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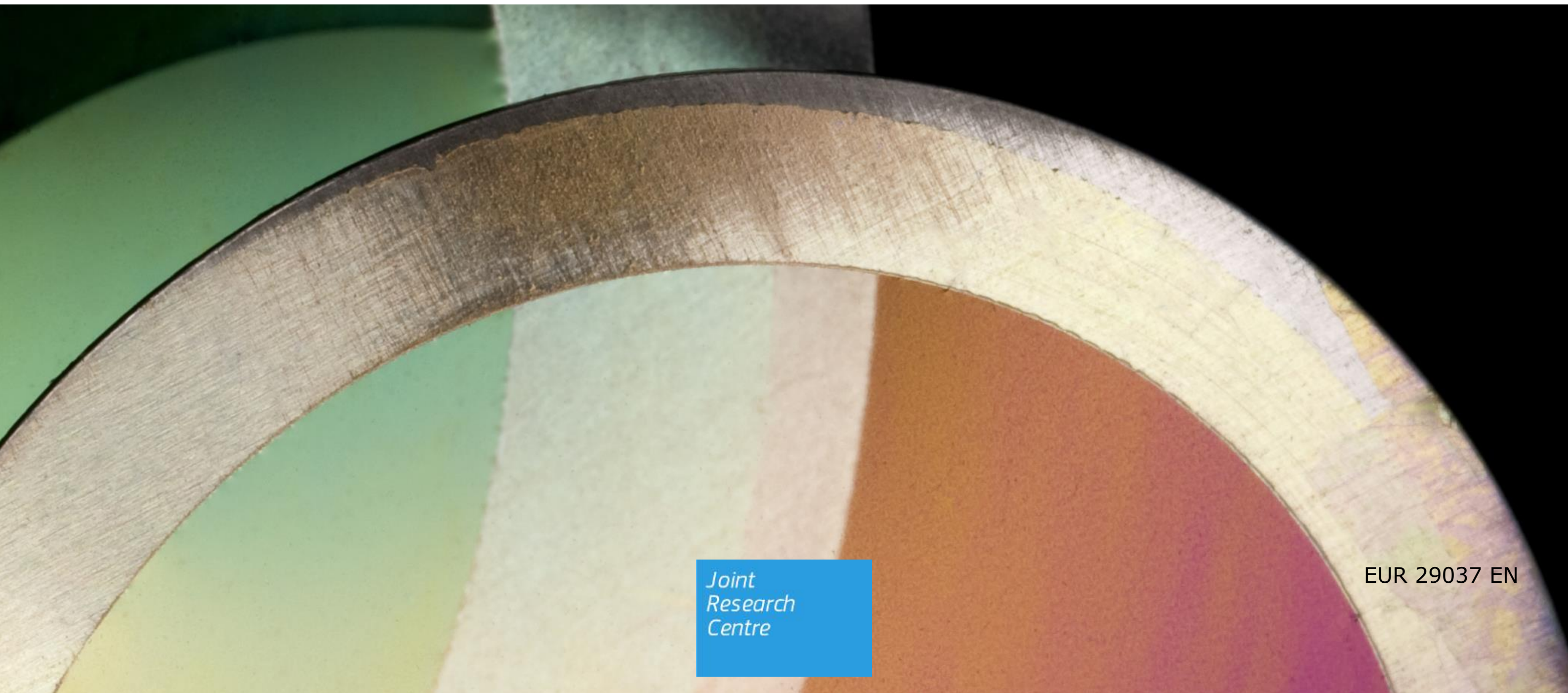

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Vocational training and labour market outcomes: Evidence from Youth Guarantee in Latvia

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Abstract

The aim of this report is to evaluate the impact of a vocational training (VT) programme introduced in Latvia in 2014 and targeted at unemployed youth. The training programme is part of the Youth Guarantee scheme supporting young people aged 15-29 who are not in education, employment or training (NEETs). This study is one of the first evaluations of a Youth Guarantee programme implemented in the programming period 2014–2020. Exploiting a priority rule given to Latvian youth under the age of 25, we use a *Fuzzy Regression Discontinuity Design* (FRDD) in order to identify the causal effect of participating in the VT programme on employment outcomes. The priority rule is used to estimate the model through instrumental variables techniques by means of Two Stages Least Squares estimators. We merge rich administrative data from the State Employment Agency of Latvia, which provide information on persons who are registered as unemployed (participants and non-participants), with data from the Latvian State Revenue Service, which provide information on income before and after the programme. The estimated effects of the programme on employment and monthly income are positive but not statistically significant, although we find a strong positive effect of the priority rule on programme participation. Overall, our findings are in line with those from the literature on the evaluation of active labour market policies targeting youth.

Foreword

The Counterfactual Impact Evaluation (CIE) of the vocational training programme implemented in Latvia under the Youth Guarantee schemes was carried out within the "Data Fitness Initiative for CIE," launched in February 2016 by the Directorate General Employment, Social Affairs and Inclusion (DG EMPL) and the Centre for Research on Impact Evaluation (CRIE) to promote the use of CIE for the assessment of European Social Fund (ESF) interventions. Based on the quality of the data and on the policy relevance of the intervention proposed, in June 2016 the Latvian project and data were selected by CRIE to establish a collaboration agreement with the Evaluation Division of the EU Funds Strategy Department of the Ministry of Finance of the Republic of Latvia, and work together on the evaluation of the programme. This collaboration resulted very fruitful, both for strengthening interactions between the ESF Managing Authorities and the European Commission, and for improving the scientific knowledge on the impact of ESF interventions.

Acknowledgements

CRIE would like to thank the Evaluation Division of the EU Funds Strategy Department of the Ministry of Finance of the Republic of Latvia for granting access to and collecting the data used in this report from the State Employment Agency and the State Revenue Service.

1 Introduction

The global financial crisis was followed by an increase in unemployment rates all over Europe. Young people were particularly hit. In 2013 the youth unemployment rate (for youth under the age of 25) peaked at 23.9% in Europe on average, and exceeded 50% in countries such as Greece (58.3%) and Spain (55.5%). It reached the lowest value in Germany (7.8%), while in Latvia it attained the 23.2% (Eurostat, 2013).

In order to reduce the levels of youth unemployment in the most affected regions, since 2013 collective and centralised efforts of the European Union added to the national initiatives, as the English New Deal for Young People (NDYP), the Danish Youth Unemployment Program (YUP) and the German Jugend mit Perspektive (JUMP).

In February 2013 the European Council launched the Youth Employment Initiative (YEI) package to increase the EU financial support to regions and individuals suffering most from youth unemployment and inactivity. The YEI typically subsidises the provision of apprenticeships, traineeships, job placements and further education leading to a qualification. It exclusively supports young people not in employment, education or training (NEETs), including long-term unemployed youngsters or those not registered as job-seekers, in regions experiencing youth unemployment rates above 25%. The YEI package was designed primarily with a purpose to support the implementation of the Youth Guarantee (YG), which is a "political commitment, in the form of a Council recommendation of April 2013, to give every young person a good-quality offer of employment, continued education, apprenticeships or traineeships within a period of four months of becoming unemployed or leaving formal education".[1] One of the common aspects within the current YG in Europe is, for instance, the preparation of customised analyses of the needs of unemployed young people, together with the crucial role played by the Public Employment Services (PES) in providing these services.

Although the implementation details of the YG at country level are well documented (Cabasés Piqué et al., 2016; Pastore, 2015; Escudero and Mourelo, 2015), evidence of the effectiveness of the recent ALMPs financed through the YEI in Europe has not yet been established in the literature. These measures were introduced very recently and the data collection process needed to perform a rigorous impact evaluation is still ongoing.

The scientific knowledge on the YG initiative mostly relies on the evaluation studies of similar training programmes conducted in Northern European countries, which activated these programmes

[1] European Commission (2016), Communication: The Youth Guarantee and Youth Employment Initiative three years on.

in the 1980s and the 1990s.[2] Sweden introduced the first YG in 1984, Norway in 1993, and Denmark and Finland in 1996. A similar scheme, known as New Deal for Young People (NDYP), was implemented in the UK in 1998 to target unemployed youth in the age group 18–24. The evaluation studies of such interventions find moderate effects in the short-term and negligible effects in the long-term.[3] To date, the evidence on the long-term effects of training programmes using counterfactual impact evaluation (CIE) techniques, is not very broad.

For Sweden, Carling and Larsson (2005) show that the reform passed in 1998 had positive effects on youth employability in the short-term but had no impact in the long-term. A recent paper by Hämäläinen et al. (2014) examines the YG programme introduced in Finland in 2005. The reform consisted of an early intervention, monitoring and individualised job search plans for unemployed young persons. Using the age threshold set at 25 years, the authors find that the YG adopted in 2005 moderately increased unsubsidised employment while having a negligible impact on unemployment in the age range of 23-24. Furthermore, estimates based on level of education show that the reform did not improve the labour market prospects of unskilled youth.

A key result from this literature is that the timing of measuring the impact of the training programmes matters: the effect on employability one year after participation has been found to be small or even negative, reflecting the "lock-in" effect hypothesis, that is the fact that participants, as opposed to non-participants, did not fully use their time on job-search during the treatment. The lock-in effect theory does not rule out the possibility that such training can increase participants' employment prospects however. Perhaps, the same programme could prove being effective if evaluated in the medium or long-term, when lock-in effects fade away or are outweighed by the beneficial effects of the programme.

Some studies regarding the developing countries (Ibarrarán et al., 2015) and others analysing different activation measures such as job-search assistance and counseling services (Blundell et al., 2004) find mainly positive but moderate effects in the long-term.

The aim of this study is to evaluate the impact of a YEI Vocational Training (VT) programme for unemployed youths introduced in Latvia in 2014, exploiting rich data on participants and non-participants, and measuring their employability between 1.5 and 3.5 years after registering for the programme. This programme is part of the YG in Latvia; it is financed by the YEI, the European

[2]For an overview of these studies see Heckman et al. (1999), Kluve (2010), and Card et al. (2010).

[3]The literature refers to short-term effects for results being measured within a year after the completion of the programme, medium-term effects within two years after the end of a programme, and long-term effects to longer periods.

Social Fund (ESF), and the Latvian State Budget and managed by the State Employment Agency of Latvia (SEA).[4]

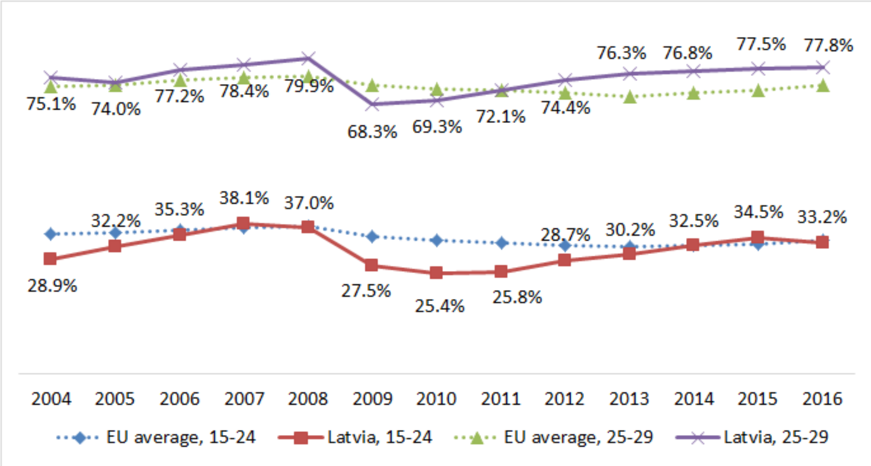
To assess the impact of the VT programme, we exploit a *Fuzzy Regression Discontinuity Design* (RDD) thanks to specific eligibility criteria adopted by the Latvian government, which gave a higher priority to young unemployed individuals aged less than 25 to participate in this programme. We use the priority rule as an instrument for participation, in order to estimate the causal effect of participation in the VT programme on labour market outcomes, accounting for confounding factors due to individual self-selection and different levels of motivation.

We use rich administrative data from the SEA, which provides information on individuals who are registered as unemployed at a given date (being them participants or non-participants in the VT programme), and merge it with data from the State Revenue Service (SRS), which gathers information on individuals' income at specific dates before and after the programme. On the one hand, our results show that the priority rule highly predicts youth participation in the programme. Our first stage results are indeed strong and statistically significant. On the other hand, we find a positive but statistically non significant effect of the training programme on employment and income.

The remainder of this report is structured as follows. The next section describes the situation of youth unemployment in Latvia, and Section 3 presents the state of the YG and vocational training in Latvia in general, and the specific features of the training programme evaluated in this study. Section 4 describes the main characteristics of the data used in the empirical analysis, and Section 5 explains the sample selection criteria and reports some descriptive statistics. Our empirical strategy is described in Section 6. Section 7 includes a graphical analysis of the data, a test of the identifying assumptions underlying our identification strategy (FRDD), and the main results of the FRDD analysis. Section 8 explores heterogeneous effects by some individual attributes (education, gender, location, type of course). The last section summarises the main findings and concludes.

[4]In Latvian the programme of interest is called "JG Profesionālās apmācību programmas". The group of YG activities (vocational training programs) to which the programme belongs is referred to as "Profesionālā izglītība, auto un traktortehnikas vadītāja apliecības iegūšana".

Figure 1: Employment rate of youths aged 15-24 and 15-29 in Latvia compared to the EU average.



Note. Ministry of Welfare's elaborations based on data from Eurostat.

2 Youth unemployment in Latvia

Within the first three quarters of 2016, in Latvia there were on average 44,000 young NEETs [5] in the age group 15–29, of which half in the age group 15–24.[6]

NEETs in the age group 15–24 and 15–29 correspond respectively to the 11.2% and 13.3% of the total population in Latvia for the same age group. The peak was registered in 2009, as a consequence of the global financial crisis, where the share of NEETs in the age group 15–29 reached 20.8%. In the following years the rate of NEETs showed a decreasing trend, going from 19.1% in 2011 to 13.8% in 2015.

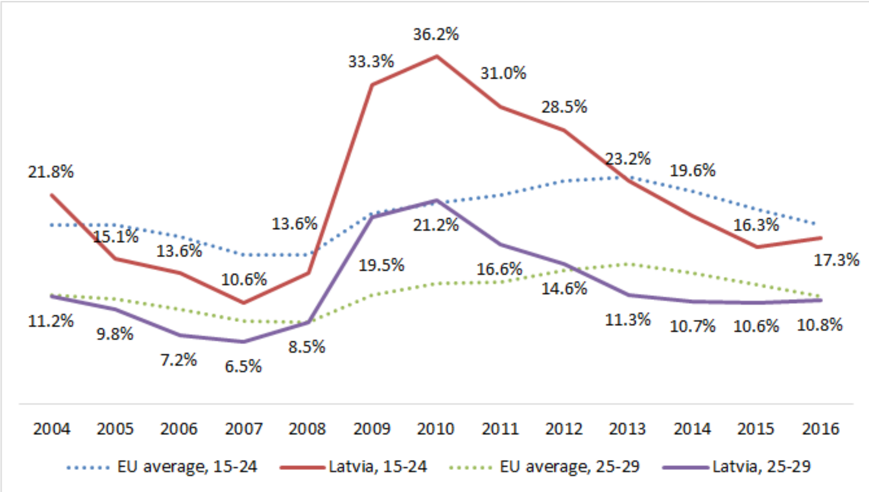
In general, labour market conditions of youths in Latvia improved in the recent years, with an increase in the employment rate for all age groups. As shown in Figure 1, the employment rate of youths aged 15-24 increased by 5 percentage points (pp) since 2012, falling behind the EU average of 33.7% for 15-24 by only 0.5 pp at the end of the third quarter of 2016. By contrast, the employment rate of those aged 25-29 increased by 3 pp within the same period, thus exceeding the EU average of 73.1% for 25-29 by 5 pp.

From Figure 2 we can see that the unemployment rate of youths in the age-group 15–24 decreased by 11 pp since 2012, remaining 1 pp below the EU average of 18.7% for the same age-group at the

[5]Data source: Eurostat.

[6]In 2015 NEETs counted 6% more compared to 2016, while in 2014 they counted 18% more with respect to 2016.

Figure 2: Unemployment rate of youths aged 15-24 and 15-29 in Latvia compared to the EU average.



Note. Ministry of Welfare's elaborations based on data from Eurostat.

end of the third quarter of 2016. Likewise, the unemployment rate of youths aged between 25-29 decreased by 4 pp within the same period of time, again exceeding the EU average of 11.2% for 25-29 by almost 1 pp.

By comparing the unemployment rate of youths in the age-group 15–24 with the total unemployment rate, it emerges that, similarly to the EU average, in Latvia the youth unemployment rate was about twice as large as the total unemployment rate (17.7% and 9.5% respectively in the third quarter of year 2016).

This can be partly explained by the difficulties faced by youths in the transition from school to work and by the effects of labour market institutions (minimum wages, dual labour markets), which are particularly detrimental at labor market entry and, hence, for youths.

As for the Latvian labour market in general, the increase in the total employment rate, observed in the last years (reaching 72.3% in 2015 for people aged 20–64) together with a decreasing labour supply, could be explained by several factors such as, firstly, an increase in the number of new vacancies. Secondly, on the demographic side, the increase in the total employment rate was partially affected by a sizable decline of 15% of the working age population since 2006 (the highest value registered in the EU). This latter was due to negative natural growth, population ageing and high emigration (mostly as a result of better labour market conditions abroad). Youth outward migration was considerable, as more than 40% of the emigrants were in the age group 20–35.[7]

Concerning the level of education of youths, in Latvia in 2016 the percentage of young people aged 20-24 with upper secondary, post-secondary non-tertiary and tertiary education (ISCED levels 3-8) was slightly higher than the EU average (84.8% vs 83.1%).[8]

As regards the unemployed youths, a relatively large proportion only has basic or general secondary education, without any professional qualification. This could indicate shortcomings in the career guidance system or limited access to post-secondary education for unemployed young people. Although the tertiary education attainment rate is high (well above the Europe 2020 target of 34–36%), the supply of university graduates in knowledge intensive sectors such as technology, engineering, and mathematics (STEM) fields remains among the lowest in the EU (17.9% in 2013). As for the vocational education and training (VET) system, it was reformed over the years but challenges remain in terms of updating of work-based learning components and curricula. Moreover, apprenticeship type schemes are considered to be underdeveloped in Latvia.[9]

In numbers, labour force statistics by age and educational attainment level (International Standard Classification of Education, ISCED 2011) show that in Latvia in 2016 the unemployment rate for the age group 15–24 was 27.2% for people with less than primary, primary and lower secondary education (ISCED levels 0-2), 14.7% for people with upper secondary and post-secondary non-tertiary education (ISCED levels 3-4) and 16.2% for people with tertiary education (ISCED levels 5-8). Similarly, the unemployment rate for the age group 25-29 was 16.3% for ISCED levels 0-2, 14.4% for ISCED levels 3-4, and 5.8% for ISCED levels 5-8.[10] For both age groups, therefore, the highest rates of unemployment were observed for people with the lowest levels of education.

Given Latvia's demographic challenges, the activation of young people not in employment or training is crucial. The field work to reach out to young NEETs has been considerably delayed; as a consequence the labour supply potential of young people is not fully utilised.[11]

Coverage of the unemployed by ALMP measures remains low. For instance, only 10.4% of the registered unemployed were activated in 2014. The funding for ALMP was reduced in 2015, but increased again in 2016. In 2016 the largest share of ALMP spending was dedicated to the YG (39%) and other training (39%) measures.[12] The registered unemployed youths represented

[7] European Commission, European Semester: Country Report Latvia 2016.

[8] Eurostat indicator "Population by educational attainment level, sex and age".

[9] European Commission, European Semester: Country Report Latvia 2016.

[10] Eurostat, European Union Labour Force Survey (EU-LFS) series – detailed annual survey results.

[11] European Commission, European Semester: Country Report Latvia 2016.

[12] European Commission, European Semester: Country Report Latvia 2016.

on average 8% of all registered unemployed and 35% of the total number of young NEETs in the country. At the end of 2016, 15,072 unemployed in the age-group 15–29 were registered at the SEA (7% or 1,150 persons less compared to year 2015), 40% of whom were aged between 15 and 24 years. Since the launch of the YG, i.e. from 2014 to 2016, more than 111,000 people aged 15–29 years participated in the programme's activities.

3 Youth Guarantee and vocational training programmes in Latvia

The programme under analysis is part of the YG programme and is financed by the ESF, the YEI, and the Latvian budget for a total funding of 9.2 million Euros (Latvian Ministry of Finance).[13]

"According to the Article 16 of the ESF Regulation[14], the YEI shall target all young persons under the age of 25 not in employment, education or training, residing in eligible regions, who are inactive or unemployed including the long term unemployed, and whether or not registered as seeking work. On a voluntary basis, MS may decide to extend the target group to include young persons under the age of 30".[15] Given the high unemployment rate of this age group, in Latvia the possibility to participate was extended also to young people aged up to 29 years.

The intervention: In Latvia, the YG is the biggest support program for youths aged 15–29.

As highlighted also in Caliendo and Schmidl (2016), who compare the youth unemployment rates and the stock of young ALMP participants relative to the youth active working population in selected European countries in 2012, in Latvia the average youth unemployment rate was at 30%, but, on average, only 2% of the active youths participated in ALMP (see Figure 3).

The intervention of interest for this evaluation is a VT programme implemented by the SEA. This programme aims at youths acquiring or increasing their vocational qualifications in accordance with the labour market demand.

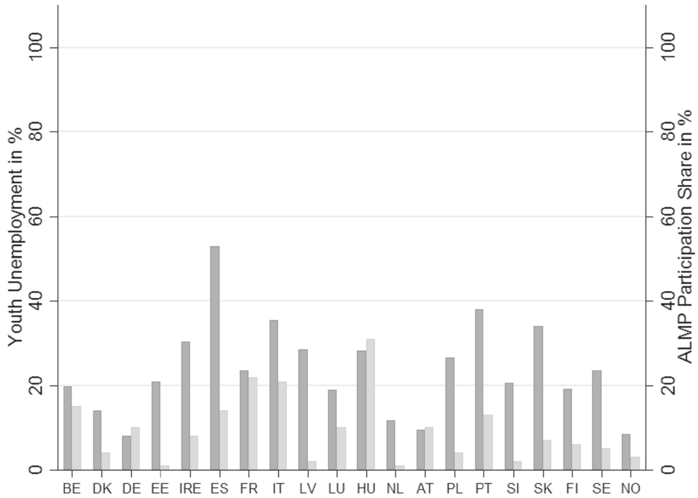
The VT system is accompanied by specific ICT tools available on the web page of the SEA, which are accessible to all and include: (i) performance measurement system of training institutions, (ii) booking system, and (iii) labour market short-term forecasting systems. The performance measurement system allows future training participants to compare the performance of training

[13]The programme is ongoing and it is supposed to continue until January 2018.

[14]The Regulation can be accessed here: Regulation (EU) No. 1304/2013, 17 December 2013.

[15]European Commission, Guidance on implementing the Youth Employment Initiative, European Social Fund thematic paper 2014.

Figure 3: Youth unemployment rates and total stock of ALMP participants relative to the active youth population, 2012



Note. This figure was extracted from the paper by Caliendo and Schmidl (2016).

institutions in terms of job finding rates, while the forecasting system shows both professions in high demand and those where demand is falling for the coming year.

The Training Commission lead by the Ministry of Welfare, consisting of, among others, governmental institutions, social partners and employers, sets at least once per year the training areas that can be covered by this programme. The training for unemployed is organised only in those areas where there is labour demand. For the assessment of the labour market demand, the Training Commission takes into account short- and long-term forecasts, numbers of unemployed and vacancies in each sector, and views of the sector experts, such as work councils or employers. As for the training providers, both private and public training institutions can be part of the programme and offer training activities if they meet some quality criteria previously set, such as being licensed and accredited institutions/programmes.

The VT programme offers a number of different training courses through a voucher system: unemployed youths receive a voucher which can be spent in one of the vocational education institutions in the country. After passing a final examination, participants receive a certification which confirms the acquired vocational qualification. Classes consist on average of 10-12 students. The length of training courses varies from 3 up to 9 months. The start and end dates of courses can vary across participants. During the training programme, participants receive a monthly allowance of 100 Euros and eventually a reimbursement of the travel costs related to commuting if they wish to attend a course that it is not available in their area of residence.

The programme started on 1 January 2014.[16] While the programme is ongoing until 2018, this evaluation considers the participation period from the start of the programme, i.e. January 2014, until December 2015.

The programme of interest was advertised also through a pilot project, implemented from March to December 2015 to raise awareness among young people on YG measures in Finland, Latvia, Portugal and Romania. The activities comprised press publications, meetings with journalists, regional visits, and press conferences. Moreover, the SEA publishes information on different measures available for young NEETs on a regular basis.

Eligibility criteria: The intervention targets young NEETs in the age-group 15–29. However, the programme can reach only young NEETs who register as unemployed at the SEA.

A young unemployed can participate in a VT programme if:

- his/her vocational qualification acquired previously or his/her professional experience is not demanded in the labour market or it does not conform to the requirements laid down for the relevant profession, hence making it impossible to find appropriate work;
- he/she has lost his or her vocational skills;
- he/she has not previously acquired a vocational qualification.

Since the intervention targets the NEETs registered as unemployed, hereinafter participants will be referred to both as NEETs and as unemployed.

3.1 Practical implementation of the vocational training programme

The voucher system part of the VT programme consists of the following steps.

1. *Registration*: after registering at the SEA, unemployed individuals receive job-search assistance. In order to promote efficient and targeted provision of the measures offered to the unemployed, the SEA carries out the profiling of unemployed, so as to propose the most

[16] According to the Rules of Cabinet laying down the provisions of the measure, the intervention was financed as from 1 January 2014 and the first participants were enrolled in February. The regulation was adopted on 28 April 2015.

suitable option among the active labour market programmes available. Such profiling takes place in a meeting between the unemployed and the SEA officer. During the meeting the unemployed individual applies for participation in the training measures. The SEA officer checks that candidates satisfy the eligibility requirement for participation before registering the application in the SEA database.

2. *Selection of a programme*: the unemployed may choose a suitable programme from the list of training programmes (approximately 75 types of VT programme).

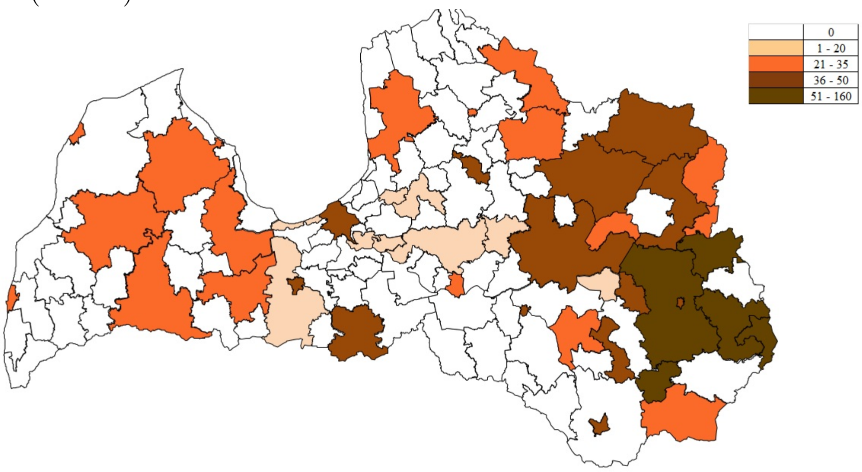
3. *Voucher receipt*: the SEA officer makes a phone call and invites the unemployed to receive a training voucher. The voucher consists of two parts: one is for the training provider and the other should be returned to the SEA officer. It contains information on the maximum amount of expenses covered by the SEA.

4. *Choice of the training provider*: the unemployed selects a training provider within the first 10 working days after the SEA's job search assistance. The choice is made from the list of procured training providers published on the SEA's website.[17] The training provider has to determine the suitability of a person for participating in a training programme.

   Figures 4 and 5 show, respectively, the distribution of training programmes across Latvia as well as the distribution of participants in the VT programme. The shading of both maps shows that the areas with the highest number of both training programmes and participants are in the Eastern part of Latvia.

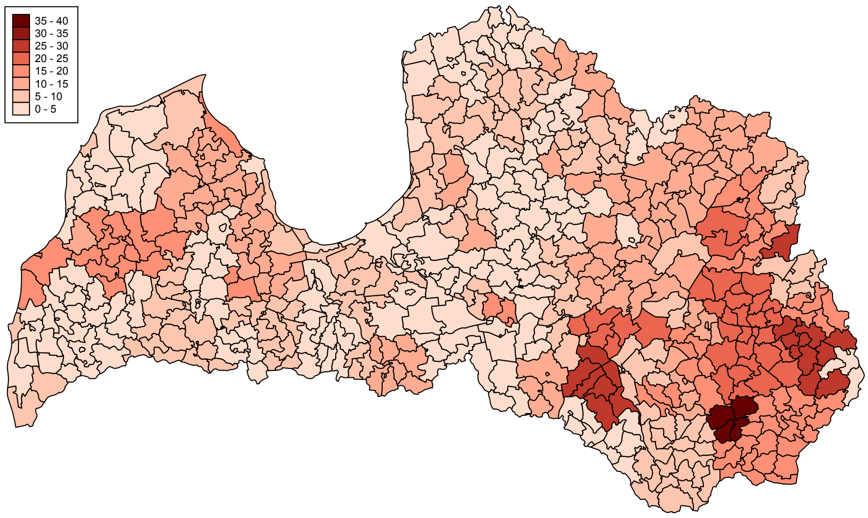
[17]However, other training providers may also be selected, if they are ready to make an agreement with the unemployed and follow the next procurement procedure.

Figure 4: Distribution of the professional training programmes (160 hours - 960 hours) in local authorities level (novadi) for 2016.



Note. State Employment Agency's elaborations based on data from 2016. This graph shows the distribution of the professional training programmes by geographical administrative units in Latvia. The darker the colour, the larger the number of activated programmes in a given area.

Figure 5: Distribution of the participants in the VT programme in Latvia.



Note. Authors' elaborations based on data provided by the State Employment Agency for 2016. This graph shows the percentage of the VT participants at the local authorities level (novadi), calculated as the ratio between the number of participants in each local authority level over the total population of participants. The darker the colour, the higher the percentage of the VT participants. As in Figure 4, the numbers refer to the aggregation level of local authorities (novadi), but in this map we report the borders of the parishes (NUTS3).

Table 1 shows the distribution of participants in the different training courses within the VT programme. It would be difficult to perform a separate analysis for each type of training programme due to the low sample size.

Therefore, we use the International Standard Classification of Occupations (ISCO) endorsed by the International Labour Organization (ILO), and classify the VT courses part of the YG programme into seven categories. Table 2 shows the distribution of the participants in the training courses offered by the VT programme, according to the ISCO classification.

The courses with the highest number of participants are those that classify in the ISCO group: "Services and Sales Workers" (ISCO skill level 2), "Technicians and Associate Professionals" (ISCO skill level 3) and "Craft and Related Trades Workers" (ISCO skill level 2) (25.61%, 23.27% and 23.72%, respectively). This means that the majority of participants (62.82%) concentrates in qualification courses that require lower level of skills (ISCO skill level 1 and 2). In Section 8 we will provide a separate analysis for courses belonging to the "high skill" and "medium to low skill" categories.[18]

5. *Bringing back the voucher*: once the unemployed and the training provider sign the agreement, the latter fills in the voucher, signs it and returns it to the unemployed, who brings it back to the SEA officer within one month before the voucher expires.

6. *Contract*: the SEA officer prepares an agreement with the unemployed and with the training provider. The contract specifies, among others, the terms and the time of the training, the mutual duties and rights during the training, and the provisions for interruptions and termination of the course. It also specifies the organisation of the final examinations.

7. *Training*: The training has to start within one month of signature of the training voucher. The SEA officer controls the quality of the training services and the client satisfaction.

4 Data

In this study we use individual records obtained by merging the data from the SEA with data from the SRS (i.e. the State Tax Authority).[19]

[18]See 19 for the mapping of occupations to skill level using the ISCO-08 classification. Due to low sample size we have to group some of these categories.

[19]We would like to thank the Evaluation Division of the EU Funds Strategy Department of the Ministry of Finance of the Republic of Latvia for granting access to and collecting the data from the SEA and the SRS.

Table 1: Distribution of participants (treated group) in the different training courses.

Training course	Number of participants	Frequency	Cumulative frequency
Accounting and taxes	2	0.22	0.22
Project management	36	4.01	4.23
Small business management	10	1.11	5.35
Accounting	2	0.22	5.57
Baker	2	0.22	5.79
Builder	12	1.34	7.13
Car mechanic	14	1.56	8.69
Computer system technician	24	2.67	11.36
Confectioner assistant	81	9.02	20.38
Cook	3	0.33	20.71
Customer service operator	95	10.58	31.29
Dresser	25	2.78	34.08
Electrician	20	2.23	36.30
Electrocar driver	11	1.22	37.53
Hand welding	2	0.22	37.75
Logistic services	1	0.11	37.86
Office manager	170	18.93	56.79
Plumber	8	0.89	57.68
Postal operator	1	0.11	57.80
Practical marketing	1	0.11	57.91
Project management	57	6.35	64.25
Retail services worker	12	1.34	65.59
Security work	100	11.14	76.73
Services of social care	5	0.56	77.28
Small business management	16	1.78	79.06
Social care	18	2.00	81.07
Specialist of hospitality services	14	1.56	82.63
Storekeeper	4	0.45	83.07
Tailor	14	1.56	84.63
Welding	134	14.92	99.55
Woodworker	4	0.45	100.00
Total	898	100.00	

Table 2: Distribution of participants in the training programmes using ISCO-08 classification.

Qualification group	Freq.	Percent	Cum.	ISCO skill level
Professionals	125	13.92	13.92	4
Technicians and Associate Professionals	209	23.27	37.19	3
Clerical Support Workers	96	10.69	47.88	2
Services and Sales Workers	230	25.61	73.50	2
Craft and Related Trades Workers	213	23.72	97.22	2
Plant and Machine Operators	13	1.45	98.66	2
Elementary Occupations	12	1.34	100.00	1
Total	898	100.00		

The SEA administrative database gathers data on persons who are registered as unemployed in Latvia. From the day of the registration at the SEA, unemployed individuals receive job-search assistance, which can last up to 4 months. In this phase, the SEA case-workers screen the profiles of registered unemployed individuals, assess their needs, and check whether they are eligible to attend training courses. For all persons who are registered as unemployed, the SEA collects individual characteristics such as gender, exact birth date, residence, nationality, highest level of education attained, and exact date of registration at the SEA database, which represents the starting date of the unemployment spell.

Administrative databases from the SEA provide us with data on *the NEETs registered as unemployed in any given period between June 2013 and December 2015.* These include those participating in the VT programme (*treated units*) and those who did not participate in the VT programme or in any other training programme at the SEA (*control units*). Both groups received job-search assistance after the registration at the SEA. As for the participants, information regarding the VT programme includes the start and end dates of the training, the type of the attended course, whether it was completed or not (dropout), and if one participated in another programme after the completion of the training. It is also possible to observe if the individual had participated in another programme under the YG package before participating in the considered training.

The administrative data from the SRS report information on labour market performance of each individual at specific dates.[20] This allows us to define an indicator of formal employment

[20]The SRS database collects monthly reports from the employers which declare employees' monthly income, social insurance, working hours, the quality of the job (based on the ISCO-88), the sector of the firm (Statistical Classification of Economic Activities in the European Community, i.e. NACE category), as well as the size of the firm (number of

at specific points in time. For individuals who are formally registered as employed in the SRS database, it is also possible to observe labour earnings, the sector of activity, and the size of the firm. This information was extracted for each individual in the sample at the following dates: January 2012, June 2012, December 2012, June 2013, December 2013, June 2014, December 2014, June 2015, December 2015, June 2016, December 2016, and June 2017. Since the intervention starts in January 2014, the information collected between January 2012 and December 2013 is used to construct pre-intervention measures of individuals' labour market careers (e.g., employment status, monthly income, hours worked, and social contributions). Data collected in December 2015, June 2016, December 2016, and June 2017 serve as outcome variables to evaluate the labour market performance of the individuals from one to two years after the intervention.

Data from the SEA are hence merged with data from the SRS to obtain information on labour market status both in the pre-intervention and post-intervention period for all individuals in the sample (the treated and the control group).

5 Sample selection and descriptive statistics

Our initial sample is composed of 1,890 treated units and 38,564 control units. The programme officially started in January 2014; since individuals could enrol in the programme at any time (provided they met the eligibility criteria), we had to impose some sample selection criteria. The research design is set as follows. First, we select all individuals who registered as unemployed at the SEA from 1 January 2014 to 31 December 2014 and at the registration date were aged between 15 and 29 years of age.[21] All these individuals are eligible for the YG package.

Second, for each individual we fix a window of one year from the date of registration, in order to assess his/her participation in the training programme. The treatment status is defined as a binary indicator that equals 1 if the individual participates in the training programme within the first year of the registration date (treated group), and 0 otherwise (control group). Hence, if someone registers at the SEA on 31 December 2014, and starts the training programme by the end

employees).

[21] We do so to avoid potential dynamic sample selectivity issues. Indeed, including the long-term unemployed in the sample, e.g. those registered in 2012 or 2013, would introduce potentially substantial unobserved individual heterogeneity in the analysis. For instance, those who firstly registered at the SEA in 2012 and remain unemployed in 2014 could be the least employable, due to a lack of skills or low job-search effort. By selecting those registered at the SEA in 2014, we seek to limit these potential concerns.

of December 2015, she is included in the treated group.[22] By contrast, an individual is included in the control group if she registered as unemployed at the SEA in 2014 but did not participate in a YG training programme (or any other SEA programme) in the same period.

The final sample is composed of 11,565 individuals. Among these, 898 individuals participate in the VT programme forming the treated group. The remaining 10,667 individuals form the control group. The outcome variable is measured for all individuals in June 2016, December 2016, and June 2017.

Table 3 reports descriptive statistics for the variables used in the analysis (mean, standard deviation, and sample size), for the control and treated groups separately (whole sample).[23]

[22]From the total number of individuals who registered at the SEA in 2014 (938), we drop 40 individuals who participated in the training programme one year after the registration date.

[23]Table 20 in the Appendix provides similar descriptives for separate age bandwidth.

Table 3: Descriptive Statistics.

Variable	Controls (A) Mean	St.Dev.	N	Treated (B) Mean	St.Dev.	N	t-test Diff. (A)-(B)	t-stat
Outcome variables								
Employed June 2016	0.45	0.50	10,667	0.41	0.49	898	0.0392*	(2.27)
Income June 2016	303.89	461.05	10,667	204.86	307.49	898	99.02***	(6.32)
Employed December 2016	0.43	0.50	10,667	0.40	0.49	898	0.0367*	(2.13)
Income December 2016	316.86	515.38	10,667	219.93	336.55	898	96.93***	(5.54)
Employed June 2017	0.45	0.50	10,667	0.43	0.50	898	0.0223	(1.29)
Income June 2017	337.85	519.18	10,667	254.50	367.99	898	83.35***	(4.71)
Control variables								
Female	0.49	0.50	10,667	0.57	0.50	898	-0.0833***	(-4.80)
Foreign nationality	0.37	0.48	10,667	0.35	0.48	898	0.0202	(1.20)
Lower than primary or primary	0.31	0.46	10,667	0.39	0.49	898	-0.0815***	(-5.05)
General secondary	0.29	0.46	10,667	0.37	0.48	898	-0.0733***	(-4.61)
Professional secondary	0.23	0.42	10,667	0.17	0.38	898	0.0563***	(3.87)
Higher education	0.16	0.37	10,667	0.07	0.25	898	0.0979***	(7.76)
Capital city	0.23	0.42	10,667	0.11	0.31	898	0.124***	(8.60)
Rural area	0.37	0.48	10,667	0.41	0.49	898	-0.0412*	(-2.46)
Average income before 2014	281.41	349.43	10,667	180.95	233.53	898	100.5***	(8.46)
Nr.years with positive income before 2014	1.90	1.79	10,667	1.36	1.62	898	0.549***	(8.89)

Note. Descriptive statistics are computed for the larger bandwidth used in the FRDD (ages 15-29), including 11,565 individuals.

As shown by the results of the t-tests on the difference in the means, the treated and the control units are balanced in terms of nationality, since the proportion of individuals with a foreign nationality status is non statistically different in the two groups. As regards gender, the proportion of females is higher in the treated group than in the control group, being the difference between the two means negative and statistically different from zero. The two groups also differ in terms of educational level, area of residence, and income. Treated unemployed are on average less educated: the proportion of unemployed with lower than primary or primary and general secondary education is higher in the treated group than in the control one, while the proportion of unemployed with professional secondary or higher education is higher in the control group. The proportion of unemployed living in the capital city is higher in the control group compared to the treated group, whereas the proportion of unemployed residing in a rural area is higher in the treated group. As regards prior work histories, the average income and the number of years with positive income in the pre-treatment period (before 2014) are higher in the control group compared to the treated one. All in all, these statistics suggest that individuals participating in VT may be the least employable in terms of observable characteristics (e.g. past work experience, education) and perhaps also of unobservable characteristics (motivation, job search effort, etc.).

6 Empirical strategy

The main identification issue that needs to be tackled when assessing the causal effect of the VT programme on the employment status after the programme is that the unemployed individuals are not randomly allocated to the VT programme, but can choose to participate or not. This gives rise to a self-selection problem driven by factors such as ability or motivation. There might be concerns that participants in the VT programme may differ from non-participants in terms of unobservable characteristics (that cannot be observed by the analyst), and this could have a direct impact on their employment status after the treatment period, invalidating the analysis.

To overcome this identification issue we exploit a specific feature of the programme, namely the fact that the SEA gave a higher priority for participation in the VT programme to unemployed people under the age of 25, even though the YG targets all individuals in the age range of 15–29. Since we do not know the exact date in which the profiling-phase took place, we assume that for each individual in the sample the eligibility conditions for the participation in the VT programme were assessed on the day of registration at the SEA.

These features of the programme make it ideal for the use of a *Fuzzy Regression Discontinuity Design* (FRDD), a methodological approach used when there is a threshold in a given individual attribute that determines assignment to a treatment (sharp RDD) or the probability of being treated (FRDD). The RDD setting is often view as a local randomisation at the threshold value, so that assignment to treatment at the threshold can be considered "as good as random". This means that on average, treated and control units around the age of 25 have identical observable and unobservable characteristics.

In our analysis, age is the individual attribute (or the running variable) that determines the probability of participating in the VT programme, with the age of 25 representing the threshold, or cut-off point. Age is measured on the date of registration at the SEA and is a continuous variable (expressed in days).

According to the priority rule, an individual who is under the age of 25 on the day of registration at the SEA, has a higher probability of participating in the programme compared to individuals above the age of 25. Since participation is a voluntary choice, the probability of participation for those who are less than 25 years old is strictly less than one. The running variable is centred at the cut-off point, so it is equal to 0 for those who register at the SEA on the day of ther 25^{th} birthday, and takes a negative (positive) value for those who at the time of registration are below (above) age 25. As such, the running variable represents the difference between age at the time of registration and the cut-off value ($age = 25$): larger negative values correspond to individuals who are exposed to the priority rule for a longer period. Note that, since the running variable is measured for each individual on the starting date of the unemployment spell (i.e. the date of registration at the SEA, which is assumed to coincide with the day in which the profiling takes place), the probability of participating in the programme for each individual in the sample jumps from zero to a positive value at the cut-off point.

We now show a more formal presentation of the identification strategy and the estimation procedure. The causal effect of participation in the VT programme on employment status later on, can be estimated via Instrumental Variables, using a Two-Stages Least Square (2SLS) estimator. In our setting the discontinuity in the probability of participating in the programme given by the age-specifc rules, can be used as an instrument for participation status (Angrist and Pischke 2008). The 2SLS estimation strategy consists of two stages: i) in the first stage, we regress a binary indicator of the treatment status on the binary indicator for being under the age of 25 (priority rule); ii) in the second stage equation, we use the estimated probability of participation to compute the effect of the treatment (participation in the VT programme) on the outcome variable of interest.

Our equation of interest is:

$$Y_i = \beta_1 T_i + f(\tilde{x_i}) + \beta^\top \mathbf{W}_i + \epsilon_i, \tag{1}$$

where Y_i is the employment status (or monthly wage) of individual i at a certain point in time after the training is completed (June 2016, December 2016 and June 2017), T_i is the treatment variable, which is equal to 1 f the individual is registered at the SEA as unemployed for the period of January - December 2014, and completes the VT programme by December 2015. $\tilde{x_i}$, is the running variable, i.e. age measured on the date of registration at the SEA and centred at the cut-off point. $f(\cdot)$ is a polynomial in the running variable, that represents the relationship between the running variable and the outcome. $\mathbf{W}_i$ is a vector of individual covariates such as gender, nationality, level of education, residence area, number of years worked, and average income in the pre-treatment period, including the intercept term. ϵ_i is an individual specific error term.

As explained above, we estimate equation (1) via Two-Stages Least Squares (2SLS). The excluded instrument is a binary indicator for being under the age of 25 at the registration day, i.e. being subject to the programme priority rule $Z = \mathbf{1}(x < 25)$.

The corresponding first stage equation in the case of a linear polynomial reads as follows:

$$T_i = \gamma_1 Z_i + \gamma_2 \tilde{x}_i + \gamma^\top \mathbf{W} + \eta_i, \tag{2}$$

where Z_i is the instrument for T_i and η_i is an individual error term. In the analysis, we specify the polynomial in the running variable as either linear or quadratic.

That is, the main equation in the case of a linear polynomial becomes:

$$Y_i = \beta_1 T_i + \beta_2 \tilde{x}_i + \beta^\top \mathbf{W}_i + \epsilon_i, \tag{3}$$

where $\beta_2 \tilde{x}_i$ is a parametric function in the running variable that can be linear or quadratic.[24] The main results are discussed in Section 7.

7 Results

7.1 Graphical analysis

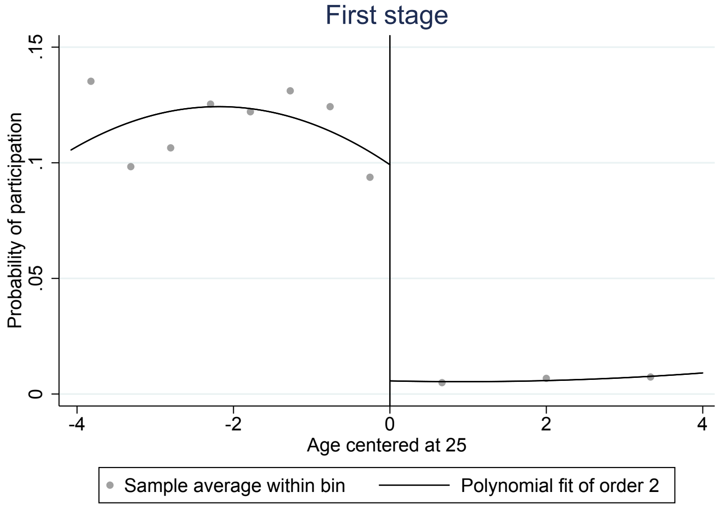
In this section we present some descriptive statistics concerning the effect of the priority rule (age-eligibility conditions of the YG) on participation in the training programme (first stage in the terminology of instrumental variables), and the effect of the priority rule on the probability of being employed in June 2016, December 2016 and June 2017 (reduced form).

Figure 6 shows the probability of participating in the VT programme, as a function of age at registration at the SEA (first stage equation), using the quadratic specification in age with normalised aged (cut-off is 0). Here we do not condition on other covariates, such as gender, nationality, place of residence, etc. The graph suggests that there is a jump in the probability of participating in the VT at the cut-off (age 25) due to the priority rule, and that this relationship is quadratic for age lower than 25. The jump is, however, small (around 10%), which points towards a low take-up rate of the programme from the target group, even in the presence of incentives related to age (i.e. the priority rule). This result is in line with Caliendo and Schmidl (2016), who show

[24] As a sensitivity analysis we estimate the same model by allowing the parametric function in the running variable to have different slopes on both sides of the cut-off, as explained in Angrist and Pischke (2009) (pages 197–198). Results do not change (available upon request).

that in Latvia the participation of youths in ALMP programmes remains low compared to other countries (i.e only 5% in 2013 when the youth unemployment rate was as high as 23%).

Figure 6: Probability of participating in the VT programme, by age of registration at the SEA.



Figures 7-9 show the probability of being employed in a given date (respectively in June 2016, December 2016 and June 2017), as a function of the age at registration at the SEA, normalised at the cut-off point, using the quadratic specification. Differently from Figure 6, we do not observe a sizeable jump at the discontinuity point, although it can be seen that the probability of being employed after the completion of the VT programme is higher for youths under the age of 25 compared to those aged 25 or above. The size of the jump is positive for employment measured in June 2016 and June 2017, and negative but very small for employment measured in December 2016. In the following section we report the FRDD estimates, which include controls for individual characteristics, in order to increase the precision of the estimates and deal with any potential bias which may stem from the voluntary participation in the VT programme.

7.2 Testing for manipulation

The identification strategy in the RDD approach relies on the local randomisation of the treatment that is due to the inability of individuals to precisely control the running variable. In our case, the running variable is the age measured at the date of registration at the SEA. Hence, the underlying identification assumption is that individuals just below and just above the threshold of age 25 are comparable to each other, except for their exposure to the priority rule, which applies only

Figure 7: Probability of being employed in June 2016, by age of registration at the SEA.

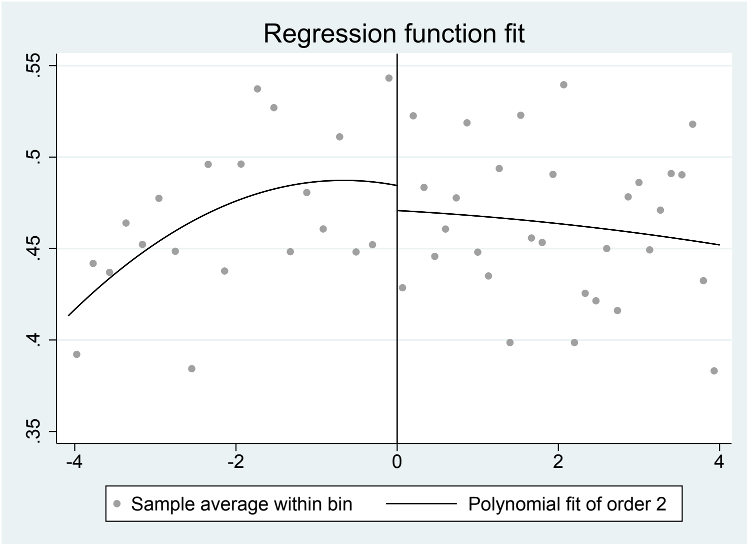


Figure 8: Probability of being employed in December 2016, by age of registration at the SEA

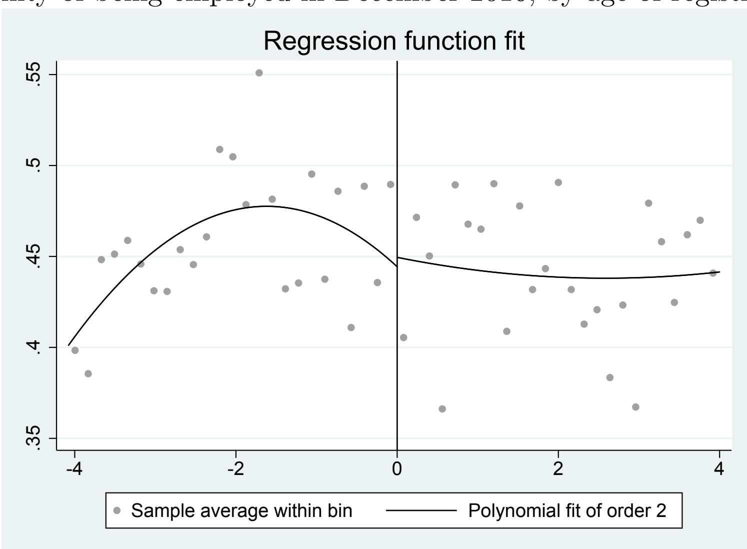
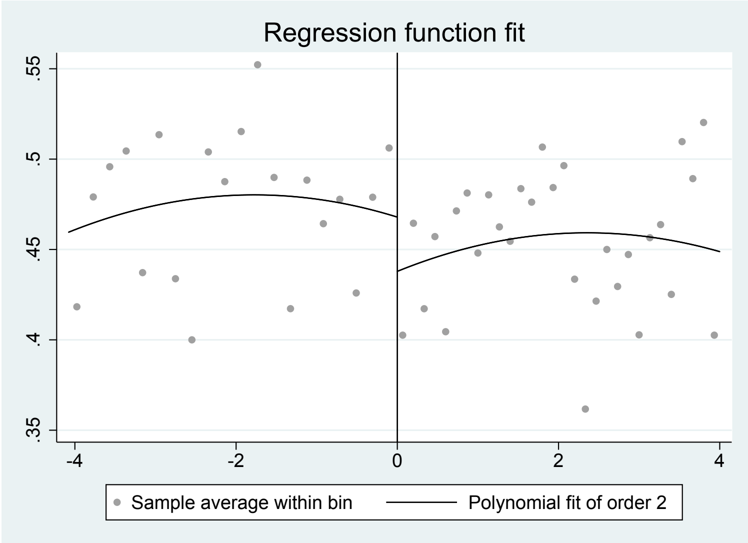


Figure 9: Probability of being employed in June 2017, by age of registration at the SEA.



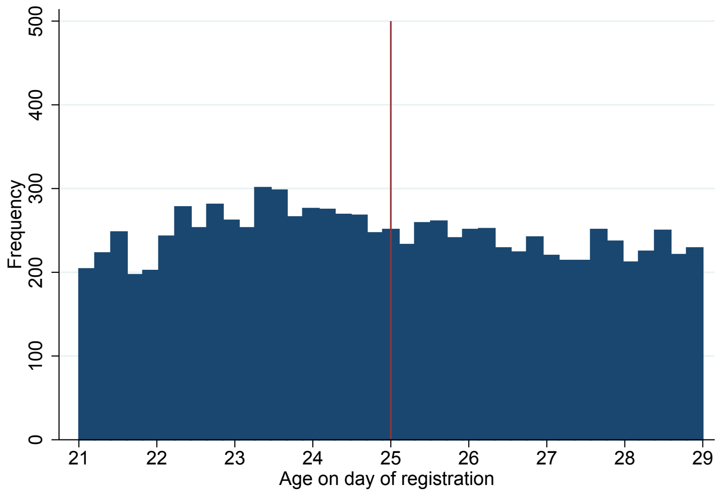
to those who are below the cut-off. Such assumption may be violated if there is anticipation of the intervention from the individuals. Such possibility would arise if people below age 25 started registering at the SEA as from January 2014 at a higher rate specifically because they knew about the training programme and wanted to participate. If this was the case, we would observe a peak at 25 years in age distribution on the day of registration at the SEA. Anticipation would bias the treatment estimate if the anticipatory behaviour was more pronounced in specific selected groups, i.e. the most (least) motivated NEETs.

To make this more explicit, assume that the priority rule was well known amongst the target population, i.e. the pool of NEETs aged 15-29 years. Assume that, in expectation of the treatment, the most motivated NEETs below 25 years of age decide to register at the SEA in 2014 in order to participate in the training programme. Moreover, assume that the registration rate among the NEETs above 25 remains unaffected, since they know that they have little chance of participating in the training. In this case, by comparing registered unemployed persons below and above the age of 25 years, we would be comparing individuals who are also different in terms of unobserved motivation. This would violate the identifying assumption underlying the RDD, i.e. that individuals just below and just above the threshold are similar in all respects except for the treatment assignment.

To check for the presence of manipulation, we provide two pieces of evidence: first we show that the distribution of the running variable is continuous around the cut-off; this is shown in Figure 10.

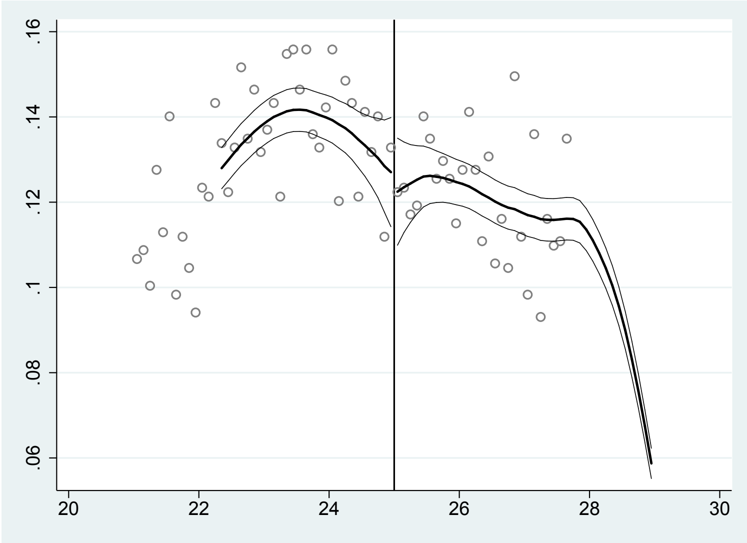
Second, we run a formal test as described in McCrary (2008). The idea of McCrary (2008)'s test is that, if individuals had precise control over assignment, one would expect the density of the running variable to be zero on the right of the cut-off and positive on the left of the cut-off (if the treatment is assigned to values smaller than the cut-off and everybody is willing to receive the treatment). If instead the individuals had imprecise control over assignment, the density of the running variable should be continuous around the cut-off. Hence, McCrary (2008) test allows for the testing of the continuity of the density of the running variable around the threshold. Results are shown in Figure 11. Figures 10 and 11 both suggest that there is no discontinuity at the cut-off in the age distribution at SEA registration. This clearly indicates that there is no evidence of manipulation in our setting and strongly supports the internal validity of the RDD.

Figure 10: Distribution of age at SEA registration in 2014 (treatment defined in a 12 month window)



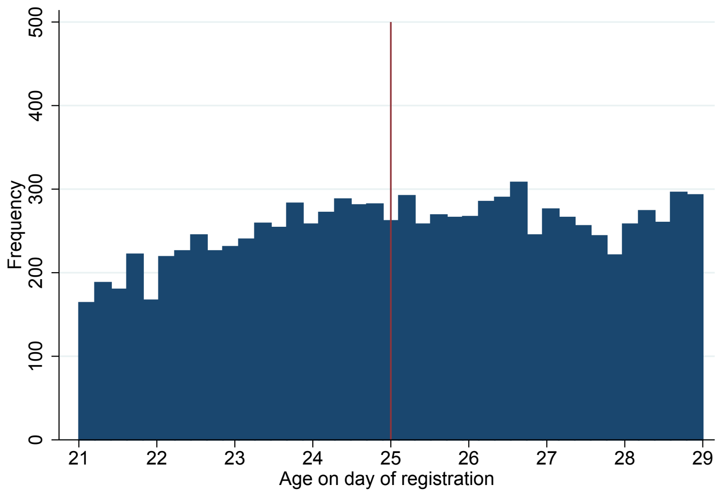
In addition, to check that the YG did not change the incentives for registering at the SEA, we plot the age distribution at SEA registration in 2013, before the start of the YG (see Figure 12). Fig. 12 suggests that the age at SEA registration for 2013 is very similar to that observed during 2014, shown in Figure 10. This again supports the empirical strategy used in the analysis. Note that, in Figure 12, the vertical red line at 25 years of age indicates the "placebo" priority rule for participating in the training programme, even though it was not yet put in place. Therefore, in 2013, there is no reason to expect a peak of registered unemployed at 25 in the age distribution at registration. By contrast, the absence of the peak in the corresponding graphs in 2014 (see Figure

Figure 11: McCrary test - treatment defined in a 12 month window



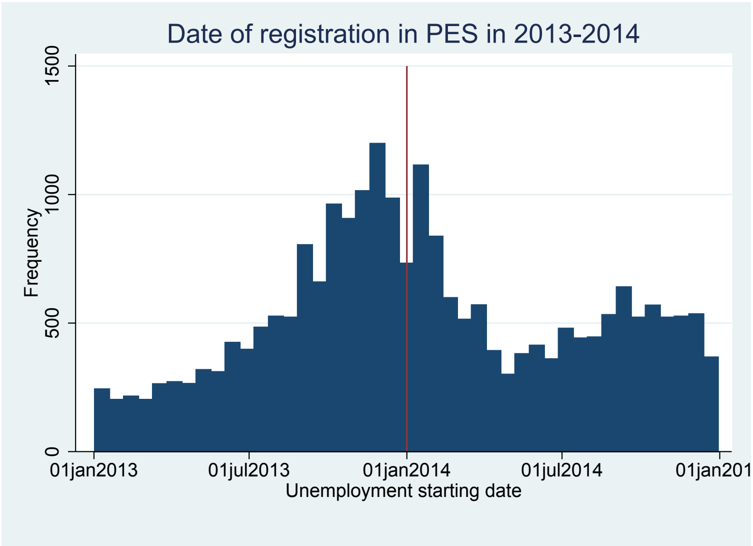
10), when the YG was in place, supports our identification strategy.

Figure 12: Distribution of age at SEA registration in 2013



Lastly, Figure 13 plots the number of individuals aged 15-29 registered at the SEA by date of entry for the period 2013 and 2014. The red line on 1 January 2014 defines the introduction of the YG. According to the figure, registration at the SEA is not uniformly distributed over time. The number of registrations increases in the second semester of 2013, reaches a peak in January 2014, and then decreases in the first semester of 2014. This does not invalidate our analysis as long as there are no differences in enrolment according to age, around the threshold of age 25. However, to improve precision, we control for this trend by including the month of registration at the SEA as an additional control in all specifications.

Figure 13: Distribution of date of registration in 2013 and 2014



7.3 Fuzzy RDD estimates

In this section, we present our main results. As mentioned in Section 'Data', we consider as treated individuals who enrol in the VT programme within 12 months from the registration at the SEA. As a sensitivity check, we run the same analysis by changing the enrolment window in the VT programme from 12 months to 6 months.[25] The main idea is that early-stage and late-stage participants in the VT programme (with respect to their date of registration at the SEA) may be two different sub-populations for whom the treatment may produce different effects.[26] Moreover, differences between these groups may also be produced by differences in lock-in effects, according to the timing of the VT programmes.

Table 4 and 5 show the results of the first stage equation for the linear and quadratic specifications respectively, using different age bandwidth, namely 15–29, 22–28, 23–27, and 24–26. From the first table, it can be observed that being subject to the priority rule, that is being under the age of 25 when registering at the SEA, increases the probability of participating in the programme by about 6.4 pp when considering all cohorts (age 15–29), and falls to 5.8 pp when considering cohorts that are close enough to the threshold (age 24–26). We observe a strong correlation between the priority rule, and participation in the programme. The F-statistics is way above the threshold of 10, and ranges between 13.1 and 71 when considering respectively the smallest bandwidth (age 24–26) and the largest bandwidth (15–29).

Results are very similar when we adopt a quadratic specification in age (Table 5). Note that the larger the bandwidth around the cut-off, the higher the precision of the estimates, as we are using more data points to fit our model. At the same time this implies that the estimates will tend to be less accurate (higher bias), due to the fact that we are using data points that are far away from the cut-off. For this reason, we report the estimates for different age windows.

We now show the estimated effects for two types of outcomes: the probability of being employed respectively in June 2016, December 2016, and June 2017 (Tables 6-8), and the monthly income declared for the same reference dates (Tables 9-11). The results are reported in three different panels, showing respectively the estimates from the ordinary least square (OLS), the reduced form (RF), and instrumental variable regression (IV). In all cases we estimate a linear and a quadratic specification in age. As previously, results are presented for different age bandwidths around the

[25]Among all individuals who registered at the SEA in 2014 and participated in the VT programme (938), 234 (24%) started the training 6 months after their registration date. Estimation results are available upon request.

[26]Results do not change. They are available upon request.

cut-off.

OLS estimates from Table 6 show that participating in the VT programme does not have any effect on the probability of being employed in June 2016 (estimates are non statistically different from 0). Results do not differ very much when considering the linear and quadratic specifications. However, OLS estimates can be biased because of unobserved factors that can affect the outcome of interest (i.e ability or motivation). For this reason, we also report the IV estimates. We see that participating in the VT programme increases the probability of being employed in June 2016 by 51.3 pp, although this result is statistically different from zero at the 5% level, and only when we consider the largest bandwidth (age 15–29). In general, narrowing the bandwidth reduces the potential bias induced by considering age groups which are too far away from the cut-off, and makes it less necessary to include high-order polynomials to control in a flexible way for potential age effects on employment. The IV estimates in the 21-29, 22-28, 23-27 and 24-26 bandwidths all show no effect of participating in the VT programme in terms of employability.[27] Overall, these results are in line with the findings from the literature analysing youth participation in ALMPs (Carling and Larsson, 2005; Ibarrarán et al., 2015) the effects tend to show up only in the short One plausible explanation is the presence of lock-in effects, namely that participants, unlike non-participants, have less time to devote to job search. To test this hypothesis, it can be informative to follow both participants and non-participants over time in order to check for medium to long-term effects. This is often costly as it requires to follow people over time and run surveys (in absence of administrative data), and as a consequence the evidence on the long-term effects in this literature is limited.

For this reason, we extend our analysis by looking at labour market outcomes in December 2016 and June 2017 (Table 7 and 8), respectively 1 to 2 years after the completion of the programmes. The OLS estimates are never statistically significant at conventional levels. The point IV estimates are somehow sensitive to the choice of the bandwidths and to the order of the polynomial, but are never statistically significant, except for the estimates in the largest bandwidth. The latter are however also those more likely to be affected by an estimation bias as individuals enrolling in SEA at 15 years, for instance, are very likely to differ sharply from those enrolling at 29, even after controlling for observable characteristics and a flexible polynomial in age.

Tables 9-11 show the results on monthly wages in June 2016, December 2016, and June 2017

[27]The IV estimates are somehow sensitive to the choice of bandwidth but are never statistically significant at conventional levels when focusing on narrow bandwidths.

(income is coded as zero for unemployed individuals). OLS estimates in Table 9 point towards a negative and statistically significant association between participation in the VT programme and monthly income, which suggests perhaps that individuals enrolling in those courses may be the least employable or those with a lower earning capacity. The association turns out to be statistically non significant only when we narrow the bandwidth. Nevertheless, these coefficients generally lose statistical significance in December 2016 or June 2017, as shown in tables 10 and 11, respectively. As for the IV estimates, they do not point to any statistically significant effect of participation in the VT programme on monthly income. The point estimates are sometimes very sizable, mostly because they capture the effects on income conditional on being employed (we attribute a zero income to unemployed). The results are positive but statistically not significant for the age bandwidth 24-26.

A general concern with the estimates based on the Fuzzy RDD and estimated via 2SLS, is that the 2SLS estimates are much bigger in magnitude compared to the OLS estimates. This could either be due to a lack of precision or the presence of weak instruments. However, strong results of the first-stage equation and the lack of statistical significance in the reduced form regressions seem to exclude that weak instruments are the primary reason for obtaining no effect in the 2SLS regression.

More generally, the findings in our study are very much in line with the findings from studies from other European countries evaluating the impact of ALMP targeted at youth. Most do not find any effect of training programmes in either the short and or medium -term. Some studies find a moderate effect in the long-term only when considering other types of ALMPs (such as job counseling or wage subsidies).

In the following section we will explore possible heterogeneous effects of the VT training programme. In particular, we will investigate whether our findings differ by population subgroups (i.e. gender, level of education, area of residence, and qualification group of the training programs).

Table 4: First stage results, linear specification.

Window width	15–29	21–29	22–28	23–27	24–26
Age< 25	0.064 ***	0.082 ***	0.080 ***	0.065 ***	0.058 ***
	(0.008)	(0.008)	(0.010)	(0.012)	(0.016)
Age centred at 25	-0.004 ***	0.001	-0.001	-0.009 *	-0.017
	(0.001)	(0.002)	(0.003)	(0.005)	(0.013)
Female	0.019 ***	0.018 ***	0.018 ***	0.023 ***	0.024 ***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)
Foreign nationality	0.006	0.007	0.007	0.008	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Lower than primary or primary	0.018 **	0.014 **	0.018 **	0.025 ***	0.015
	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
General secondary	0.023 ***	0.026 ***	0.028 ***	0.030 ***	0.021 *
	(0.007)	(0.006)	(0.007)	(0.008)	(0.011)
Professional secondary	-0.006	0.003	0.005	0.012	0.012
	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
Not specified	-0.039	-0.021	-0.021	-0.068	0.000
	(0.093)	(0.103)	(0.120)	(0.208)	(.)
Local center	0.017 *	0.010	0.015	0.007	-0.000
	(0.010)	(0.010)	(0.011)	(0.014)	(0.019)
National center	-0.039 ***	-0.037 ***	-0.037 ***	-0.040 ***	-0.043 ***
	(0.007)	(0.006)	(0.007)	(0.009)	(0.012)
National dev. center	0.919 ***	0.918 ***	0.915 ***	0.913 ***	0.913 ***
	(0.016)	(0.017)	(0.019)	(0.023)	(0.032)
Regional center	0.072 ***	0.060 ***	0.057 ***	0.059 ***	0.042 ***
	(0.008)	(0.008)	(0.009)	(0.011)	(0.014)
Rural area	0.041 ***	0.024 ***	0.023 ***	0.020 **	0.010
	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
Nr.years with positive income before 2014	-0.000	-0.000	-0.000	0.002	0.003
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Average income before 2014	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	-0.033 ***	-0.035 ***	-0.039 ***	-0.050 ***	-0.028
	(0.011)	(0.011)	(0.012)	(0.014)	(0.019)
F-stat	70.9	97.1	68.9	30.4	13.1
N. obs.	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the estimated coefficients from the first stage regressions using a linear specification in age. The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. Standard errors are in parentheses.

Table 5: First stage results, quadratic specification.

Window width	15–29	21–29	22–28	23–27	24–26
Age< 25	0.080 ***	0.082 ***	0.079 ***	0.065 ***	0.059 ***
	(0.009)	(0.008)	(0.010)	(0.012)	(0.016)
Age centred at 25	0.001	0.001	-0.001	-0.008 *	-0.016
	(0.002)	(0.002)	(0.003)	(0.005)	(0.013)
Age squared centred at 25	0.001 ***	-0.000	-0.001	0.003	0.016
	(0.000)	(0.000)	(0.001)	(0.002)	(0.012)
Female	0.019 ***	0.018 ***	0.018 ***	0.023 ***	0.023 ***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)
Foreign nationality	0.006	0.007	0.006	0.008	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Lower than primary or primary	0.016 **	0.014 **	0.019 **	0.025 ***	0.015
	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
General secondary	0.023 ***	0.026 ***	0.028 ***	0.030 ***	0.021 *
	(0.007)	(0.006)	(0.007)	(0.008)	(0.011)
Professional secondary	-0.006	0.003	0.005	0.012	0.012
	(0.007)	(0.007)	(0.008)	(0.009)	(0.012)
Not specified	-0.041	-0.021	-0.020	-0.069	0.000
	(0.093)	(0.103)	(0.120)	(0.208)	(.)
Local center	0.017 *	0.010	0.015	0.007	0.000
	(0.010)	(0.010)	(0.011)	(0.014)	(0.019)
National center	-0.038 ***	-0.037 ***	-0.038 ***	-0.039 ***	-0.042 ***
	(0.007)	(0.006)	(0.007)	(0.009)	(0.012)
National dev. center	0.920 ***	0.918 ***	0.915 ***	0.913 ***	0.912 ***
	(0.016)	(0.017)	(0.019)	(0.023)	(0.032)
Regional center	0.073 ***	0.060 ***	0.057 ***	0.060 ***	0.042 ***
	(0.008)	(0.008)	(0.009)	(0.011)	(0.014)
Rural area	0.042 ***	0.024 ***	0.023 ***	0.020 **	0.010
	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
Nr.years with positive income before 2014	0.000	-0.000	-0.000	0.002	0.003
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Average income before 2014	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	-0.048 ***	-0.034 ***	-0.037 ***	-0.055 ***	-0.035 *
F-stat	83.5	97	68.5	30.9	13.5
N. obs.	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the estimated coefficients from the first stage regressions using a quadratic specification in age. The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. Standard errors are in parentheses.

Table 6: Results for the probability of being employed in June 2016.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	0.004	-0.008	-0.011	-0.007	0.047
	(0.020)	(0.024)	(0.027)	(0.032)	(0.048)
			RF		
Age< 25	0.033 **	0.019	0.015	0.004	0.023
	(0.016)	(0.020)	(0.022)	(0.027)	(0.039)
			IV		
Treated	0.513 **	0.227	0.183	0.069	0.396
	(0.259)	(0.239)	(0.282)	(0.421)	(0.676)
F-stat	70.9	97.1	68.9	30.4	13.1
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated	0.004	-0.008	-0.011	-0.008	0.047
	(0.020)	(0.024)	(0.027)	(0.032)	(0.048)
			RF		
Age< 25	0.016	0.018	0.014	0.006	0.024
	(0.019)	(0.020)	(0.022)	(0.027)	(0.039)
			IV		
Treated	0.202	0.222	0.177	0.086	0.401
	(0.233)	(0.239)	(0.283)	(0.418)	(0.667)
F-stat	83.5	97	68.5	30.9	13.5
N. obs.	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using an indicator for being employed in June 2016 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 7: Results for the probability of being employed in December 2016.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	0.018	0.022	-0.006	0.020	0.073
	(0.020)	(0.024)	(0.027)	(0.032)	(0.047)
			RF		
Age< 25	0.030	0.023	-0.001	0.010	0.041
	(0.018)	(0.020)	(0.022)	(0.027)	(0.039)
			IV		
Treated	0.906 ***	0.276	-0.012	0.131	0.667
	(0.272)	(0.238)	(0.280)	(0.420)	(0.682)
F-stat	70.9	97.1	68.9	30.4	13.1
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated	0.017	0.022	-0.006	0.019	0.071
	(0.020)	(0.024)	(0.027)	(0.032)	(0.047)
			RF		
$Age < 25$	0.007	0.003	0.009	0.009	0.005
	(0.010)	(0.011)	(0.013)	(0.016)	(0.022)
			IV		
Treated	0.373	0.276	-0.016	0.157	0.696
	(0.234)	(0.238)	(0.281)	(0.416)	(0.674)
F-stat	83.5	97	68.5	30.9	13.5
N. obs.	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using an indicator for being employed in December 2016 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 8: Results for the probability of being employed in June 2017.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	0.034 *	0.020	0.024	0.031	0.013
	(0.020)	(0.024)	(0.027)	(0.032)	(0.047)
			RF		
Age< 25	0.045 ***	0.020	0.017	0.035	0.058
	(0.016)	(0.020)	(0.022)	(0.027)	(0.038)
			IV		
Treated	0.706 ***	0.245	0.219	0.537	0.996
	(0.264)	(0.238)	(0.281)	(0.430)	(0.714)
F-stat	70.9	97.1	68.9	30.4	13.1
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated	0.034 *	0.020	0.024	0.029	0.012
	(0.020)	(0.024)	(0.027)	(0.032)	(0.047)
			RF		
Age< 25	0.033 *	0.021	0.018	0.037	0.059
	(0.019)	(0.020)	(0.022)	(0.027)	(0.038)
			IV		
Treated	0.414 *	0.252	0.222	0.573	1.003
	(0.236)	(0.238)	(0.282)	(0.428)	(0.704)
F-stat	83.5	97	68.5	30.9	13.5
N.obs	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using an indicator for being employed in June 2017 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 9: Results for monthly income in June 2016.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	-44.423 ***	-54.807 **	-72.215 ***	-59.298 **	-10.930
	(17.121)	(21.418)	(24.385)	(29.505)	(42.840)
			RF		
Age < 25	19.990	11.161	-0.313	-4.039	47.192
	(14.083)	(17.574)	(20.293)	(24.874)	(34.872)
			IV		
Treated	310.975	135.762	-3.937	-62.282	814.937
	(222.835)	(214.272)	(254.543)	(382.402)	(641.176)
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated	-44.716 ***	-54.894 **	-72.400 ***	-59.568 **	-11.466
	(17.119)	(21.418)	(24.387)	(29.512)	(42.857)
			RF		
Age < 25	8.615	10.733	-0.663	-3.684	48.045
	(16.143)	(17.578)	(20.301)	(24.887)	(34.907)
			IV		
Treated	107.839	130.588	-8.349	-56.353	817.029
	(202.461)	(214.317)	(255.198)	(379.483)	(632.160)
N. obs.	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using the gross monthly income reported in June 2016 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 10: Results for monthly income in December 2016.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	-23.098	-29.147	-61.065 **	-42.658	-8.903
	(19.076)	(24.151)	(26.811)	(31.959)	(46.924)
			RF		
$Age < 25$	34.929 **	8.182	-5.611	10.674	60.200
	(15.664)	(19.795)	(22.285)	(26.897)	(38.007)
			IV		
Treated	534.345 **	99.484	-69.931	161.721	1026.326
	(248.049)	(240.702)	(277.158)	(407.977)	(703.437)
N.obs	11615	9632	7506	5143	2597
			Quadratic		
			OLS		
Treated	-23.722	-29.155	-60.929 **	-43.359	-10.148
	(19.070)	(24.152)	(26.814)	(31.961)	(46.934)
			RF		
$Age < 25$	15.082	8.143	-5.362	11.662	61.963
	(17.953)	(19.799)	(22.292)	(26.905)	(38.032)
			IV		
Treated	187.859	99.032	-66.958	175.549	1041.956
	(224.525)	(240.761)	(277.750)	(405.668)	(695.983)
N. obs.	11615	9632	7506	5143	2597

*, **, *** statistically significant at the 10%, 5% and 1% levels, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using the gross monthly income reported in December 2016 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors in parentheses.

Table 11: Results for monthly income in June 2017.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated	0.974	-16.155	-29.166	-9.356	-18.799
	(19.250)	(24.277)	(27.194)	(33.172)	(48.198)
			RF		
Age < 25	33.893 **	8.344	10.659	20.353	62.756
	(15.806)	(19.897)	(22.597)	(27.912)	(39.040)
			IV		
Treated	518.498 **	101.457	132.846	308.351	1069.906
	(248.990)	(241.897)	(281.782)	(425.545)	(725.311)
N.obs	11615	9632	7506	5143	2597
			Quadratic		
			OLS		
Treated	0.404	-16.149	-29.257	-10.328	-19.155
	(19.245)	(24.278)	(27.197)	(33.169)	(48.220)
			RF		
Age < 25	16.266	8.385	10.510	21.746	63.317
	(18.117)	(19.901)	(22.604)	(27.916)	(39.07)
			IV		
Treated	202.605	101.965	131.240	327.340	1064.726
	(226.467)	(241.961)	(282.374)	(423.314)	(715.372)
N.obs	11615	9632	7506	5143	2597

*, **, *** statistically significant at the 10%, 5% and 1% levels, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using the gross monthly income reported in June 2017 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors in parentheses.

8 Heterogeneous effects

8.1 Accounting for different individual characteristics

In order to check for the presence of heterogeneous effects, in Tables 12-14 we show estimates obtained by interacting the treatment variables and our instrument with specific individual attributes, namely an indicator for having less than secondary education, an indicator for being male, and an indicator for living in a rural area. We show the results for the probability of being employed respectively in June 2016, December 2016, and June 2017.[28] In each table we report the results for the first stage, reduced form and IV estimates. Columns 1-3 in each table show the heterogeneous effects by level of education. In Table 12, we report the results for the probability of being employed in June 2016. In column 1, we report the first stage results which show that being under the age of 25 and having at least secondary education increases the probability of participating in the programme by 8.5 pp. compared to older individuals with the same level of education. Vice versa, being under the age of 25 and having less than secondary education increases the probability of participating in the programme by about 12 pp. In column 2 we report the results from the reduced form regression. Being under the age of 25 and having at least secondary education increases the probability of being employed by 4.7 pp, while being under the age of 25 and having a level of education lower than secondary reduces the employability by -2.7 pp., compared to equally educated but older individuals. Hence, differently from the baseline estimates, we do obtain statistically significant results of the reduced form equation. In terms of 2SLS estimates, the change in employability is 42 pp for secondary educated individuals and -22 pp for lower educated individuals. This finding may point to stronger lock-in effects of the programme on low skilled individuals.

Columns 4-6 show results by gender. Being under the age of 25 and being male leads to an increase in the probability of participating in the programme of 7.5 pp, while being female increases the probability of being employed by 11 pp (column 4). However, columns (5) and (6) do not show any significant heterogeneity by gender for the effect of VT participation on employment.

Columns 7-9 show heterogeneous effects by area of residence. Living in urban area (Riga or other cities) and being under the age of 25 increases the probability of participating in the programme by 7.3 pp; this probability rises to about 11 pp for those who have the same characteristics but live in a rural area (column 7). Based on the reduced form results in column 8, being under the age

[28] In this case we report estimates from the linear specification in age. Results for the quadratic specification are available upon request.

of 25 increases the probability of being employed by 5.7 pp, and by about 1 pp for those living in rural areas. The IV estimates in column 9 confirm the effectiveness of VT courses only in urban areas, which is probably related to a higher labour demand.

Results in tables 13 and 14, referring to employment outcomes in December 2016 and June 2017, are qualitatively similar. The only difference is a larger effect of the VT programme on males compared to females. In June 2017, for instance, while participating in VT increases women's employment by 34 pp, the effect is doubled for men (about 74 pp).

Table 12: Heterogenous effects for the probability of being employed in June 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FS	RF	IV	FS	RF	IV	FS	RF	IV
	Less than secondary education			Male			Rural area		
Age<25	0.085***	0.047***		0.108***	0.025		0.073***	0.057***	
	(0.009)	(0.017)		(0.010)	(0.019)		(0.010)	(0.019)	
Treated			0.420**			0.279			0.573***
			(0.186)			(0.172)			(0.215)
(Age<25)*(< Sec.Edu)	0.036***	-0.074***							
	(0.011)	(0.020)							
(Treated)*(< Sec.Edu)			-0.636***						
			(0.160)						
(Age<25)*(Male)				-0.033***	0.014				
				(0.010)	(0.018)				
(Treated)*(Male)						0.224			
						(0.176)			
(Age<25)*(Rural)							0.036***	-0.048***	
							(0.010)	(0.018)	
(Treated)*(Rural)									-0.517***
									(0.170)
Less than secondary	-0.005	-0.100***	-0.093***	0.016***	-0.145***	-0.150***	0.017***	-0.145***	-0.151***
	(0.009)	(0.016)	(0.018)	(0.006)	(0.010)	(0.011)	(0.005)	(0.010)	(0.010)
Male	-0.025***	0.012	0.012	-0.006	0.005	0.005	-0.025***	0.013	0.018*
	(0.005)	(0.009)	(0.010)	(0.008)	(0.014)	(0.016)	(0.005)	(0.009)	(0.010)
Rural area	0.022***	-0.011	-0.017	0.022***	-0.011	-0.019*	0.000	0.017	0.021
	(0.005)	(0.010)	(0.011)	(0.005)	(0.010)	(0.011)	(0.008)	(0.015)	(0.016)
F-stat			60.8			48.6			60.7
N.obs	11565	11565	11565	11565	11565	11565	11565	11565	11565

$*p < 0.10, **p < 0.05, ***p < 0.01$. We use a linear specification and consider the largest age window 15–29.

Control variables and polynomial in age are not reported. We use an indicator for education being lower than secondary education. Standard errors are in parentheses.

Table 13: Heterogenous effects for the probability of being employed in December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FS	RF	IV	FS	RF	IV	FS	RF	IV
	Less than secondary education			Male			Rural area		
Age<25	0.085***	0.069***		0.108***	0.038**		0.073***	0.078***	
	(0.009)	(0.017)		(0.010)	(0.018)		(0.010)	(0.019)	
Treated			0.675***			0.451**			0.848***
			(0.189)			(0.179)			(0.220)
(Age<25)*(< Sec.Edu)	0.036***	-0.067***							
	(0.011)	(0.020)							
(Treated)*(< Sec.Edu)			-0.652***						
			(0.163)						
(Age<25)*(Male)				-0.033***	0.035*				
				(0.010)	(0.018)				
(Treated)*(Male)						0.490***			
						(0.184)			
(Age<25)*(Rural)							0.036***	-0.044**	
							(0.010)	(0.018)	
(Treated)*(Rural)									-0.567***
									(0.174)
Less than secondary	-0.005	-0.111***	-0.103***	0.016***	-0.152***	-0.159***	0.017***	-0.152***	-0.162***
	(0.009)	(0.016)	(0.018)	(0.006)	(0.010)	(0.011)	(0.005)	(0.010)	(0.011)
Male	-0.025***	0.006	0.012	-0.006	-0.014	-0.014	-0.025***	0.007	0.018*
	(0.005)	(0.009)	(0.011)	(0.008)	(0.014)	(0.016)	(0.005)	(0.009)	(0.011)
Rural area	0.022***	-0.027***	-0.038***	0.022***	-0.027***	-0.041***	0.000	-0.001	0.003
	(0.005)	(0.010)	(0.011)	(0.005)	(0.010)	(0.011)	(0.008)	(0.015)	(0.016)
F-stat			60.8			48.6			60.7
N.obs	11565	11565	11565	11565	11565	11565	11565	11565	11565

$*p < 0.10, **p < 0.05, ***p < 0.01$. We use a linear specification and consider the largest age window 15–29.

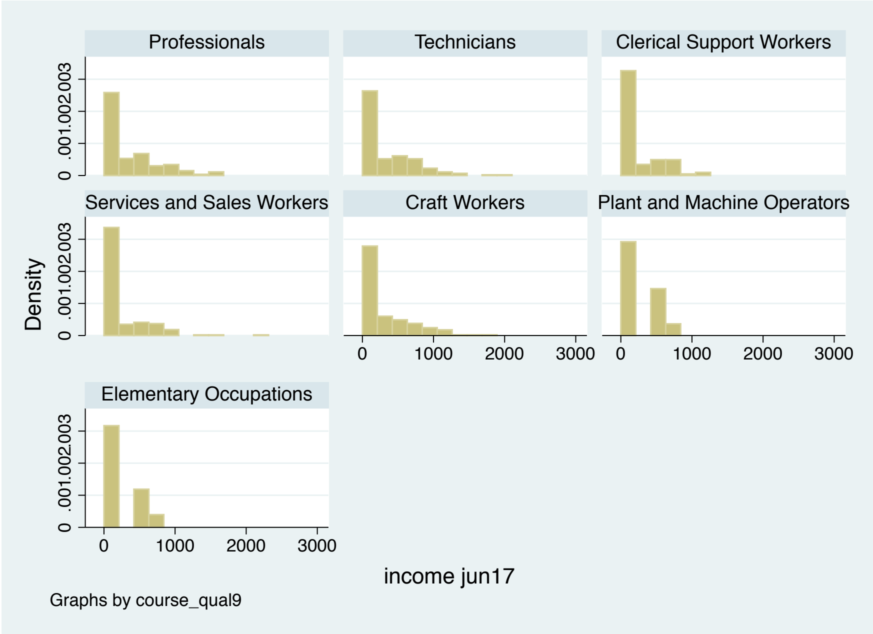
Control variables and polynomial in age are not reported. We use an indicator for education being lower than secondary education. Standard errors are in parentheses.

Table 14: Heterogenous effects for the probability of being employed in June 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FS	RF	IV	FS	RF	IV	FS	RF	IV
	Less than secondary education			Male			Rural area		
Age<25	0.085***	0.054***		0.108***	0.028		0.073***	0.059***	
	(0.009)	(0.017)		(0.010)	(0.019)		(0.010)	(0.019)	
Treated			0.522***			0.343**			0.648***
			(0.187)			(0.175)			(0.216)
(Age<25)*(< Sec.Edu)	0.036***	-0.051**							
	(0.011)	(0.020)							
(Treated)*(< Sec.Edu)			-0.502***						
			(0.160)						
(Age<25)*(Male)				-0.033***	0.029				
				(0.010)	(0.018)				
(Treated)*(Male)						0.399**			
						(0.179)			
(Age<25)*(Rural)							0.036***	-0.032*	
							(0.010)	(0.018)	
(Treated)*(Rural)									-0.419**
									(0.171)
Less than secondary	-0.005	-0.126***	-0.119***	0.016***	-0.157***	-0.163***	0.017***	-0.157***	-0.165***
	(0.009)	(0.016)	(0.018)	(0.006)	(0.010)	(0.011)	(0.005)	(0.010)	(0.011)
Male	-0.025***	0.041***	0.046***	-0.006	0.024*	0.024	-0.025***	0.042***	0.051***
	(0.005)	(0.009)	(0.010)	(0.008)	(0.014)	(0.016)	(0.005)	(0.009)	(0.010)
Rural area	0.022***	-0.019*	-0.027**	0.022***	-0.019*	-0.029***	0.000	0.000	0.003
	(0.005)	(0.010)	(0.011)	(0.005)	(0.010)	(0.011)	(0.008)	(0.015)	(0.016)
F-stat			60.8			48.6			60.7
N.obs	11565	11565	11565	11565	11565	11565	11565	11565	11565

$*p < 0.10, **p < 0.05, ***p < 0.01$. We use a linear specification and consider the largest age window 15–29.
Control variables and polynomial in age are not reported. We use an indicator for education being lower than secondary education. Standard errors are in parentheses. Standard errors are in parentheses.

Figure 14: Distribution of declared income in June 2017 by qualification group of VT courses.



In Figure 14 we show the distribution of declared income as of June 2017, by qualification group of VT courses. It can be observed that the income distribution is more spread-out for the ISCO categories which fall in the highest qualification type (professionals), whereas for the lowest categories of ISCO (plant machine operators and elementary occupation), it is more concentrated in the lowest income classes.

8.2 Separate regressions by type of occupation.

In the previous section we showed that participating in the VT programme led to a positive and significant effect in the probability of finding a job when considering the widest age window around the threshold (age 15-29).[29] For the same specification we now show whether participating in the training programme increases (or decreases) the probability of finding a high skill occupation or a low skill occupation. We show the results only for the 15-29 age bandwidth due to sample size issues. Unfortunately, information on the quality of occupation using the ISCO classification is missing for about 50% of the sample, hence results should be taken with caution.

To define our outcome variable we use the ISCO classification, considering the first digit. According to this classification, occupations are listed in 9 categories, namely: 1 "Managers", 2 "Professionals", 3 "Technicians and Associate Professionals", 4 "Clerical Support Workers", 5 "Services and Sales Workers", 6 "Craft Workers", 7 "Plant and Machine Operators", 8 "Elementary Occupations", 9 "Armed Forces Occupations". We construct two indicators: an indicator of finding a high skilled occupation (categories 1, 2 and 3, corresponding to ISCO skill level 4 and 3) and an indicator for finding a low skilled occupation or elementary occupation (categories 8 and 9, corresponding to ISCO skill level 2 and 1)), respectively on June 2016, December 2016, and June 2017. Tables 15 and 16 summarise the results.

8.3 Results by type of training programme

We now show how the results vary depending on the qualification of the training programme in terms of the level of skills (high vs medium to low skill). For the sake of comparability we show the results only for outcomes observed in June 2017.

First of all, we show how participation in the training programme depends on the type of the course. Figures 15 and 16 show that the effect of the priority rule on participation in the VT programme is similar, although slightly larger for courses classified in the high skill category (0.54 pp versus 0.51 pp).

Second, we analyse how the Fuzzy RDD estimates differ depending on the type of the courses attended. Tables 17 and 18 summarise the results of the OLS, reduced form and IV regressions. We again see that the results appear to be positive and statistically significant for both groups only for the 15-29 age bandwidth and statistically non significant when we restrict the sample. When

[29] Nevertheless, this effect becomes statistically non different from 0 when we restrict the sample to individuals that are closer to the cut-off (age 21-29, 22-28, 23-27 and 24-26).

Table 15: Being employed in a high skill job.

Outcome	June 2016	December 2016	June 2017
		Linear	
		OLS	
Treated	-0.005	-0.040*	-0.040*
	(0.023)	(0.024)	(0.023)
		RF	
Age<25	0.033*	0.021	0.021
	(0.018)	(0.019)	(0.019)
		IV	
Treated	0.458*	0.262	0.300
	(0.266)	(0.249)	(0.280)
F-stat	46.2	51.6	40.4
N.obs	5694	5551	5805
		Quadratic	
		OLS	
Treated	-0.006	-0.041*	-0.040*
	(0.023)	(0.024)	(0.023)
		RF	
Age<25	0.027	0.013	0.013
	(0.020)	(0.021)	(0.021)
		IV	
Treated	0.326	0.144	0.159
	(0.249)	(0.241)	(0.260)
F-stat	51	54.3	46
N.obs	5694	5551	5805

Note. This table shows the OLS, reduced form and 2SLS results, using an indicator for being employed in a high skilled job as a manager, professional or technician respectively in June 2016, December 2016 and June 2017 (column 1-3) as the outcome. In this exercise we use the largest age window, namely 15–29. Control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 16: Being employed in a low skill job.

Outcome	June 2016	December 2016	June 2017
		Linear	
		OLS	
Treated	-0.026	-0.013	-0.038*
	(0.024)	(0.023)	(0.023)
		RF	
Age<25	-0.026	-0.010	0.018
	(0.019)	(0.019)	(0.019)
		IV	
Treated	-0.370	-0.126	0.258
	(0.270)	(0.242)	(0.275)
F-stat	46.2	51.6	40.4
N.obs	5694	5551	5805
		Quadratic	
		OLS	
Treated	-0.026	-0.013	-0.038*
	(0.024)	(0.023)	(0.023)
		RF	
Age<25	-0.023	0.005	0.026
	(0.021)	(0.021)	(0.021)
		IV	
Treated	-0.281	0.056	0.314
	(0.255)	(0.236)	(0.260)
F-stat	51	54.3	46
N.obs	5694	5551	5805

Note. This table shows the OLS, reduced form and 2SLS results, using an indicator for being employed in a high skilled job as a manager, professional or technician respectively in June 2016, December 2016 and June 2017 (column 1-3) as the outcome. In this exercise we use the widest age window, namely 15–29. Control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

comparing the two tables, we see that the magnitude of the IV coefficient is slightly larger for those who participate in medium to low skill courses compared to those participating in the high skill courses. Nevertheless, since the results are statistically significant only for the large sample (15-29 age bandwidth), we cannot conclude that those participating in the medium to low skill courses have a higher probability of finding a job after the completion of the course.

Figure 15: First stage regression: high skill courses.

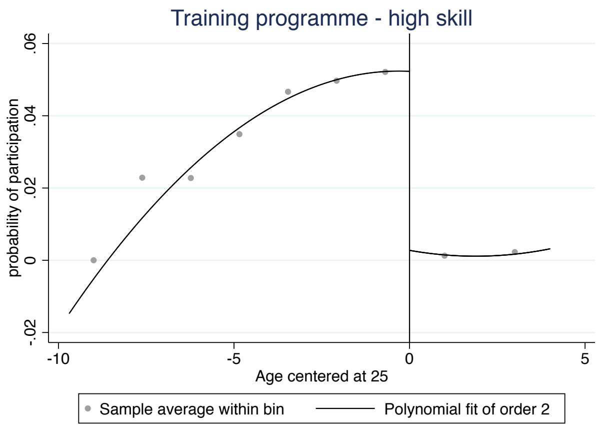


Figure 16: First stage regression: medium to low skill courses

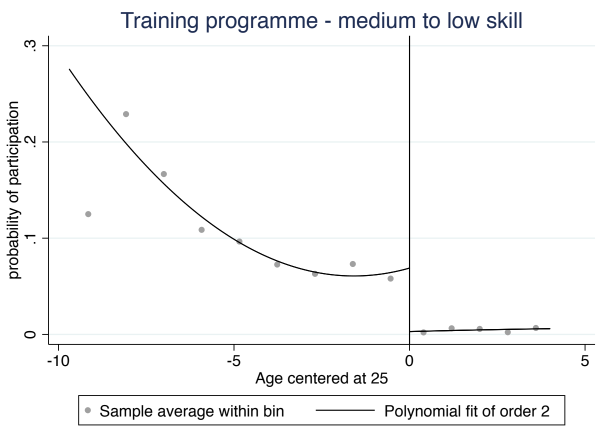


Table 17: Results for monthly income in June 2017. Treatment status: participation in high skill courses.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated-HS	0.048 *	0.024	0.036	0.054	0.083
	(0.028)	(0.032)	(0.036)	(0.042)	(0.060)
			RF		
Age< 25	0.095 ***	0.030	0.022	0.036	0.067 *
	(0.016)	(0.020)	(0.023)	(0.028)	(0.040)
			IV		
Treated-HS	1.545 ***	0.580	0.415	0.851	2.141
	(0.298)	(0.390)	(0.434)	(0.681)	(1.542)
F-stat	131	66.2	51.4	20.5	5.74
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated-HS	0.033	0.024	0.035	0.053	0.082
	(0.028)	(0.032)	(0.036)	(0.042)	(0.060)
			RF		
Age< 25	0.047 **	0.030	0.022	0.039	0.068 *
	(0.019)	(0.020)	(0.023)	(0.028)	(0.040)
			IV		
Treated-HS	0.873 **	0.580	0.409	0.901	2.133
	(0.368)	(0.391)	(0.436)	(0.681)	(1.512)
F-stat	74.5	65.8	50.8	20.7	5.96
N.obs	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using monthly income in June 2017 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

Table 18: Results for monthly income in June 2017. Treatment status: participation in medium to low skill courses.

Window width	15–29	21–29	22–28	23–27	24–26
			Linear		
			OLS		
Treated-LS	-0.040 *	-0.068 **	-0.083 ***	-0.106 ***	-0.129 **
	(0.022)	(0.027)	(0.031)	(0.038)	(0.056)
			RF		
Age<25	0.095 ***	0.030	0.022	0.036	0.067 *
	(0.016)	(0.020)	(0.023)	(0.028)	(0.040)
			IV		
Treated-LS	3.567 ***	0.541	0.430	0.746	1.887
	(1.139)	(0.367)	(0.455)	(0.604)	(1.384)
F-stat	14.2	56.5	36.1	22.2	6.32
N.obs	11565	9596	7480	5127	2601
			Quadratic		
			OLS		
Treated-LS	-0.035	-0.068 **	-0.083 ***	-0.108 ***	-0.130 **
	(0.022)	(0.027)	(0.031)	(0.038)	(0.056)
			RF		
Age<25	0.047 **	0.030	0.022	0.039	0.068 *
	(0.019)	(0.020)	(0.023)	(0.028)	(0.040)
			IV		
Treated-LS	0.902 **	0.538	0.421	0.785	1.871
	(0.395)	(0.366)	(0.453)	(0.600)	(1.349)
F-stat	40.5	56.8	36.2	22.7	6.62
N.obs	11565	9596	7480	5127	2601

*, **, *** statistically significant at the 10%, 5% and 1% level, respectively.

Note. This table shows the OLS, reduced form and 2SLS results, using monthly income in June 2017 as the outcome. We use two different specifications for age: linear (top panel) and quadratic (bottom panel). The columns show the results for different age windows: 15–29, 21–29, 22–28, 23–27 and 24–26. The control variables are the same as reported in the first stage regressions. Standard errors are in parentheses.

8.4 Discussion

The effectiveness on the unemployed of vouchers specific for vocational training has recently been discussed in the literature by Strittmatter (2016), with reference to German and US active labor market policies.

As highlighted in the paper, voucher systems may enhance competition between training providers, since vouchers recipients are allowed to choose among different training courses providers. Secondly, having the possibility to choose among different courses, recipients can also better accommodate their own individual preferences, also in terms of vocational training programmes goals. These are generally identified either as rapid reintegration or high human capital accumulation.

As regards the effectiveness of vocational training vouchers, one relevant element is the possibility of non-redemption. The decision to not redeem their vouchers may in fact induce efficiency losses of voucher award systems.

From the comparison of voucher provision with mandatory course assignment performed by Strittmatter (2016), two main elements emerge. On the one hand, the possibility to choose courses better suited to their own needs should make the voucher recipients more motivated and more likely to increase their human capital accumulation. In addition, receiving counselling from a case worker with regard to course choice increases returns to vocational training. On the other hand, the so called lock-in effect of training courses could be exacerbated under the voucher provision system with respect to the mandatory assignment course system since, for instance, voucher recipients may reduce their job search efforts also while they look for courses to attend.

Both features help explain the evidence of positive effects of voucher provision system on employment opportunities, especially in the long-term and for short-duration courses.

9 Conclusion

In this study, we provide recent evidence from the implementation of the Youth Guarantee scheme in Latvia. In particular, we focus on the evaluation of a vocational training (VT) programme targeted at unemployed youths, aged 15-29 who are not in education, employment or training (NEETs).

We rely on rich administrative data provided by the State Employment Agency (SEA), which provides information on the population of registered unemployed individuals at a given date (including both participants and non-participants in the VT programme), and match it with data from the State Revenue Service (SRS), which provides information on individuals' income at specific dates before and after the programme (from 2012 to 2017).

We apply a Fuzzy Regression Discontinuity Design (RDD) thanks to a specific eligibility criterion adopted by the Latvian government, which gave a higher priority for participation in this programme to young unemployed under the age of 25.

We exploit this priority rule and compare the outcomes of interest between those who are just below age 25 and those who are just above, since the former have a higher probability of participating in the programme, accounting for differences in terms of gender, level of education, residence area, previous labour market history, and nationality.

Being under 25 years of age increases the probability of participating in the VT programme by 8 percentage points (first stage result). This implies that specific eligibility rules are helpful in reaching the aimed target group (in our case the youngsters aged 15-24). This can be considered a positive outcome in terms of youth engagement.

The strength of the RDD approach is that we account for both observable and unobservable characteristics when comparing the treated and control units (differently from matching techniques which rely on observable characteristics only). This methodology allows to estimate causal effects and not simple correlations (strong internal validity). On the other hand, the identified causal effect refers only to the subgroup of unemployed youth who are close to the cut-off of age 25, hence not allowing to infer the impact for age-groups that are farther away from the cut-off.

Our baseline result points towards positive albeit statistically non significant effects of the programme in terms of both the probability of being employed between 1 to 3 years after the completion of the training programme and the gross monthly income declared. However, we do find positive and statistically significant results by specific sub-groups of participants after the end of the course suggesting the presence of heterogeneous effects. In particular, we find that young males with more than secondary education and youths resident in the capital city of Riga or other cities (not rural area) have a higher probability of finding a job in the post-treatment period. For these specific groups we find a positive and significant causal effect for participating in the VT programme, at least in the short-term.

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Appendix: Additional material

Table 19: Mapping of ISCO-08 major groups to skill levels.

	Major groups	Skill level
1	Managers	3+4
2	Professionals	4
3	Technicians and associate professionals	3
4	Clerical support workers	2
5	Services and sales workers	2
6	Skilled agricultural, forestry and fishery workers	2
7	Craft and related trades workers	2
8	Plant and machine operators	2
9	Elementary occupations	1
0	Armed forces occupations	1+2+4

Note. The VT programme implemented in Latvia does not include training courses that map into the category 1 "Managers", 6 "Skilled agricultural and fishery workers"m 0 "Armed forces".

Table 20: Descriptive statistics by treatment status for different age bandwidths.

Age group 21-29.

Variable	Controls	Treated
Female	0.491	0.602
Foreign nationality	0.375	0.372
Lower than primary or primary	0.276	0.291
General secondary	0.288	0.391
Professional secondary	0.240	0.221
Higher education	0.195	0.097
Capital city	0.244	0.138
Rural area	0.535	0.604
Other cities	0.221	0.258
No income before 2014	0.726	0.638
Employed June 2016	0.468	0.440
Income June 2016	323.678	227.410
Employed Dec 2016	0.452	0.438
Income Dec 2016	338.663	249.403
Employed June 2017	0.466	0.448
Income June 2017	360.725	273.189
N.Obs	8980	616

Age group 22-28.

Variable	Controls	Treated
Female	0.493	0.609
Foreign nationality	0.377	0.374
Lower than primary or primary	0.276	0.292
General secondary	0.282	0.368
Professional secondary	0.234	0.222
Higher education	0.209	0.117
Capital city	0.241	0.144
Rural area	0.532	0.595
Other cities	0.226	0.261
No income before 2014	0.732	0.660
Employed June 2016	0.472	0.449
Income June 2016	329.096	228.453
Employed Dec 2016	0.455	0.428
Income Dec 2016	343.247	237.454
Employed June 2017	0.465	0.447
Income June 2017	363.583	267.064
N.Obs	6994	486

Age group 23-27.

Variable	Controls	Treated
Female	0.492	0.624
Foreign nationality	0.377	0.393
Lower than primary or primary	0.278	0.296
General secondary	0.268	0.334
Professional secondary	0.222	0.228
Higher education	0.232	0.142
Capital city	0.235	0.148
Rural area	0.535	0.589
Other cities	0.230	0.263
No income before 2014	0.733	0.672
Employed June 2016	0.482	0.464
Income June 2016	337.595	241.818
Employed Dec 2016	0.461	0.444
Income Dec 2016	348.231	244.239
Employed June 2017	0.472	0.447
Income June 2017	372.527	276.774
N.Obs	4789	338

Age group 24-26.

Variable	Controls	Treated
Female	0.489	0.637
Foreign nationality	0.390	0.401
Lower than primary or primary	0.279	0.287
General secondary	0.273	0.325
Professional secondary	0.220	0.229
Higher education	0.228	0.159
Capital city	0.220	0.159
Rural area	0.536	0.573
Other cities	0.243	0.268
No income before 2014	0.739	0.701
Employed June 2016	0.479	0.484
Income June 2016	333.813	264.195
Employed Dec 2016	0.452	0.471
Income Dec 2016	338.893	262.376
Employed June 2017	0.458	0.433
Income June 2017	358.491	269.630
N.Obs	2444	157

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