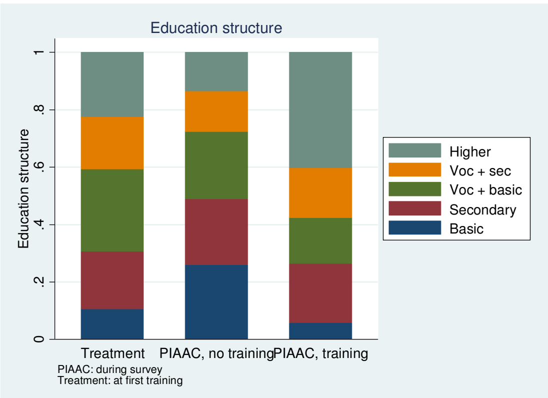
Annex 3. Socio-economic structure of treatment and unmatched comparison group

Age-gender structure



Note: unweighted data

Educational structure in treatment and unmatched comparison group



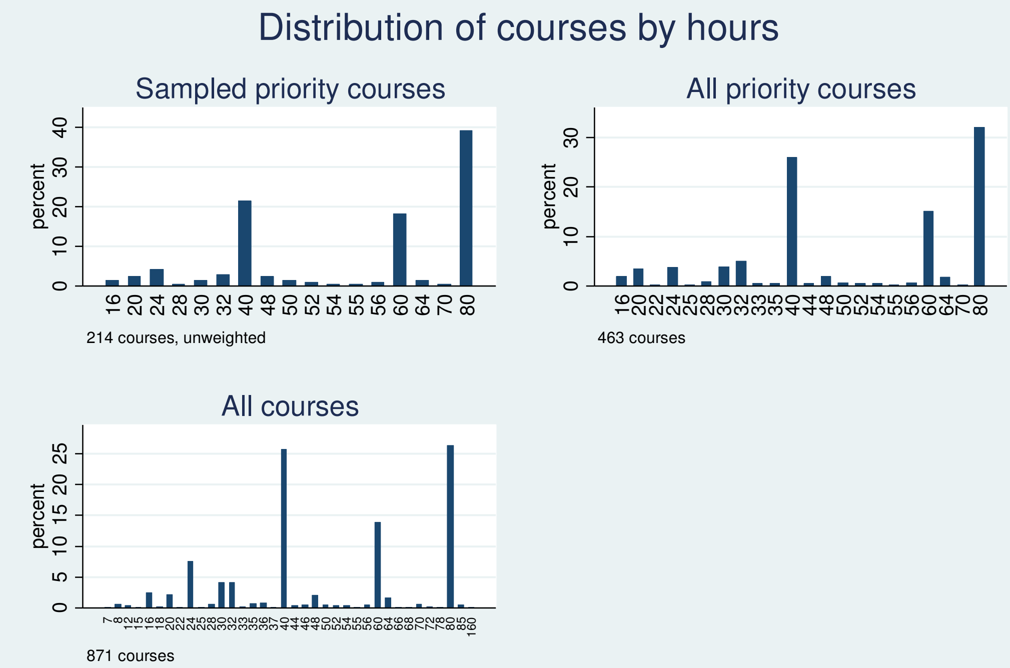
Note: unweighted data

Annex 4. Participants by course area and occupational background, %

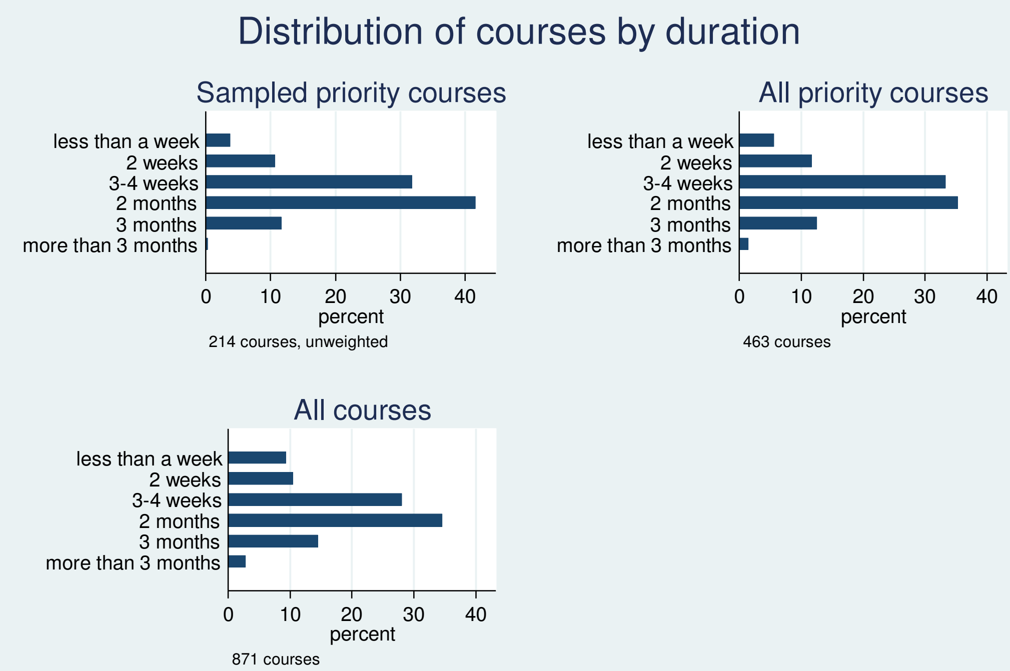
Occupation	Computer science	Construction	Electronics	Electrotechnics and energy	Wholesale and retail sale	Accommodation	Material	Mechanics and metal work	Total
Unemployed	35.2	41.1	15.9	38.5	51.1	32.3	29.3	35.7	34.5
Occupation unknown	10.2	14.4	9.9	6.9	3.7	8.6	17.8	18.1	11.3
Metal, machinery and related trades workers	2.2	6.0	8.9	2.6	0.0	0.0	5.1	21.0	5.8
Electrical and electronic trades workers	1.4	0.5	18.9	19.5	0.0	0.0	1.9	2.0	4.8
Personal service workers	1.2	0.0	0.0	0.0	2.1	24.7	1.3	0.0	4.6
Science and engineering associate professionals	2.7	2.2	15.2	8.2	1.1	0.5	1.9	2.6	4.1
Production and specialised services managers	3.9	4.6	3.3	6.5	1.6	1.2	5.1	2.6	3.4
Science and engineering professionals	5.7	1.4	8.0	4.3	2.1	0.7	1.3	0.6	3.1
Sales workers	5.3	1.1	0.0	0.9	17.9	1.2	1.3	0.6	3.0
Building and related trades workers, excluding electricians	0.4	12.0	2.0	1.3	0.0	0.2	2.6	3.4	2.8
Hospitality, retail and other services managers	2.3	1.6	0.3	0.9	2.6	5.4	3.8	0.6	2.2
Teaching professionals	4.7	1.4	0.3	1.7	0.5	3.0	1.3	1.1	2.1
Stationary plant and machine operators	1.4	0.8	5.3	0.4	0.5	0.7	5.7	4.0	2.1
Business and administration associate professionals	3.3	0.8	0.7	0.4	3.2	1.6	1.3	0.9	1.6
Administrative and commercial managers	2.5	1.9	0.0	0.9	3.2	2.1	0.6	0.6	1.6
Food processing, wood working, garment and other craft and related trades workers	1.2	0.8	2.7	0.0	1.1	1.2	7.6	0.3	1.5
Business and administration professionals	2.9	0.0	1.0	0.4	1.1	1.4	1.3	0.0	1.1
Customer services clerks	0.6	0.0	0.0	0.0	1.6	4.7	0.0	0.0	1.0
Protective services workers	0.8	2.5	0.3	2.2	0.0	0.0	0.6	1.4	1.0
Drivers and mobile plant operators	0.4	1.1	0.7	0.4	0.0	0.0	1.9	2.8	0.9
Numerical and material recording clerks	2.2	0.5	0.0	0.0	0.5	0.7	1.9	0.3	0.8
Information and communications technology professionals	2.7	0.3	0.0	0.0	0.5	0.2	1.9	0.3	0.8

Occupation	Computer science	Construction	Electronics	Electrotechnics and energy	Wholesale and retail sale	Accommodation	Material	Mechanics and metal work	Total
Assemblers	0.2	0.5	4.0	0.0	0.0	0.0	1.3	0.0	0.7
Cleaners and helpers	0.8	0.5	0.0	0.0	0.0	2.3	0.0	0.3	0.7
Legal, social, cultural and related associate professionals	0.6	0.3	0.0	0.4	0.5	2.6	0.0	0.0	0.7
Refuse workers and other elementary workers	0.6	0.5	0.0	1.3	1.1	0.7	1.3	0.0	0.6
Health associate professionals	0.6	0.3	0.0	0.4	0.5	0.7	0.6	0.0	0.4
Labourers in mining, construction, manufacturing and transport	0.0	0.8	0.0	0.4	0.5	0.2	0.0	0.9	0.4
Information and communications technicians	0.2	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.3
General and keyboard clerks	0.4	0.0	0.7	0.4	0.0	0.5	0.0	0.0	0.3
Other clerical support workers	0.6	0.5	0.0	0.0	0.5	0.2	0.0	0.0	0.3
Non-commissioned armed forces officers	0.2	0.0	0.0	0.4	2.1	0.0	0.0	0.0	0.2
Food preparation assistants	0.0	0.0	0.0	0.0	0.0	1.4	0.0	0.0	0.2
Market-oriented skilled agricultural workers	0.2	0.8	0.0	0.0	0.5	0.0	0.6	0.0	0.2
Personal care workers	0.6	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.2
Chief executives, senior officials and legislators	0.8	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.2
Legal, social and cultural professionals	0.6	0.0	0.0	0.4	0.0	0.2	0.0	0.0	0.2
Health professionals	0.6	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.2
Market-oriented skilled forestry, fishery and hunting workers	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Handicraft and printing workers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0
Subsistence farmers, fishers, hunters and gatherers	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Commissioned armed forces officers	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Annex 5. Distribution of courses by hours and days

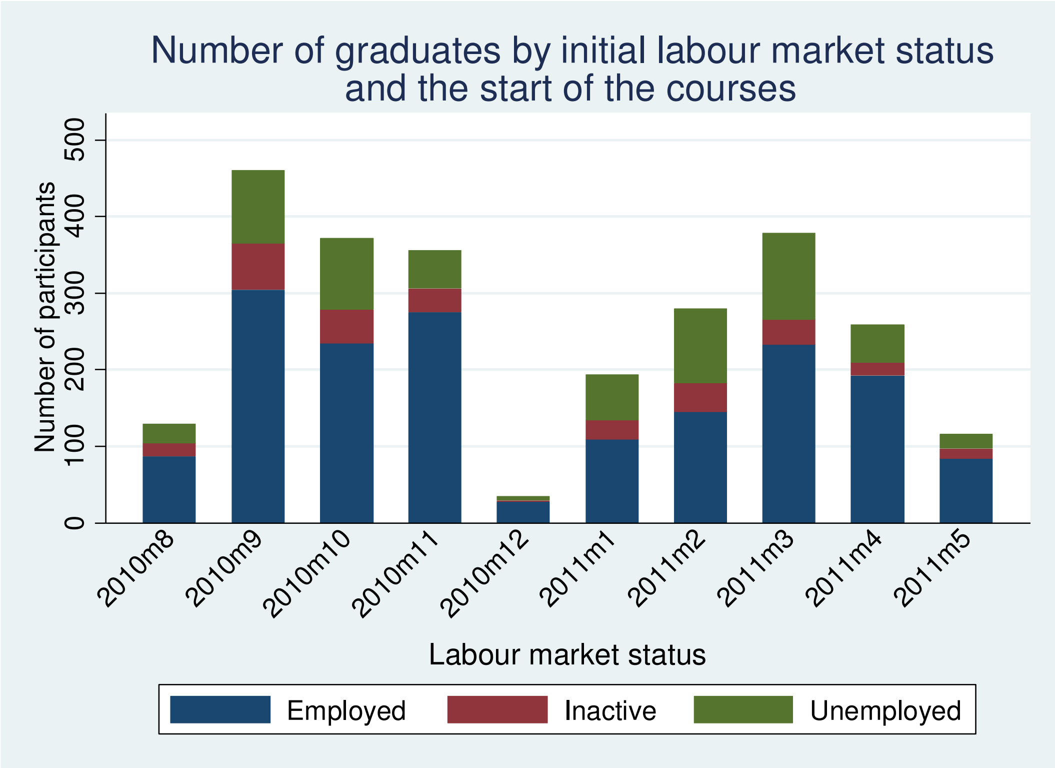


Source: Ministry of Education and Research, own calculations
Data covers July 2010 - June 2011



Source: Ministry of Education and Research, own calculations
Data covers July 2010 - June 2011

Annex 6. Distribution of participants by labour market status



Annex 7. Definition of outcome and explanatory variables

Variable	Definition	Treatment group	Comparison group
Employed in a given month	Employed if in the given month at least one employer has declared taxable earnings on behalf of the person	Merged tax authority data January 2010–December 2013	
Annual earnings	Sum of monthly taxable earnings that employers have declared		
Number of months employed	Number of different months in a year when employers have declared positive earnings		
Number of employers in a year	Number of different employers that have declared positive earnings in one year		
Average monthly wage	Annual sum of monthly earnings that employers have declared dividend by the number of months employed. Zero for those who have no earnings		
Age and gender	Gender and birthdate are derived from the ID number (*isikukood*)	ID from the application form. Age at the time of applying to the course	ID from the PIAAC survey. Age at the time of the survey
Education	Education at the time of: a) entering training programme (treatment group) b) survey (comparison group) First two categories were aggregated Those people from PIAAC data who have obtained education abroad were excluded in later analysis (34 observations)	Information from the application. Classification: 1 Primary education 2 Basic education 3 Secondary education 4 Vocational education after basic education 5 Vocational education after secondary education 6 University education 9 Unknown	Merged from national version of the PIAAC data to public user file. (Variable b_q01aee_cat6) Classification: 1 Primary education 2 Basic education 3 Secondary education 4 Vocational education after basic education or without basic education 5 Vocational education after secondary education 6 University education 7 Education from abroad
Job	ISCO8, aggregated to the first-digit code	Four-digit ISCO code, verbal description from the application form coded by Statistics	Four-digit ISCO code merged from national version of PIAAC data to public user file

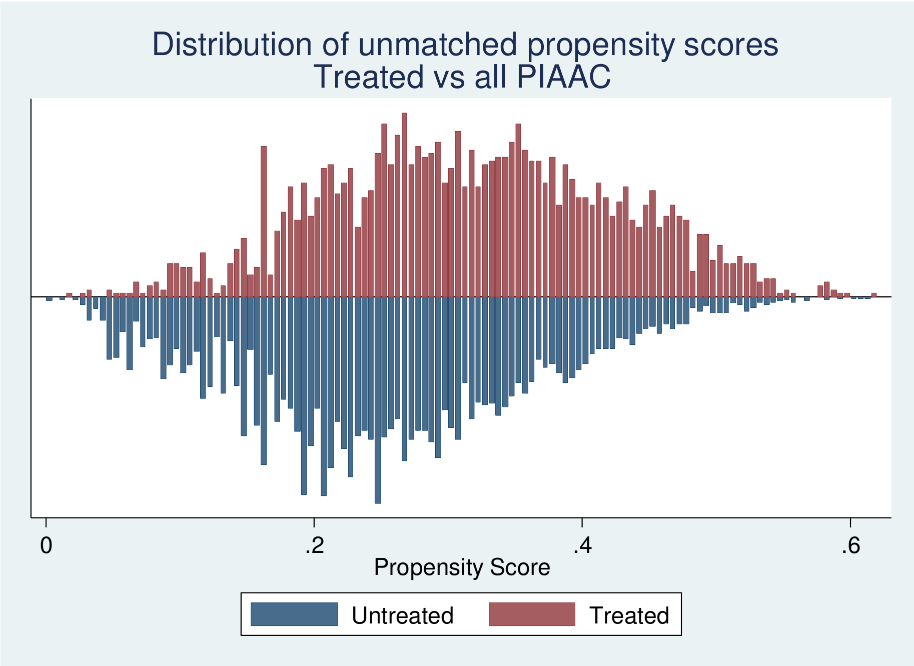
Variable	Definition	Treatment group	Comparison group
		Estonia	
Language	1 – if main language is Estonian 0 – other	Information from the application. Classification: 1 Estonian 2 Other	First language learned in the childhood. Classification: 1 Estonian 2 Russian 3 Other 4 Unknown
County		County of the training centre, entered manually	County of residence. Merged from national version of the PIAAC data to public user file. (Variable “maakond”)

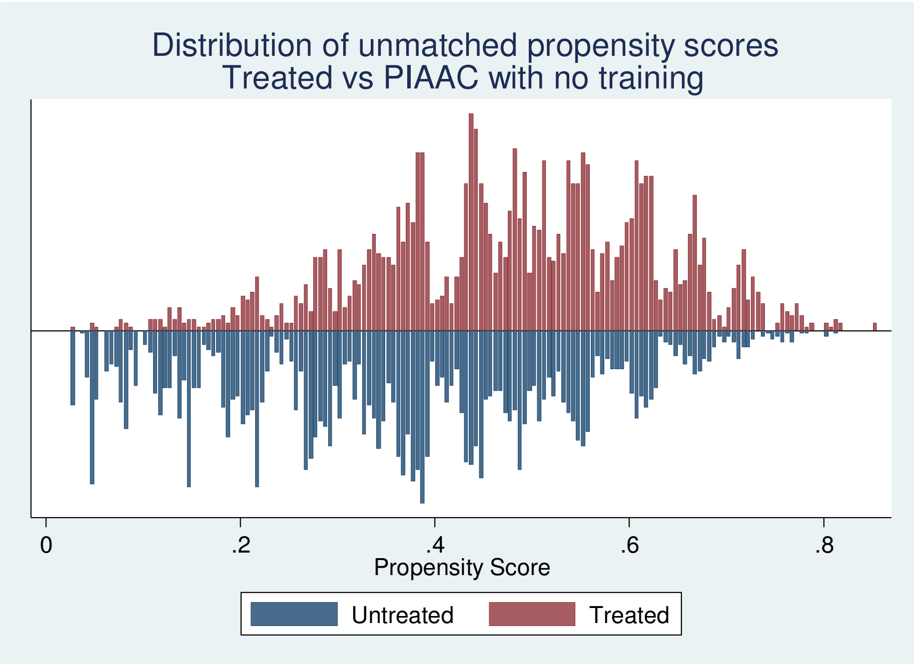
Annex 8. Definition of treatment variables in different comparison groups

	(1)	(2)	(3)
Comparison	Treated vs PIAAC	Treated vs PIAAC with no non-formal training	Treated vs PIAAC with non-formal training
Treated (D = 1)	All people that graduated from the courses in the schools that were included in the sample (including 19 observations that happened to be also in the PIAAC dataset)		
Non-treated (D= 0)	All PIAAC except those who studied in formal education (and less 19 observations that received training)	All PIAAC except those who studied in formal education or who participated in courses outside formal education (see below that are excluded)	All PIAAC except those who studied in formal education or did not participate in courses outside formal education (see below that are excluded)
PIAAC observations excluded from analysis	Observations with: B_Q02A==1 or B_Q04A==1 where B_Q02A: Are you currently studying for any kind of formal qualification? (1- yes) B_Q04A: During the last 12 months…have you studied for any formal qualification, either full-time or part-time? (1- yes) As a result, 1373 observations dropped from PIAAC analysis	Column (1) + B_Q12a_T = 1 (1- yes) B_Q12a_T: Participated in courses outside of program of studies in last 12 months	Column (1) + B_Q12a_T ≠ 1 (1- yes) B_Q12a_T: Participated in courses outside of program of studies in last 12 months

Annex 9. Distribution of propensity scores

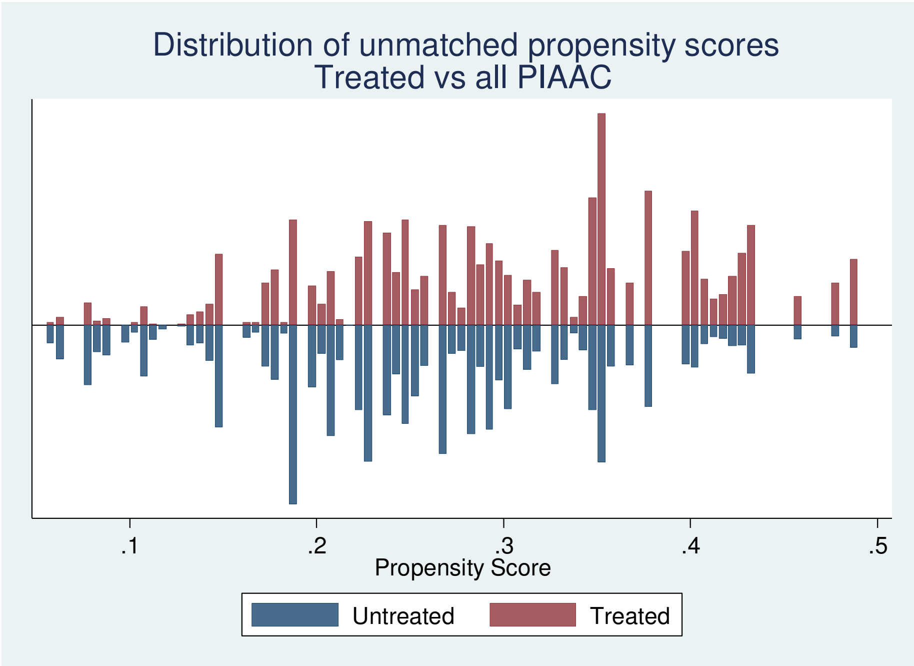
Distribution of estimated propensity scores of treatment and different comparison groups for kernel and radius matching

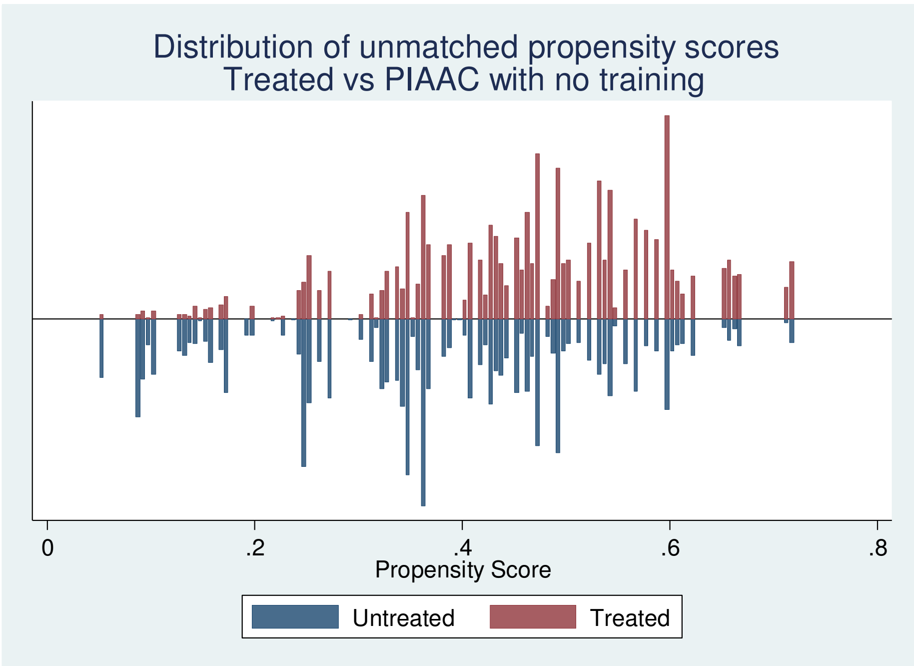




Note: Propensity score was estimated using age, gender, language, education, number of employers (including non-working) and monthly wage in 2008 and 2009. PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Distribution of estimated propensity scores of treatment and different comparison groups for difference-in-difference analysis





Note: Propensity score was estimated using age, gender, language, and education. PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Annex 10. Matching quality after radius matching

Comparison group – PIAAC observations without non-formal training

Variable	Unmatched (U)	Mean		%bias	t-test	
	Matched (M)	Treated	Comparison		t	p-value
Age group 16-19	U	.0083	.0169	-7.7	-2.75	0.006
	M	.00832	.00911	-0.7	-0.29	0.774
Age group 20-29	U	.25066	.14136	27.8	10.38	0.000
	M	.24869	.2414	1.9	0.57	0.567
Age group 30-39	U	.25328	.17763	18.5	6.85	0.000
	M	.25394	.24855	1.3	0.42	0.675
Age group 40-49	U	.25721	.22803	6.8	2.51	0.012
	M	.25788	.269	-2.6	-0.85	0.394
Age group 50-59	U	.19563	.27259	-18.2	-6.62	0.000
	M	.19615	.20296	-1.6	-0.58	0.565
Male	U	.60393	.49324	22.4	8.19	0.000
	M	.60289	.59328	1.9	0.66	0.508
Estonian language	U	.65284	.65089	0.4	0.15	0.881
	M	.65193	.66538	-2.8	-0.96	0.338
Secondary education	U	.19956	.23448	-8.5	-3.09	0.002
	M	.20009	.1978	0.6	0.19	0.846
Vocational education after basic education	U	.28603	.28181	0.9	0.34	0.732
	M	.28678	.28346	0.7	0.25	0.804
Vocational education after secondary education	U	.18603	.16257	6.2	2.28	0.023
	M	.18651	.18942	-0.8	-0.25	0.802
University education	U	.22183	.14935	18.7	6.96	0.000
	M	.21979	.22375	-1.0	-0.32	0.747
Number of months employed in 2008	U	8.6686	7.067	32.3	11.70	0.000
	M	8.6616	8.7455	-1.7	-0.63	0.532
One employer in 2008	U	.569	.5335	7.1	2.62	0.009
	M	.57049	.58512	-2.9	-1.00	0.317
Two employers in 2008	U	.22052	.14352	20.1	7.46	0.000
	M	.22023	.21856	0.4	0.14	0.892
Three or more employers in 2008	U	.08035	.0378	18.1	6.85	0.000
	M	.07881	.07247	2.7	0.81	0.418
Monthly wage in 2008	U	.62564	.45973	31.5	11.54	0.000

Variable	Unmatched (U)	Mean		%bias	t-test	
	Matched (M)	Treated	Comparison		t	p-value
	M	.6254	.63891	-2.6	-0.81	0.419
Number of months employed in 2009	U	7.7904	6.1687	31.2	11.36	0.000
	M	7.7815	7.8566	-1.4	-0.51	0.609
One employer in 2009	U	.60175	.51659	17.2	6.30	0.000
	M	.60333	.61312	-2.0	-0.68	0.498
Two employers in 2009	U	.15371	.11125	12.5	4.66	0.000
	M	.15324	.15352	-0.1	-0.03	0.979
Three or more employers in 2009	U	.05895	.03042	13.8	5.21	0.000
	M	.05736	.0529	2.2	0.66	0.510
Monthly wage in 2009	U	.52748	.3815	31.5	11.54	0.000
	M	.52713	.53166	-1.0	-0.32	0.752

Note: PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Summary statistics of matching

Sample	Propensity score model R^2	LR chi2	p>chi2	Mean bias	Median bias
Unmatched	0.097	726.05	0.000	16.7	18.1
Matched	0.001	6.35	0.999	1.6	1.6

Comparison group – all PIAAC observations

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Control	%bias	t	p-value
Age group 16-19	U	.0083	.01835	-8.8	-3.31	0.001
	M	.0083	.0089	-0.5	-0.22	0.825
Age group 20-29	U	.25066	.16239	21.9	9.31	0.000
	M	.25033	.2525	-0.5	-0.17	0.866
Age group 30-39	U	.25328	.21712	8.5	3.53	0.000
	M	.25339	.24705	1.5	0.49	0.621
Age group 40-49	U	.25721	.2405	3.9	1.59	0.113
	M	.25732	.2594	-0.5	-0.16	0.872
Age group 50-59	U	.19563	.24959	-13.0	-5.21	0.000
	M	.19572	.19586	-0.0	-0.01	0.990
Male	U	.60393	.45518	30.1	12.26	0.000
	M	.60376	.60311	0.1	0.04	0.964
Estonian language	U	.65284	.70071	-10.2	-4.22	0.000
	M	.65312	.65794	-1.0	-0.34	0.731
Secondary education	U	.19956	.19601	0.9	0.37	0.715
	M	.19965	.19993	-0.1	-0.02	0.981
Vocational education after basic education	U	.28603	.23335	12.0	4.99	0.000
	M	.28615	.28584	0.1	0.02	0.981
Vocational education after secondary education	U	.18603	.17441	3.0	1.24	0.214
	M	.18567	.18465	0.3	0.09	0.929
University education	U	.22183	.27623	-12.6	-5.06	0.000
	M	.22193	.22679	-1.1	-0.39	0.694
Number of months employed in 2008	U	8.6686	8.0892	12.1	4.84	0.000
	M	8.6671	8.6456	0.4	0.16	0.873
One employer in 2008	U	.569	.55456	2.9	1.19	0.235
	M	.56924	.56895	0.1	0.02	0.984
Two employers in 2008	U	.22052	.17327	11.9	4.97	0.000
	M	.22062	.22209	-0.4	-0.12	0.905
Three or more employers in 2008	U	.08035	.06561	5.7	2.37	0.018
	M	.07995	.07974	0.1	0.03	0.979
Monthly wage in 2008	U	.62564	.63354	-1.3	-0.51	0.611
	M	.62576	.62534	0.1	0.03	0.979
Number of months employed in 2009	U	7.7904	7.4359	7.0	2.81	0.005

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Control	%bias	t	p-value
	M	7.789	7.7451	0.9	0.30	0.765
One employer in 2009	U	.60175	.56349	7.8	3.16	0.002
	M	.60201	.60187	0.0	0.01	0.992
Two employers in 2009	U	.15371	.13495	5.3	2.21	0.027
	M	.15334	.15316	0.1	0.02	0.986
Three or more employers in 2009	U	.05895	.05505	1.7	0.69	0.489
	M	.05898	.06087	-0.8	-0.27	0.787
Monthly wage in 2009	U	.52748	.56448	-6.7	-2.54	0.011

Note: PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Summary statistics of matching

Sample	Propensity score model R^2	LR chi2	p>chi2	Mean bias	Median bias
Unmatched	0.056	553.38	0.000	8.9	7.8
Matched	0.000	1.35	1.000	0.4	0.3

Annex 11. Matching quality after kernel matching

Comparison group – PIAAC observations without non-formal training

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Comparison	%bias	t	p-value
Age group 16-19	U	.0083	.0169	-7.7	-2.75	0.006
	M	.00832	.00881	-0.4	-0.18	0.858
Age group 20-29	U	.25066	.14136	27.8	10.38	0.000
	M	.24869	.23834	2.6	0.81	0.416
Age group 30-39	U	.25328	.17763	18.5	6.85	0.000
	M	.25394	.2485	1.3	0.42	0.672
Age group 40-49	U	.25721	.22803	6.8	2.51	0.012
	M	.25788	.27221	-3.3	-1.10	0.273
Age group 50-59	U	.19563	.27259	-18.2	-6.62	0.000
	M	.19615	.20227	-1.5	-0.52	0.605
Male	U	.60393	.49324	22.4	8.19	0.000
	M	.60289	.58592	3.4	1.17	0.243
Estonian language	U	.65284	.65089	0.4	0.15	0.881
	M	.65193	.66455	-2.7	-0.90	0.368
Secondary education	U	.19956	.23448	-8.5	-3.09	0.002
	M	.20009	.20166	-0.4	-0.13	0.894
Vocational education after basic education	U	.28603	.28181	0.9	0.34	0.732
	M	.28678	.28674	0.0	0.00	0.998
Vocational education after secondary education	U	.18603	.16257	6.2	2.28	0.023
	M	.18651	.18301	0.9	0.31	0.760
University education	U	.22183	.14935	18.7	6.96	0.000
	M	.21979	.22347	-0.9	-0.30	0.765
Number of months employed in 2008	U	8.6686	7.067	32.3	11.70	0.000
	M	8.6616	8.6899	-0.6	-0.21	0.833
One employer in 2008	U	.569	.5335	7.1	2.62	0.009
	M	.57049	.5841	-2.7	-0.93	0.352
Two employers in 2008	U	.22052	.14352	20.1	7.46	0.000
	M	.22023	.21847	0.5	0.14	0.886
Three or more employers in 2008	U	.08035	.0378	18.1	6.85	0.000
	M	.07881	.07004	3.7	1.13	0.259

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Comparison	%bias	t	p-value
Monthly wage in 2008	U	.62564	.45973	31.5	11.54	0.000
	M	.6254	.63571	-2.0	-0.62	0.538
Number of months employed in 2009	U	7.7904	6.1687	31.2	11.36	0.000
	M	7.7815	7.7904	-0.2	-0.06	0.952
One employer in 2009	U	.60175	.51659	17.2	6.30	0.000
	M	.60333	.60971	-1.3	-0.44	0.659
Two employers in 2009	U	.15371	.11125	12.5	4.66	0.000
	M	.15324	.15179	0.4	0.14	0.891
Three or more employers in 2009	U	.05895	.03042	13.8	5.21	0.000
	M	.05736	.05462	1.3	0.40	0.687
Monthly wage in 2009	U	.52748	.3815	31.5	11.54	0.000
	M	.52713	.52994	-0.6	-0.19	0.846

Note: PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Summary statistics of matching

Sample	Propensity score model R^2	LR chi2	p>chi2	Mean bias	Median bias
Unmatched	0.097	726.05	0.000	16.7	18.1
Matched	0.001	7.41	0.997	1.5	1.3

Comparison group – all PIAAC observations

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Control	%bias	t	p-value
Age group 16-19	U	.0083	.01835	-8.8	-3.31	0.001
	M	.0083	.00894	-0.6	-0.23	0.815
Age group 20-29	U	.25066	.16239	21.9	9.31	0.000
	M	.25033	.24345	1.7	0.54	0.589
Age group 30-39	U	.25328	.21712	8.5	3.53	0.000
	M	.25339	.24842	1.2	0.39	0.698
Age group 40-49	U	.25721	.2405	3.9	1.59	0.113
	M	.25732	.26195	-1.1	-0.36	0.721
Age group 50-59	U	.19563	.24959	-13.0	-5.21	0.000
	M	.19572	.2008	-1.2	-0.43	0.666
Male	U	.60393	.45518	30.1	12.26	0.000
	M	.60376	.59405	2.0	0.67	0.503
Estonian language	U	.65284	.70071	-10.2	-4.22	0.000
	M	.65312	.66119	-1.7	-0.57	0.566
Secondary education	U	.19956	.19601	0.9	0.37	0.715
	M	.19965	.20139	-0.4	-0.15	0.883
Vocational education after basic education	U	.28603	.23335	12.0	4.99	0.000
	M	.28615	.28226	0.9	0.29	0.770
Vocational education after secondary education	U	.18603	.17441	3.0	1.24	0.214
	M	.18567	.18389	0.5	0.16	0.877
University education	U	.22183	.27623	-12.6	-5.06	0.000
	M	.22193	.22863	-1.6	-0.54	0.588
Number of months employed in 2008	U	8.6686	8.0892	12.1	4.84	0.000
	M	8.6671	8.6345	0.7	0.24	0.809
One employer in 2008	U	.569	.55456	2.9	1.19	0.235
	M	.56924	.5722	-0.6	-0.20	0.840
Two employers in 2008	U	.22052	.17327	11.9	4.97	0.000
	M	.22062	.21795	0.7	0.22	0.828
Three or more employers in 2008	U	.08035	.06561	5.7	2.37	0.018
	M	.07995	.07764	0.9	0.29	0.772

Variable	Unmatched	Mean			t-test	
	Matched	Treated	Control	%bias	t	p-value
Monthly wage in 2008	U	.62564	.63354	-1.3	-0.51	0.611
	M	.62576	.62321	0.4	0.16	0.872
Number of months employed in 2009	U	7.7904	7.4359	7.0	2.81	0.005
	M	7.789	7.7557	0.7	0.23	0.821
One employer in 2009	U	.60175	.56349	7.8	3.16	0.002
	M	.60201	.60129	0.1	0.05	0.961
Two employers in 2009	U	.15371	.13495	5.3	2.21	0.027
	M	.15334	.15295	0.1	0.04	0.970
Three or more employers in 2009	U	.05895	.05505	1.7	0.69	0.489
	M	.05898	.05919	-0.1	-0.03	0.976
Monthly wage in 2009	U	.52748	.56448	-6.7	-2.54	0.011
	M	.52763	.52533	0.4	0.17	0.869

Note: PIAAC observations do not include those who participated in formal training during the last 12 months before the survey.

Summary statistics of matching

Sample	Propensity score model R^2	LR chi2	p>chi2	Mean bias	Median bias
Unmatched	0.056	553.38	0.000	8.9	7.8
Matched	0.000	2.04	1.000	0.8	0.7

Annex 12. Models with duration of courses

Table. Estimated effects of duration of training on labour market outcome, comparison group without non-formal training

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
Duration up to 40 hours	0.066***	0.057***	0.849***	0.564**	725.947**	567.249*	67.516***	49.711*
	(0.021)	(0.022)	(0.255)	(0.263)	(290.612)	(333.008)	(24.315)	(27.839)
40-59 hours	0.085***	0.105***	1.263***	1.065***	937.681***	970.686***	68.501***	83.633***
	(0.015)	(0.015)	(0.185)	(0.181)	(195.238)	(215.884)	(15.947)	(17.815)
60-79 hours	0.050***	0.061***	0.429*	0.284	597.382**	532.234*	49.437**	65.430***
	(0.019)	(0.021)	(0.240)	(0.247)	(270.548)	(307.588)	(22.084)	(25.270)
80-119 hours	0.054***	0.056***	0.401**	0.302	73.778	-1.515	15.008	15.348
	(0.015)	(0.016)	(0.185)	(0.189)	(203.327)	(227.346)	(16.915)	(19.075)
Participated in more than one course	-0.001	-0.052*	-0.237	-0.393	80.386	64.200	22.917	-8.509
	(0.027)	(0.031)	(0.329)	(0.364)	(391.867)	(459.770)	(32.446)	(39.435)
Age group 16-19	0.402***	0.417***	3.907***	4.514***	4029.715***	5165.915***	376.245***	494.317***
	(0.073)	(0.072)	(0.748)	(0.759)	(654.343)	(791.405)	(57.415)	(68.384)
Age group 20-29	0.277***	0.288***	2.631***	3.234***	2761.269***	3484.491***	275.835***	325.826***
	(0.031)	(0.032)	(0.336)	(0.345)	(355.645)	(375.818)	(30.292)	(31.926)
Age group 30-39	0.249***	0.276***	2.625***	3.338***	2495.701***	3421.871***	234.949***	302.169***
	(0.029)	(0.031)	(0.319)	(0.334)	(344.612)	(364.878)	(29.113)	(30.710)
Age group 40-49	0.239***	0.248***	2.811***	3.250***	2174.089***	2763.956***	188.989***	228.802***
	(0.029)	(0.031)	(0.310)	(0.327)	(324.959)	(342.630)	(27.491)	(29.123)
Age group 50-59	0.192***	0.212***	2.184***	2.660***	1146.588***	1568.470***	101.531***	135.681***
	(0.029)	(0.031)	(0.316)	(0.330)	(322.508)	(334.925)	(27.319)	(28.614)
Male	-0.005	-0.014	0.106	-0.163	1245.878***	1151.203***	110.694***	109.580***
	(0.012)	(0.013)	(0.149)	(0.151)	(167.628)	(190.627)	(14.056)	(15.457)
Estonian language	-0.021*	-0.006	-0.094	-0.105	-58.175	-40.110	-10.538	-2.142
	(0.011)	(0.012)	(0.140)	(0.143)	(154.489)	(169.752)	(12.905)	(14.410)
Secondary education	-0.018	-0.015	-0.026	-0.294	197.006	-29.126	11.289	0.749
	(0.020)	(0.021)	(0.242)	(0.248)	(243.198)	(269.236)	(20.547)	(23.478)
Vocational education after basic education	-0.006	0.005	0.253	0.008	196.767	44.367	7.851	9.627
	(0.019)	(0.020)	(0.227)	(0.234)	(215.889)	(240.264)	(18.529)	(21.209)

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
Vocational education after secondary education	0.015	0.028	0.402	0.356	552.064**	517.480*	36.997*	39.658
	(0.021)	(0.022)	(0.250)	(0.260)	(261.102)	(290.416)	(21.862)	(24.724)
University education	-0.008	-0.003	0.373	0.149	914.437***	1071.529***	65.858***	83.196***
	(0.022)	(0.022)	(0.260)	(0.266)	(287.531)	(320.116)	(24.495)	(27.492)
Number of months employed in 2008	0.004*	0.006**	0.120***	0.136***	-0.165	26.376	-2.320	-0.864
	(0.003)	(0.003)	(0.031)	(0.031)	(34.082)	(35.362)	(2.775)	(2.947)
One employer in 2008	0.052*	0.073**	-0.258	-0.196	-1035.336**	- 1265.502***	-57.560	-70.619*
	(0.030)	(0.030)	(0.321)	(0.335)	(402.963)	(467.476)	(35.705)	(39.093)
Two employers in 2008	0.075**	0.070**	-0.167	-0.296	-1012.313**	-1320.783**	-49.535	-76.913*
	(0.031)	(0.032)	(0.350)	(0.363)	(450.395)	(518.475)	(39.395)	(43.009)
Three or more employers in 2008	0.081**	0.080**	-0.243	-0.159	-738.545	-942.068	-28.358	-33.624
	(0.037)	(0.039)	(0.442)	(0.447)	(584.539)	(643.127)	(47.806)	(52.853)
Monthly wage in 2008	0.031**	0.026**	0.641***	0.631***	2572.584***	2797.390***	218.975***	225.282***
	(0.012)	(0.013)	(0.175)	(0.194)	(704.027)	(784.300)	(59.103)	(62.019)
Number of months employed in 2009	0.016***	0.017***	0.326***	0.305***	303.186***	298.026***	19.887***	20.621***
	(0.002)	(0.002)	(0.026)	(0.027)	(30.308)	(32.851)	(2.536)	(2.721)
One employer in 2009	0.169***	0.107***	0.726**	0.390	- 2108.159***	- 2241.051***	- 141.094***	- 147.007***
	(0.028)	(0.028)	(0.308)	(0.318)	(381.593)	(429.433)	(33.329)	(36.047)
Two employers in 2009	0.192***	0.138***	0.950***	0.760**	- 2040.956***	- 2032.822***	- 145.737***	- 130.750***
	(0.030)	(0.031)	(0.352)	(0.358)	(451.888)	(513.586)	(39.158)	(42.725)
Three or more employers in 2009	0.207***	0.131***	1.293***	0.523	- 2049.993***	- 2122.835***	- 149.997***	- 144.188***
	(0.036)	(0.039)	(0.445)	(0.460)	(548.250)	(627.600)	(44.584)	(51.899)
Monthly wage in 2009	0.029*	0.016	0.158	0.275	5086.780***	5163.183***	455.164***	454.781***
	(0.016)	(0.018)	(0.226)	(0.250)	(717.676)	(828.238)	(60.608)	(63.757)

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
Intercept	0.146***	0.135***	0.278	0.448	-1446.496***	-1579.710***	-78.042**	-108.100***
	(0.036)	(0.038)	(0.393)	(0.412)	(406.010)	(435.131)	(34.753)	(37.763)
N	5537	5537	5537	5537	5537	5537	5537	5537
R^2	0.221	0.190	0.263	0.240	0.451	0.423	0.456	0.419
F-stat	54.7	46.7	79.1	68.9	87.1	73.9	86.2	73.5
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The parameters are from a weighted linear regression model on matched sample. Robust standard errors are in parentheses. The matching model includes age, gender, language, education, wage, number of months, and number of employers in 2008 and 2009. Standard errors do not take into account that propensity scores were estimated.

Table. Estimated effects of duration of training on labour market outcome, comparison group from all PIAAC

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
Duration up to 40 hours	0.035*	0.029	0.363	0.229	12.953	-90.129	10.115	-9.293
	(0.020)	(0.021)	(0.242)	(0.251)	(270.342)	(313.660)	(22.798)	(26.398)
40-59 hours	0.052***	0.075***	0.760***	0.709***	271.538	338.481*	16.260	28.441*
	(0.013)	(0.013)	(0.168)	(0.165)	(173.303)	(194.841)	(14.150)	(16.064)
60-79 hours	0.020	0.034*	-0.028	-0.034	-46.456	-60.293	-2.370	11.931
	(0.018)	(0.020)	(0.226)	(0.234)	(249.393)	(285.987)	(20.408)	(23.479)
80-119 hours	0.027*	0.030**	-0.015	-0.014	-512.534***	-578.297***	-30.641**	-35.962**
	(0.014)	(0.015)	(0.171)	(0.176)	(183.739)	(206.157)	(15.297)	(17.340)
Participated in more than one course	0.001	-0.058*	-0.218	-0.434	136.048	62.076	27.683	-9.584
	(0.027)	(0.031)	(0.325)	(0.363)	(390.303)	(457.016)	(32.230)	(39.279)
Age group 16-19	0.430***	0.474***	4.541***	4.865***	4619.597***	5777.367***	425.671***	576.327***
	(0.064)	(0.062)	(0.682)	(0.689)	(612.685)	(755.723)	(53.728)	(63.585)
Age group 20-29	0.307***	0.302***	2.991***	3.335***	3137.364***	3835.425***	300.532***	356.754***
	(0.026)	(0.028)	(0.288)	(0.301)	(293.119)	(312.491)	(24.973)	(26.448)
Age group 30-39	0.261***	0.290***	2.719***	3.326***	2656.790***	3464.658***	253.669***	316.214***
	(0.026)	(0.027)	(0.277)	(0.292)	(290.664)	(304.168)	(24.764)	(25.838)
Age group 40-49	0.237***	0.252***	2.688***	3.190***	2071.137***	2820.557***	181.045***	234.112***
	(0.026)	(0.027)	(0.274)	(0.291)	(278.371)	(296.281)	(23.741)	(25.120)
Age group 50-59	0.195***	0.213***	2.112***	2.623***	1167.825***	1645.776***	106.063***	144.712***
	(0.026)	(0.028)	(0.280)	(0.293)	(275.851)	(287.100)	(23.581)	(24.626)
Male	-0.022**	-0.023**	-0.179	-0.297**	973.087***	962.296***	91.444***	95.267***
	(0.010)	(0.010)	(0.121)	(0.124)	(132.095)	(152.340)	(10.866)	(12.297)
Estonian language	-0.014	-0.009	-0.044	-0.103	59.429	-17.839	3.206	0.668
	(0.010)	(0.010)	(0.119)	(0.122)	(126.264)	(141.242)	(10.459)	(11.907)
Secondary education	-0.005	0.005	0.237	-0.091	347.121*	92.289	18.060	10.303
	(0.018)	(0.019)	(0.217)	(0.222)	(207.553)	(233.298)	(17.748)	(20.559)
Vocational education after basic education	0.013	0.023	0.536***	0.235	443.169**	238.956	23.550	21.674
	(0.017)	(0.018)	(0.207)	(0.212)	(189.177)	(214.540)	(16.190)	(19.030)
Vocational education after secondary education	0.019	0.040**	0.602***	0.388*	688.260***	577.036**	42.304**	51.711**

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
	(0.019)	(0.020)	(0.224)	(0.229)	(213.060)	(245.708)	(18.017)	(21.655)
University education	0.023	0.019	0.787***	0.307	1401.339***	1390.293***	105.304***	110.791***
	(0.018)	(0.019)	(0.216)	(0.226)	(223.149)	(257.104)	(18.944)	(22.173)
Number of months employed in 2008	0.005**	0.005**	0.118***	0.125***	-0.575	9.133	-2.141	-2.435
	(0.002)	(0.002)	(0.027)	(0.027)	(30.715)	(32.110)	(2.505)	(2.695)
One employer in 2008	0.079***	0.106***	0.143	0.196	-898.162***	- 1030.119***	-55.616**	-50.624*
	(0.027)	(0.027)	(0.292)	(0.300)	(311.486)	(347.914)	(26.156)	(28.721)
Two employers in 2008	0.090***	0.100***	0.175	0.055	-843.923**	- 1182.389***	-50.196*	-61.386**
	(0.028)	(0.028)	(0.311)	(0.319)	(336.066)	(375.783)	(28.006)	(31.308)
Three or more employers in 2008	0.106***	0.112***	0.115	0.226	-714.889	-652.945	-28.545	-13.210
	(0.031)	(0.033)	(0.368)	(0.371)	(445.904)	(475.294)	(35.663)	(39.002)
Monthly wage in 2008	0.021	0.021	0.513***	0.648***	2703.648***	3155.486***	236.180***	254.179***
	(0.013)	(0.013)	(0.187)	(0.169)	(513.923)	(474.028)	(35.953)	(37.620)
Number of months employed in 2009	0.017***	0.016***	0.307***	0.285***	269.847***	276.648***	18.051***	18.807***
	(0.002)	(0.002)	(0.023)	(0.023)	(26.886)	(29.464)	(2.234)	(2.349)
One employer in 2009	0.149***	0.107***	0.660**	0.467*	- 2119.603***	- 2103.648***	- 146.971***	- 139.986***
	(0.025)	(0.025)	(0.278)	(0.280)	(288.631)	(314.590)	(24.994)	(26.823)
Two employers in 2009	0.178***	0.142***	0.930***	0.900***	- 2020.888***	- 1834.075***	- 140.828***	- 117.298***
	(0.026)	(0.026)	(0.304)	(0.306)	(330.379)	(364.778)	(27.669)	(30.921)
Three or more employers in 2009	0.162***	0.107***	0.971***	0.467	- 1876.798***	- 1644.060***	- 145.246***	- 113.889***
	(0.031)	(0.033)	(0.375)	(0.390)	(452.000)	(494.215)	(36.825)	(41.509)
Monthly wage in 2009	0.037**	0.026	0.444**	0.363*	5628.925***	5305.202***	495.473***	477.088***
	(0.015)	(0.016)	(0.218)	(0.220)	(573.595)	(630.099)	(44.961)	(45.039)
Intercept	0.146***	0.131***	0.366	0.504	- 1297.537***	- 1471.990***	-68.421**	- 102.235***
	(0.031)	(0.033)	(0.336)	(0.356)	(335.622)	(365.007)	(28.892)	(31.742)

	Employed		Months employed		Annual earnings		Monthly wage	
	2012	2013	2012	2013	2012	2013	2012	2013
N	8443	8443	8443	8443	8443	8443	8443	8443
R^2	0.240	0.204	0.276	0.249	0.477	0.434	0.476	0.428
F-stat	73.245	60.641	103.910	91.030	150.660	128.604	141.262	118.932
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The parameters are from a weighted linear regression model on matched sample. Robust standard errors are in parentheses. The matching model includes age, gender, language, education, wage, number of months, and number of employers in 2008 and 2009. Standard errors do not take into account that propensity scores were estimated.

Annex 13. Training activities and dissemination of the project

This annex describes in more detail the activities under Task 4 "Preparing general and special training modules and providing training courses for civil servants in public sector". Under this task both introductory and in-depth training courses on impact evaluations were conducted.

Introductory training courses were two-day events, which took place on 25-26.03.2015 and 31.03.-01.04.2015 in Tallinn. Written outputs include training programme and slides (in Estonian), which were distributed to participants. Training was targeted to policy makers and experts from different ministries, who were responsible for commissioning impact evaluations. In total 58 civil servants from the Ministry of Education and Research, Ministry of Finance, Ministry of the Interior, Ministry of Culture, Ministry of Environment, Astangu Vocational Rehabilitation Centre, Ministry of Social Affairs, Ministry of Economic Affairs and Communications, Ministry of Justice, Ministry of Agriculture, Ministry of Foreign Affairs, National Institute for Health Development and Chancellery of Riigikogu participated in training courses. Training consisted of lectures using the counterfactual impact evaluation of the Estonian adult vocational training activity as an example.

In-depth training course was a five-day event, which took place between 30.04.2015-28.05.2015 (on Thursdays) in Tallinn. Written outputs include training programme, slides (in Estonian) and Stata data and do fails, which were distributed to participants. Training consisted each day on lectures and computer tutorials. The following topics were covered during the course: before-after estimator, difference-in-difference estimator, regression adjustment method, instrumental variable method, Heckman selection model, inverse probability weighting, combined regression adjustment and inverse probability weighting, nearest neighbour matching, propensity score matching, caliper matching, radius matching, coarsened exact matching, regression discontinuity design. The data collected during this project and analytical Stata do-files were used throughout this course. Training was targeted to the civil servants working in the analyses departments conducting impact evaluations and policy analyses. In total 20 civil servants from the Ministry of Finance, Statistics Estonia, Estonian Unemployment Insurance Fund, Ministry of Agriculture, Enterprise Estonia, Ministry of Economic Affairs and Communications, Ministry of Social Affairs, and Ministry of the Interior. The materials (Stata do-files and slides) were made available to participants also after the end of the course in the following link: http://kodu.ut.ee/~avork/files/praxis/impev/.

In addition to these courses, the methodology of the project together with intermediate and final results were presented for the steering committee of the project (29 April 2014, 9 October 2014, 17 May 2015) and to the analysts and experts from the Ministry of Education and Research (10 September 2015). In both courses and presentations to managing authorities we highlighted what kind of data and statistical tools are ideally needed for a counterfactual impact evaluation. Access to various Estonian registry and survey data, and comparative advantages of Stata, R and SPSS were also discussed in these courses.

After finalizing the project, a research article based on the analysis will be submitted for a publication in a peer-reviewed journal and an overview article in Estonian will be submitted to the journal of the Estonian parliament "*Riigikogu Toimetised*".

2015