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IZA DP No. 12074

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ABSTRACT

Assessing the Impact of Off- and On-The-Job Training on Employment Outcomes: A Counterfactual Evaluation of the PIPOL Program*

This evaluation study aims to assess the impact of PIPOL, an integrated program of active labor policies, on the employment integration of benefit recipients. To address the issue, we have resorted to a counterfactual approach with data from two main sources: the program administration and compulsory communications on employment and unemployment spells. We found a net impact of 5% on average for on-the-job training, but no impact for off-the-job training. On-the-job training also affects the probability to find permanent work (+3%). This is consistent with the view that young people have excellent theoretical, but very little work-related competences. Off-the-job training does affect the probability to experience at least one labor contract after 2016. These results are partly due to a lock-in effect, namely the tendency of those who attend training programs to delay their job search. Interestingly, we found that the program has a different impact for different typologies of recipients and different types of intervention. In a nutshell, active labor policy works when it generates work-related competences.

JEL Classification: D04, J48

Keywords: youth unemployment, school-to-work transition, professional training, on-the-job training, matching, evaluation

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1. Introduction

This paper studies the effect of PIPOL, an integrated program of active labor policies launched by the Region Friuli Venezia Giulia in 2014. The program collects different financial sources, including those coming from the European Social Fund (ESF) and the Youth Employment Initiative (YEI), and is aimed at smoothing the school- or university-to-work transition and supporting people to re-enter the labor market, by providing participants with a set of new competences.

The evaluation exercise focuses on the first stage of PIPOL, in particular on the interventions of off-the-job and on-the-job training completed by the end of 2016. The aim is to understand the impact of PIPOL on the employment integration of benefit recipients. To address the issue, we have resorted to a counterfactual approach: a control group is extracted by propensity score matching (PSM) among those who registered in the program over the years 2014-'16, but have never benefited of the program[1].

The study regards 7,175 people, of which 4,059 women. Overall, 3.911 attended off-the-job training; 2,945 attended on-the-job training; 319 both types of intervention. The data is collected from two main sources: first, is the monitoring data gathered during the implementation of the program. Moreover, information on the outcome variables is obtained from compulsory communications (COBs Comunicazioni obbligatorie) that employers have to send to employment offices whenever a labor contract is started or discontinued.

Overall, this is an excellent data set especially for Italy. First, it is unusually large for both the target and control group. Second, it contains a lot of information not only on the individual characteristics of the beneficiaries, but also on the type of program implemented and services provided and on different outcome variables. Regarding participants, we have information also on previous work experience, which is uncommon in other data sets, and proves to be particularly interesting when looking at the performance of young people. This study represents hence an important addition to the Italian literature on program evaluation, considering the small number of previous studies, noted also in the recent review of the literature by Card et al. (2010). Furthermore, this study is one of the first analysis of effects of measures implemented wthin the YEI. To our knowledge, there is only a previous paper assessing the impact of YEI in Latvia (Bratti M. et al. 2018) and the evaluation of the Italian YEI (Isfol, 2016), this latter focusing on the very short-term effects.

The study shows positive effects of the PIPOL program on the employment status of recipients on average. The result is due especialy to the effect of the on-the-job training.

The remainder of the papers is organized as follows. Section two describes the main characteristics of the PIPOL program. Section three reviews the previous literature on active labor policy evaluation. The following two sections discuss methodology and data. Section 6 presents the descriptive analyses and section 7 the results of the impact analysis. Some concluding remarks follow.

[1] As a robustness check, we have implemented different matching methodologies to select the control group, such as PSM and Mahalanobis. The Mahalanobis approach to select the control group is more rigorous as it selects only observations in the control group which are identical to those in the target group, from the viewpoint of the observed charatcteristics.

2. The main features of PIPOL

Friuli Venezia Giulia (FVG) adopted PIPOL[2] by integrating several financial resources, among which the ESF and YEI. The aim was to bring together several types of active labor market measures under a unique tool. The first phase of PIPOL, which is our focus, lasted from 2014 to 2017. The program's budget was around EUR million 71.5, of which EUR million 30.6 were funded by ESF.

PIPOL is targeted at different groups of people with different needs: Group 1 includes young people aged 15-19 years at risk of dropping out of school[3]; Group 2 includes young NEETs (Not-in-Education-Employment-or-Training) under the age of 30; Group 3 includes under-30 youngsters with a high school diploma or a professional qualification attained within 12 months; Group 4 includes young people under-30 with a university degreee obtained at least 12 months earlier; Group 5 includes unemployed people or at risk of unemployment.

The participation in PIPOL is structured in three phases. Phase one is registration: people who think to be eligibile can register to the program on-line or going to a Public Employment Service (PES) or other institutions for some groups[4]. In phase two, people receive orientation services and they are profiled according to their needs band; this service has to be offered to people by 60 days from the registration to the PESs. An individual action plan (PAI – *Piano di azione individuale*) is established, showing the type of active policies to be received. Phase three is the implementation of active measures, such as on-the-job training, classroom trainership, labour incentives, support to business creation. The active measures have to be delivered within 4 months from the beginning of the PAI.

Our analysis focused on 4,962 off-the-job training courses and 3,361 internships, that were completed by the end of 2016. Most part of on-the-job training programs are insertion ones; they are full time (38 hours per week) and last about 6 months. In 20% of the cases, on-the-job training is in the manufacturing sector, then, in trade, liberal professions, scientific (17%) and technical (15%) jobs; the rest represents less than 10% of the total.

Different kinds of off-the-job training were carried out: 40% out of total were life long learning courses, 30% training aimed at acquiring qualifications, 20% other types, such as courses to learn a foreign language.

3. Literature review

The international literature does not find clear evidence of the impact of active labour policies. Card et. al. (2010), for instance, analyse 97 studies implemented from 1995 to 2007 and find that training programs show negative or insignificant results in the short run (up to one year from the completion of interventions), but generate more positive impacts than other active measures in the long run.

[2] PIPOL is the acronym for "*Piano d'azione per il sostegno all'accesso, rientro o permanenza nel mercato del lavoro";* in Italian the word PIPOL recalls the sound of the English word people.

[3] Since the main aim of the analysis is to look at the emplotyment impact, group 1 of recipients (under 19 years old school dropouts or at risk of dropping out of education) is excluded from the analysis.

[4] For example, people falling undert the group 3 can register also at schools.

Later, the same authors have updated the 2010 research and analysed more than 200 studies implemented from 2007 on (Card et al. 2018). In addition to confirm previous results (more robust effects in the medium-long run of training programs), the study shows that the impact tends to be different according to the target group considered, with larger effects for women and long-run unemployed. Besides, less clear-cut results appear for programs addressing young people. Moreover, pro-active schemes are more effective in times of economic crisis than in periods of economic expansion, especially the programs of training and of skill development.

Another recent meta-analysis by Vooren et al. (2018) based on 55 studies implemented with experimental or quasi-experimental methods from 1990 to 2015 finds that the most effective measures are incentive and hiring subsidies in the private sector, which appear the most effective both in the short and in the long run, immediately followed by training interventions.

Kluve et al. (2019) review 113 evaluations on specific programs relative to young people, implemented in both industrialised and developing countries. Overall, only just more than a third of the evaluations show positive results of youth programs, as measured in terms of employment insertion or of the impact on wages. In more industrialized countries the types of interventions implemented are less important than the context and the way in which they are implemented. Authors also underline that interventions aimed at integrating different types of programs have a greater chance of being effective.

For Italy there are not many studies applying the counterfactual approach. In the following we present the findings of both published articles and of what we could call a grey literature, mainly based on evaluations carried out for the European Social Fund (ESF), but never published as journal articles.

Irpet (2011) studies training programs financed by ROP (regional Operational Porgram) FSE 2000-2006 in Tuscany between 2007 and 2008 and find a positive effect on the employment probability three years from the end of the program, with a positive differential with respect to the control group equal to 10pp for the unemployed and 20pp for young people entering the labor market for the first time. However, only for the latter, the impact on the probability to find stable employment is greater than zero, while for the unemployed training does not add value to employability in permanent jobs. Moreover, among the unemployed, the effects are greater for men (for women the effect is positive, but not statistically significant), with a low level of education and above thirty. Among the inactive group, a positive impact is found for those with a diploma of high secondary school and under the age of 20 years old. For both groups, the impact is greater when the recipient enters the training program being a long term unemployed.

Ismeri Europa (2011) studies the impact of DLF (Dote lavoro and formazione: voucher for work and training) Lombardy in 2009-'10. They find a null impact on the short run (less than a year) employment probability, but a positive empowerment impact. Recipients had 8pp greater of probability to become active job seekers than the control group. There was no difference between those who received a voucher for training and one for training and placement services.

On-the-job training programs (employment and research grants, of which the first represented 70% of the total) were implemented in the Marche region with the ESF ROP of 2007-2013 (Fondazione Brodolini, 2013). The analysis shows a positive impact in the months immediately following the experience, which tend to disappear after a year. On-the-job training positively affected also the length of subsequent employment by about 40-50 days in 12 months as compared to the control group.

Mazzolini and Orlando (2014) study training programs in an Italian region over the years 2010-’11 financed with the ESF and cannot find statistically significant impact on the employment probability after the course’ end, not even in the medium term. This result is true only for training courses finalized to re-placement, while the post-diploma training shows positive results 18 months from the end of the program 16pp higher than the control group.

Severati et al. (2015) analyse post-diploma training courses for 20-29 years old people in different Italian regions at the end of the 2000. They find positive impact in Piedmont (5pp), starting from 12 months from the beginning of the courses, but a negative impact on the probability to find stable employment. The youngest recipients show a higher impact; women not[5].

In the 1st assessment report of the YEI, Isfol (2016) has evaluated the employment impact of interventions from May 2014 to Spetember 2015. They focus in particular on the employment status at the end of the program (September 2015). The control group is constituted of young people registered to the program and waiting for treatment or to be taken in charge in the program and young under 30 not registered in the YEI. The results show a greater employment probability of the treated by about 7.8pp on average and 8.9pp for on-the-job training.

Recently, Bazzoli et al. (2017) have evaluated the impact of several programs implemented in Trentino either within the ESF or with regional funds. For the latter, they note a positive impact 12 months from the end of the program on the employment probability. 24 months after the program’s end the impact is equal to 6pp. The impact is greater for women and the least young, but is not statistically significant for foreign women. Moreover, ESF based training courses appear more effective than the regional ones: the employment probability is 27pp greater for the target group 24 months from the end of the program.

Ghirelli et al. (2019) evaluated the impact of on-the-job training for graduates in the Umbria region within the ROP ESF 2017-’13 on the employment probability in 2015, two years from the beginning of the program. The results show a positive impact by 12-14 pp on the employment probability of the treated.

Duranti and Sciclone (2017) have studied the impact of on-the-job training programs implemented in Tuscany over the years 2007-13 finding an impact on the employtment probability 18 months after the beginning of the program by 8.2pp (3.7pp when considering employment in permanent contracts). The program is especially effective in the case of the oldest recipients, with the lowest educational level and in long-term unemploymenjt. The greatest impact is found in the case of combined programs of on-the-job and off-the-job training.

4. Methodology

[5] Based on the same data, Mo Costabella (2017) shows also that the greatest iumpact is especially for those who entered training programs without work experience in the previous 24 months; these recipients had an employment probability 13% higher than the control group four years later.

The analysis follows a counterfactual approach with a comparison between a target and a control group chosen for the high degree of comparability under some important observed characteristics.

A first methodological choice was to analyze the effects of PIPOL interventions by distinguishing between on-the-job and off-the-job training. In fact, the latter may have different logics and therefore the effects may be different. In particular, in room training mainly has an "educational-training" content, while internships are short-term professional experiences, in which beneficiaries may develop also work-related competences.

A second methodological choice is related to the variable used to quantify the impact. We use employment status in January 2018. However, we also use open-ended employment contracts as a possible outcome.

A third choice concerns the method used for impact analysis. In the counterfactual analysis the main challenge is to limit the selection bias of the control group, which would result in an underestimation/overestimation of the impact of treatment. In other words, it is necessary to ensure that the target and control group differ for the treatment only, all other conditions that affect the employability of an individual (e.g. personal features, previous training, previous work experiences, etc.) being equal (see, among others, Angrist and Pischke, 2009; and Cerulli, 2015).

In order to create a "quasi-experimental" observation environment, that is to minimize the significant differences between treated and untreated, we use PSM. This is a statistical matching technique that identifies the control group in untreated subjects having observable characteristics the most similar to the treated subjects.

Following Angrist and Pischke (2009), we estimate the so-called ATT (Average Treatment Effect on the Treated), i.e. the average effect of treatment on the treated. The ATT represents the impact of the program on the treated in the event of participation as compared to the counterfactual case where the treaties themselves did not participate in the program. At least this would be the condition in the physical sciences, in which experiments can be reproduced by changing some conditions only and keeping all the others constant. However, in the case of social sciences, the counterfactual situation is not possible since the same individual cannot be observed having and not having been the beneficiary of the intervention. The common practice of evaluation to overcome this problem is to look for a control group that mimics the target group in case it did not experience the treatment.

Once a control group is available that has the same characteristics as the target group but has not participated in the program, it will be possible to define something very similar to an ATT. More analytically:

$$ATT = (Y^1|D = 1) - E(Y^0|D = 1)$$

where D is a variable equal to 1 if the treatment occurs and 0 if it does not occur; Y^1 is the value of the outcome variable given the treatment and Y^0 is the result variable in the absence of treatment. In abstract, Y^1 and Y^0 refer to the case when the target group has and has not undergone treatment. But, again, since the same target group can not be observed after receiving and without receiving the treatment, the ATT is estimated by comparing the values of Y^1 and Y^0 relative to a target and a control group, that is to say individuals who have the same characteristics as the target group, but did not participate in the program.

The correct identification of the ATT requires that at least 3 fundamental hypotheses are verified:

- conditional independence hypothesis (ICC), or analytically: $(Y^1, Y^0)D \perp, X$;
- SUTVA (Stable-Unit-Treatment-Value Assumption) hypothesis;
- Common Support Assumption: $0 < P(D = 1 \perp X = x) < 1$;

where X represents a set of characteristics that can confuse the analysis as they are related both to the selection in the probability of receiving the treatment and the possible outcome.

Hypothesis 1) implies that the outcome is independent of participation in the program, the treatment, conditional on the observation of the characteristics X. In other words, checking for all observable characteristics, the decision to participate in the program should not be related to the possible result. The extent to which this occurs depends on data availability. This hypothesis actually suggests that the proposed approach is not exempt from the problems of endogeneity due to unobserved variables exactly as OLS. However, the way the target and control groups are chosen in this study should prevent unobserved characteristics to play a role as shown in the data section.

Hypothesis 2) excludes the possibility of spillover effects or general economic balance that are determined by the program and indirectly influence the result of the program. This could happen, for example, if active employment policies (treatment) entailed such an increase in public expenditure and therefore in the aggregate demand to increase the probability of finding work for everyone and therefore especially for those taking part in the program. This hypothesis is certainly verified in the case under consideration, given the relatively small size of the expenditure involved and the "limited" number of participants in the program.

Hypothesis 3 implies that for any given value of the observed characteristics of individuals in the sample, X, the probability of participating in the program is not certain. In other words, for any given observed characteristic of individuals there should be no particular reason why an individual who possesses it is more likely to be in the target group or control group. This hypothesis is verified if we find a common support that is statistically not different between target and control group, ie the two groups must have similar characteristics.

Insuring that the third hypothesis is verified is the purpose of the matching procedure based on PSM. If matching is done correctly and, therefore, the control group has a common support statistically not different from that of the target group, this should ensure that the H3 is verified.

In order for the third hypothesis to be verified, the identification of a valid control group is extremely important. The most correct way would be to look for individuals in the control group who have exactly the same observed and unobserved characteristics as those in the target group. However, it is not always easy that this condition be met when the observations are not sufficiently numerous. In our case, the identification strategy of the control group was to draw it from the pool of those who were eligible to join PIPOL between 2014 and 2016, but who did not join for various reasons. These are particularly suitable subjects, as they have signed a declaration of immediate availability to participate in PIPOL and have expressed their willingness to participate in a training or internship. Moreover, the number of this group is quite large, almost 20,000 individuals..

We apply the PSM procedure. In other words, we estimate a model of the probability of being in the target group and therefore of receiving the treatment according to the variables actually observed. This estimate is usually done with a standard Probit model. On the basis of this estimatation a score is then provided, which proxies the probability of having the same characteristics for the other individuals in the target group (Bryson et al., 2002). Then, we select from the pool of those who did not attend the program, those with the most similar score to that observed for individuals in the target group.

As a robustness check, different types of matching have been used by choosing only one individual from the control group, in particular the one with the value of the propensity score that is more similar to each individual in the target group. In the second estimate, 5 individuals and in the third estimate 15 individuals were chosen with the most similar score. Subsequently the probabilities of experimenting the outcome variable of the two samples thus defined were compared. Since the third hypothesis above is respected, the MSP procedure ensures that the target and control group should have the same result in terms of counterfactual potential.

The propensity score is calculated based on a series of characteristics of those participating in the program:

- age measured at the time of the start of the program or the enrollment in PIPOL;
- gender;
- citizenship;
- level of education achieved: lower secondary, professional, upper secondary school, university degree and post-graduate education (master or doctorate);
- the presence of work-related skills acquired before the start of the program, as measured by work start-ups before the start of the program and the duration of the employment opportunity[6];
- province of residence.

Figure 1 presents the common support in the estimates of the PSM, for different types of observations (to 5 and 15) used for matching. The graphs show that there is a wide common support that allows us to adequately control for the different characteristics observed by the control and target groups. The common support is present in all estimates; naturally the common support is more complete and satisfying when there are more observations selected to belong to the control group.

Figures 2 shows the results of the test of the differences between the case of the target and control groups without matching and in the case of matching based on the Mahalanobis method. The latter, as noted above, implies that only observations with exactly the same characteristics as those of other observations of the target group are included in the control group. The consequence is that once the matching is done, there is no longer any difference between the two groups in the observed variables, which instead existed before matching, as seen from the figure itself. In the unmatched case, the differences between the variables in the target and the control group are in some cases noticeable, as in the levels of education, for example, in the age and residence in the province of Trieste, which is more frequent, as is already noted above in the descriptive analysis among individuals belonging to the control group. By resorting to a more rigorous type of matching, the Mahalanobis method completely eliminates the statistical differences in the observed characteristics of the target and control group.

[6] Several studies, including (Caliendo et al., 2017), show that including previous work experience in the variables used for matching increases the likelihood of capturing unobservable elements in the differences between the treaty group and the control group and comparing two groups as similar as possible.

5. Data used

We used three data sources. First, from the ESF program monitoring data we have identified the group of the treated (7.175), namely those who had completed PIPOL by December 2016. Two were the main sources: the "OPOC" system, containing monitoring data of the Internships funded by the NOP YEI, and NETFORMA, which includes all other PIPOL interventions. The two sources are rather rich in information regarding the socio-demographic characteristics of participants, but also the characteristics of the interventions, such as the start and end date, the type of off- and on-the-job training provided, the length of training, the industrial sectors of the traineeship[7].

Second, we use administrative data coming from ERGONET source. This source allowed us to identify the control group (19.899) and their main socio-demographic characteristics.

Third, data on so-called mandatory communications (COB: Comunicazioni Obbligatorie) and ERGONET data contain information on work start-ups, terminations and work processes of the treated and non-treated group. Note that a limitation of COB data is that it excludes self-employed workers and those who work in another region, as well as, obviously, informal workers.

6. Descriptive analysis

The following table presents the results of the t-tests on the mean differences of the main variables used for the calculation of the propensity score indicator on which the matching of the treated and the control group takes place.

[Table 1 about here]

The table shows that, berfore matching, the two groups are different under several points of view. In particular, the treatment group includes a younger sample of individuals (age differences are apparent: 3.5 years), a larger share of women (57% versus 54%) and on average a higher level of education. the treated group includes a larger proportion of individuals with university education or higher (+ 7%), while the control group includes a larger proportion of individuals with a secondary school diploma and compulsory education (+ 12%). Almost half of the target group resides in the province of Udine (47%). Furthermore, the percentage of residents in Pordenone is slightly higher than average. Finally, the target group includes a smaller proportion of foreigners (-8%), which on average are harder to employ. In terms of work start-ups before entering PIPOL, there are no significant differences in having at least one active contract in the period 2012-2014 (around 40% of the total); the treated, in any case, tend to have shorter work experience, i.e. contracts with a shorter duration.

[7] One limitation, but not significant, is that the OPOC and NETFORMA systems provide partially different information in relation to internships funded with the NOP YEI (OPOC) and those funded with other PIPOL sources; in any case, the bulk of the traineeships funded at the end of 2016 was within the NOP YEI program.

Table 3 shows the t-test results of the mean difference between treated and untreated in terms of employment status and is divided into 4 panels:
– panel (a): all participants;
– panel (b): participants who have completed the internship (on-the-job training);
– panel (c): participants who have only done professional training (off-the-job training);
– panel (d): participants who have received both types of vocational training.

As it should be now clear the differences highlighted in the table can not be interpreted in any way as a causal effect of the program on the probability of finding employment by the participants as the differences between target and control group might explain at least in part the different probability of employment of the two groups.

The overall sample shows a higher probability of being employed in January 2018, by about 10%. On the other hand, there is no higher employment rate if only permanent work is considered: as we can see, the treated group has an open-ended employment rate of 16%, compared with 14% of the control group.

Looking at the different sub-groups of recipients, the results are fairly high and statistically significant for the internships on the probability of finding a job (+ 20%) and for being employed with an open-ended contract (+ 4%).

For the recipients of vocational training the gross results on the employment variables are lower. However, in general, the impact is more on employability rather than on employment per se. Professional training can still influence the probability of finding work later. This hypothesis should be tested empirically in the future for PIPOL.

[Table 2 about here]

7. Estimation of the impact of PIPOL

In this section, we report the results of the estimates of the causal effects of PIPOL on our outcomes variables, after having selected by PSM a control group with the same characteristics as the target group. Below, we report stastical tests showing that, after PSM, differences are not statistically significant anymore.

We consider as main outcome variables:
- probability of being occupied *tout court* in January 2018;
- probability of being employed on a permanent contract in January 2018;
- probability of experiencing at least one employment opportunity in the post-program phase, i.e. after 2016.

Table 3 shows that, for the entire target group (Panel A), the results in terms of job placement are equal to +5pp, about half of the unconditional mean difference, and statistically significant. There are no statistically significant effects on the other outcomes. These estimates are in line with that found in the literature review of section 3.

[Table 3 about here]

Interestingly, much of the overall effect of the program on outcome variables stems from the effect of those who undertook internships (Panel B). They are more than twice more likely to be employed, again about half of the unconditional difference. The ATT is lower than the effect estimated by linear regression, confirming that part of the impact captured by the latter is attributable to unobserved heterogeneity. The estimate based on the Mahalanobis method is much higher and suggests that part of the effect is lost with PSM because of the less accurate selection of target and control group.

Having carried out an internship also significantly affects the probability of finding a permanent job (+2-3pp), but to a lesser extent. Interestingly, internships show a negative and statistically significant impact on "experiencing an employment chance after 2016". This is the other side of the coin of the positive impact on open ended contracts.

Vocational training (Panel C), on the other hand, has no effect on the probability of being employed in January 2018. On the other hand, there is a positive effect (3pp) in terms of having at least an employment chance after the end of the program. This suggests that training requires more time for a stable entry into the labor market. Again, this outcome is the opposite to that of experiencing an open-ended contract. Moreover, unreported estimates show that training has a positive effect on the "number of employment contracts" after 2016.

Slightly different is the case of those who receive both professional training in the classroom and internships in the company (Panel D). In this case, internship is shorter and therefore the professional content of the work experience is lower and also the ability to develop a network of knowledge in the company. The statistical insignificance of the effect on open-ended contracts is to be attributed also to the small number of observations.

These first general results are interesting for two main reasons. Firstly, they confirm the analysis of those observers who highlight the difficulty of young people in developing work related skills, rather than the theoretical ones linked to general education, which is due to the sequential nature of the school-to-work transition (first education and then work experience) (Pastore, 2016; 2018). Secondly, temporary work under certain conditions can be a good alternative to active employment policies, if it really helps to develop work related skills and to broaden the social and informal network of young people.

The heterogeneity of the effects

In the previous paragraphs, we have estimated the average impact of different types of intervention (training, internship) on several outcome variables. However, the impact of the programs may be different for heterogeneous groups, as seen in the literature review. For example, differences by gender, age and educational qualification could be not fully captured simply by using these as control variables. We focus only on the two types of program - traineeships and internship - for which there are also more observations. Moreover, among the many outcome variables available, we will use those that have obtained the most interesting results, namely employment in January 2018 and if the beneficiary had at least one employment spell after completing the program.

Impact by gender

The positive impact of PIPOL is stronger for women (+5.8-6pp) than for men (+4.8pp), differently from what was found for the case of Umbria (Ghirelli et al. 2019), but in line with Bazzoli et al. (2017) for Trentino. Again, the main positive effect of the program stems from internships for both men and women.

For training, coefficients are not statistically significant. Nonetheless, training has a positive effect on the probability of having at least an employment chance, as seen in column 2 of panel C. Gender differences are trivial under this respect.

[Table 4 about here]

Impact by age

Table 5 shows that the effect of PIPOL is slightly higher for young people under-30: +6pp against 4pp. Training has a positive and statistically significant effect only on the under-30s and their likelihood of experiencing any work experience, while it does not affect the probability of being employed in January 2018.

The internship does not seem to favor young people in particular, as the effects on employment probability in January 2018 are positive for everyone, both above and below 30 years. Indeed, for the former, the effect is even more positive.

[Table 5 about here]

Impacts by citizenship

Here, we aim to understand if there are different effects for recipients with foreign citizenship, which are 10% of the total recipients of PIPOL and who are more present in training activities (13%) than in internships (7%).

Table 6 shows that, overall (panel a), PIPOL is more effective on foreigners (+16pp) than on Italians (+4pp) in terms of employment probability. The effect of on-the-job-training is very high (+30pp). Moreover, interestingly, for foreigners also vocational training has a positive effect on the probability of being employed in January 2018.

[Table 6 about here]

Impacts by educational qualification

Table 7 shows that PIPOL has been effective above all for those with a lower educational qualification, but there are important differences by type of policy.

Overall, there are few differences between those with secondary school first and second grade (6.7pp and 5.7pp respectively), while the impact on those who have a university degree is null on average. Even when we measure the effectiveness in terms of the probability of having at least one labor contract after the program (column 2), we observe how PIPOL obtains its greatest effects for those with the lowest educational qualifications.

Even the internships (panel b), which have a positive impact on all levels of education, show double impact in the case of those who are up to high school (+15-17pp) as compared to those who have a university degree or more (+7pp). This finding is in line with, among others, Cerulli-Harms (2017), who even finds negative effects of traineeships for graduates in the short term, which then fades away over time. Ghirelli et al. (2019) find a positive effect of the same size as ours for university graduates, though.

Training has a positive effect on obtaining an employment chance at work after 2016, only for those who have medium-low academic qualifications. The highest level of education shows a negative impact, on the probability of being employed in 2018. This result may be due to the fact that graduates are already well-equipped to the labor market, so that the added value of training is not so high compared to the control group, which is also made up of graduates. Furthermore, the analysis should be completed by including additional elements to fully assess the impact, for example wages and quality of work: training might have an effect not on the employment probability, but on the "quality" of the work found.

[Table 7 about here]

The effects of different types of intervention

Here we aim to understand whether the impact is different for different types of pro-active scheme provided. We focus our attention only on the impact on employment condition in January 2018.

The effects for the different types of training

An interesting question that many evaluation studies ask is: What kind of intervention is more successful and which is not? The average result is the algebraic sum of not always positive effects and if it turns out that some types of training are less effective than others or that they actually have negative effects on employment, it may be appropriate to concentrate efforts on the most effective interventions, reducing waste of public resources. In some countries, these evaluation studies of the effectiveness of individual programs and sub-programs has helped maximizeing the effectiveness of public spending in the sector over the years.

Our data set allows us to analyze the relative effectiveness of different types of professional training (Table 8). We find that not all types of training have no effect on the probability of employment in the short term. In particular, training courses to gain a qualification have positive and statistically significant effects, similar to those found for PIPOL as a whole (+5pp). It should be actually noted that internships are a compulsory part of the pathway to achieve the basic qualification of skilled training, which may therefore be the reason for this positive result. Even for permanent training, which alone accounts for more than 40% of all courses financed, there is some weak indication of a positive effect, but the analyses should be repeated over time.

On the other hand, training courses to form competences consistent with the repertoire of regional qualifications and linguistic training have a negative effect on the employment status recorded in January 2018. On linguistic training, in any case it should be noted that its main purpose is not employment placement, but improvement of skills. When filling in the entry form with the different information required by the

Friuli Venezia Giulia Region, 70% of the participants themselves suggest that their expectation is above all of improving their skills.

[Table 8 about here]

The effect by industrial sector of the internships

Here, we try to draw some indication regarding the industrial sector where internships were carried out. We focus only on 3 macro-partitions, due to data limitations on other industrial sectors: manufacturing, construction and services.

Table 9 shows that the sector where training is most effective is manufacturing (+20pp). This probably derives from the fact that manufacturing is the sector in which the work related skills that can be learned through an internship are the greatest. This result indicates a high added value of the program as the demand factor could only partially explain this finding: in fact, it is true that the labor force of manufacturing (excluding construction) has gone up from about 123 thousand employed in 2014 to 125 thousand in 2016, but the trend is lower than that of the tertiary sector over the same period.

In any case, internships in construction and services are also effective. The impact in the construction field is only a few percentage points lower than that in manufacturing. In the service sector, the employment impact is around 10pp.

[Table 9 about here]

8. Concluding remarks

This paper has studied the effect of PIPOL, an integrated program of active labor policies, launched by the Italian Region Friuli Venezia Giulia in 2014, aimed at supporting people in finding a job. Different population targets, divided by need band, are the object of intervention. Different mixes of off- and on-the-job training are provided to participants.

The evaluation aims to understand the impact of PIPOL on the employment integration of benefit recipients. To address the issue, we have resorted to a counterfactual approach: a control group is extracted by means of PSM or Mahalanobis matching among those who registered in the program over the years 2014-'16, but have never benefited of the program. This allows us controlling for observed heterogeneity thorugh a battery of control variables (age, gender, citizenship, education, province of residence and also pre-program work experience) and for unobserved heterogeneity, by extracting the control group using the same pool of individuals registered in the program.

We used data from two main sources: first, we use different data banks coming from the administration of the program. Moreover, information on outcome variables is obtained from compulsory communications that employers have to make to employment services whenever any labor contract is signed or completed/ended.

We found that the net impact of PIPOL is equal to 5pp on average, but no impact is found for in room training. The greatest impact is found for on-the-job training. The latter affects also the probability to find permanent work (+3pp). This is consistent with the view of a youth labor market where young people have excellent theoretical competences, but very little work experience and work-related competences (Pastore, 2015; 2017).

The off-the-job training programs show not statistically significant impact on employment, but do affect the probability to experience at least one labor contract after 2016. These results are partly due to a lock-in effect, namely the tendency of those who attend training programs to put off their effort in job search.

Interestingly, we found that the program has a different impact for different typologies of recipients and different types of intervention. The scheme seems to have a greter net impact in the case of women, foreigners, low educated young people. Some forms of off-the-job training still have a positive net impact on employment chances (training to gain a qualification). Internships in manufacturing and construction show a greater impact than in the service sector, although the service sector is experiencing a larger expansion overall.

In a nutshell, our findings suggest that active labor market policy works more effectively in Italy when it generates work-related competences.

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10. Appendix of Tables and Figures

Table 1. Differences between treated and control group

	Treated*		Contro group		T-test	
	Average	**S.dev.**	**Average**	**S.dev.**	**Diff.**	**Prob.**
Age	30,54	10,53	34,06	11,79	-3,52	0,00
Woman	*0,57*	*0,50*	*0,54*	*0,50*	*0,02*	*0,00*
Primary school (5 years)	0,02	0,14	0,02	0,15	0,00	0,12
Primary school (8 years)	0,15	0,35	0,26	0,44	-0,12	0,00
Professional school (10 years)	0,11	0,31	0,10	0,10	0,01	0,00
Secondary school (13 years)	0,45	0,50	0,50	0,50	-0,04	0,00
Tertiary education	0,28	0,45	0,20	0,40	0,07	0,00
Trieste	*0,15*	*0,35*	*0,29*	*0,46*	*-0,15*	*0,00*
Udine	*0,47*	*0,50*	*0,36*	*0,48*	*0,11*	*0,00*
Pordenone	*0,24*	*0,43*	*0,21*	*0,41*	*0,03*	*0,00*
Gorizia	*0,11*	*0,32*	*0,12*	*0,32*	*0,00*	*0,46*
Other province	*0,03*	*0,16*	*0,02*	*0,15*	*0,01*	*0,01*
Foreigner	0,11	0,31	0,18	0,39	-0,08	0,00
Employment contracts bbefore PIPOL, from 2012 to 2014	*0,40*	*0,49*	*0,40*	*0,49*	*0,00*	*0,98*
Average lenght of employment contracts, from 2012 to 2014	73,26	165,67	88,08	200,93	-14,82	0,00
Observations	7.175		19.889			

*=Training + interships

Source: our elaboration.

Table 2. Mean differences in employment rates, treated and untreated

	Treated		Untreated		T-test	
	Panel (a): PIPOL					
	Average	St.dev.	Average	St.dev.	Diff.	Prob.
Employed (Jan. 2018)	0,60	0,49	0,50	0,50	0,10	0,00
Employed – open ended contract	0,16	0,36	0,14	0,35	0,01	0,01
Employed – open ended contract and full time	0,10	0,30	0,09	0,29	0,01	0,00
At least a contract after PIPOL	0,46	0,50	0,45	0,50	0,01	0,14
Observations	7.175		19.889			
	Panel (b): training					
Employed (Jan. 2018)	0,51	0,50	0,50	0,50	0,01	0,18
Employed – open ended contract	0,14	0,34	0,14	0,35	0,01	0,34
Employed – open ended contract and full time	0,09	0,28	0,09	0,29	0,01	0,27
At least a contract after PIPOL	0,49	0,50	0,45	0,50	0,05	0,00
Observations	3.911		19.889			
	Panel (c): internships					
Employed (Jan. 2018)	0,70	0,46	0,50	0,50	0,20	0,00
Employed – open ended contract	0,18	0,38	0,14	0,35	0,03	0,00
Employed – open ended contract and full time	0,12	0,33	0,09	9,29	0,03	0,00
At least a contract after PIPOL	0,41	0,49	0,45	0,50	0,04	0,00
Observations	2.945		19.889			
	Panel (d): training and interships					
Employed (Jan. 2018)	0,68	0,47	0,50	0,50	0,18	0,00
Employed – open ended contract	0,18	0,39	0,14	0,35	0,04	0,05
Employed – open ended contract and full time	0,12	0,328	0,09	0,29	0,03	0,05
At least a contract after PIPOL	0,48	0,50	0,45	0,50	0,31	0,13
Observations	319		19.889			

Source: Our elaboration.

Table 3. Impact of PIPOL on the probability to be employed

ATT	Employed	Employed – open-ended contracts	At least a contract after PIPOL
	A) PIPOL		
Regression	0,0529*** (0,0074)	0,0066 (0,0051)	-0,0109 (0,0073)
1 obesrvation	0,0467*** (0,0062)	0,0013 (0,0045)	-0,0073 (0,0063)
5 observations	0,0548*** (0,0109)	0,0104 (0,0079)	-0,0023 (0,0109)
15 Observations	0,0495*** (0,0091)	0,0041 (0,0066)	-0,0017 (0,0091)
Mahalanobis	0,0524*** (0,0187)	0,0260* (0,0136)	-0,0185 (0,0188)
	B) Internships		
Regression	0,1408*** (0,0106)	0,0293*** (0,0079)	-0,0652*** (0,0104)
1 obesrvation	0,1168*** (0,0085)	0,0237*** (0,0071)	-0,0537*** (0,0091)

5 observations	0,1307*** (0,0162)	0,0311** (0,0123)	-0,0372*** (0,0164)
15 Observations	0,1299*** (0,0131)	0,0286*** (0,0101)	-0,0430*** (0,0134)
Mahalanobis	0,1837*** (0,0288)	0,0496*** (0,0214)	-0,0410* (0,0288)
C) Training			
Regression	-0,0123 (0,0093)	-0,0118* (0,0060)	0,0277*** (0,0091)
1 obesrvation	0,0033 (0,0083)	-0,0084 (0,0056)	0,0327*** (0,0083)
5 observations	-0,0059 (0,0116)	-0,0069 (0,0081)	0,0279*** (0,0116)
15 Observations	-0,0138 (0,0104)	0,0140* (0,0072)	0,0280*** (0,0104)
Mahalanobis	-0,0260 (0,0173)	-0,0153 (0,0123)	0,0212* (0,0173)
D) Training and internships			
Regression	0,1032*** (0,0291)	0,0169 (0,0197)	0,0101 (0,0282)
5 observations	0,1090*** (0,3001)	0,0081 (0,0244)	0,0219 (0,0318)
15 Observations	0,1001*** (0,0278)	0,0113 (0,0228)	0,0169 (0,0296)
Mahalanobis	0,1097*** (0,0412)	0,0125 (0,0327)	0,0188 (0,0425)

Note: the table shows the results of the regression model (probit) and differnt PSM models. The employment status is observed at january 2018, on the basis of the administrative data (COBs). For the panel D results with only 1 obesrvation are not reported.
Significance level: ***:p<01, **:01<p<:05, *:05<p<10. Standard errors in brackets.
Source: our elaboration.

Table 4. Impact of PIPOL, by gender

		Employed at January 2018	At least a contract after PIPOL
		(a) PIPOL	
Women	Probit	0,0581*** (0,0099)	-0,0053 (0,0097)
	ATT	0,0614*** (0,0134)	-0,0041 (0,0134)
Men	Probit	0,0481*** (0,0111)	-0,0185* (0,0109)
	ATT	0,0488*** (0,0141)	0,0001 (0,0142)
		(b) Internships	
Women	Probit	0,1529*** (0,0141)	-0,0470*** (0,0138)
	ATT	0,1325*** (0,0190)	-0,0433*** (0,0194)
Men	Probit	0,1299*** (0,0160)	-0,0895*** (0,0159)
	ATT	0,1176*** (0,0203)	-0,0421*** (0,0209)
		(c) Training	
Women	Probit	-0,0162 (0,0124)	0,0264** (0,0122)
	ATT	-0,0151* (0,0143)	0,0319*** (0,0143)
Men	Probit	-0,0080* (0,0139)	0,0282** (0,0136)
	ATT	-0,0127 (-0,0162)	0,0232*** (0,0162)

Note: See notes under table 3.
Source: our elaboration.

Table 5. Impact of PIPOL, by age

ATT		Employed at January 2018	At least a contract after PIPOL
		(a) PIPOL	
Less than 30 years old	Probit	0,0615*** (0,0094)	-0,0024 (0,0096)
	ATT	0,0588*** (0,0149)	0,1376 (0,0149)
More than 30 years old	Probit	0,0400*** (0,0116)	-0,0150 (0,0114)
	ATT	0,0394*** (0,0137)	-0,0223** (0,1363)
		(b) Internships	
Less than 30 years old	Probit	0,1256*** (0,0115)	-0,0485*** (0,0118)
	ATT	0,1041*** (0,0181)	-0,0362** (0,0184)
More than 30 years old	Probit	0,1808*** (0,0249)	-0,0886*** (0,0240)
	ATT	0,1813*** (0,0249)	-0,0710*** (0,0260)
		(c) Training	
Less than 30 years old	Probit	-0,0325** (0,0136)	0,0618*** (0,0134)
	ATT	-0,0252** (0,0107)	0,0699*** (0,0172)
More than 30 years old	Probit	-0,0082 (0,0126)	-0,0011 (0,0125)
	ATT	0,0088 (0,0149)	-0,0861 (0,0149)

Note: See notes under table 3.
Source: our elaboration.

Table 6. Impact of PIPOL, by citizenship

		Employed at January 2018	At least a contract after PIPOL
		(a) PIPOL	
Italian	Probit	0,0385*** (0,0778)	-0,0193*** (0,0077)
	ATT	0,0408*** (0,0116)	-0,0014*** (0,0116)
Not italian	Probit	0,1451*** (0,2149)	0,0455** (0,0210)
	ATT	0,1607*** (0,0247)	0,0458* (0,0247)
		(b) Internship	
Italian	Probit	0,1233*** (0,0108)	-0,0713*** (0,0109)
	ATT	0,1055*** (0,0166)	-0,0441*** (0,0169)
Not italian	Probit	0,3150*** (0,0371)	-0.0022 (0,0374)
	ATT	0,3048*** (0,0434)	-0.0024 (0,0457)
		(c) Training	
Italian	Probit	-0,0289*** (0,0099)	0,0214** (0,0098)
	ATT	-0,0219** (0,0123)	0.0298*** (0,0122)
Not italian	Probit	0,0839*** (0,0246)	0,0593*** (0,0242)
	ATT	0,0908*** (0,0262)	0,05357** (0,0263)

Note: See notes under table 3.
Source: our elaboration.

Table 7. Impact of PIPOL, by level of education

		Employed	At least a contract after PIPOL
		(a) PIPOL	
8 years of school or less	Probit	0,0741*** (0,0159)	0,0482*** (0,0160)
	ATT	0,0671*** (0,0235)	0,0551*** (0,0235)
13 years of schools	Probit	0,0555*** (0,0103)	-0,0172* (0,0102)
	ATT	0,0576*** (0,0134)	-0,0060 (0,0135)
More than 13 years of school	Probit	0,0119 (0,0141)	-0,0565*** (0,01377)
	ATT	0,0175 (0,0165)	-0,0425*** (0,0164)
		(b) Internship	
8 years of school or less	Probit	0,1969*** (0,0255)	0,0060 (0,0261)
	ATT	0,1512*** (0,0407)	0,1887 (0,0416)
13 years of schools	Probit	0,1645*** (0,0152)	-0,0677*** (0,0154)
	ATT	0,1703*** (0,0199)	-0,0446*** (0,0211)
More than 13 years of school	Probit	0,0695*** (0,0175)	-0,0945*** (0,0179)
	ATT	0,0659*** (0,0211)	-0,0746*** (0,0211)
		(c) Training	
8 years of school or less	Probit	0,0215 (0,0181)	0,0660*** (0,0182)
	ATT	0,0072 (0,02289)	0,0576*** (0,0228)
13 years of schools	Probit	-0,0199 (0,0128)	0,0172 (0,0126)
	ATT	-0,0204** (0,0143)	0,0225** (0,0143)
More than 13 years of school	Probit	-0,0624*** (0,0207)	-0,0103 (0,0202)
	ATT	-0,0460*** (0,0220)	0,0002 (0,0219)

Note: See notes under table 3
Source: our elaborations.

Table 8. Impact of PIPOL, by type of training (only people in training measures).

Vocational training	Probit	-0,0023 (0,1906)
	ATT	-0,0030 (0,0210)
Training to gain a qualification	Probit	0,0505** (0,0249)
	ATT	0,0640*** (0,0264)
Permanent training	Probit	0,0085 (0,1448)
	ATT	0,0132* (0,0168)
Training in languages	Probit	-0,1438*** (0,0266)
	ATT	-0,1250*** (0,0306)
Repertoire training	Probit	-0,0520*** (0,0200)
	ATT	-0,0322** (0,0212)
Other type of training	Probit	0,0129 (0,0344)
	ATT	0,0343 (0,0357)

Note: see notes under table 3
Fonte: our elaborations.

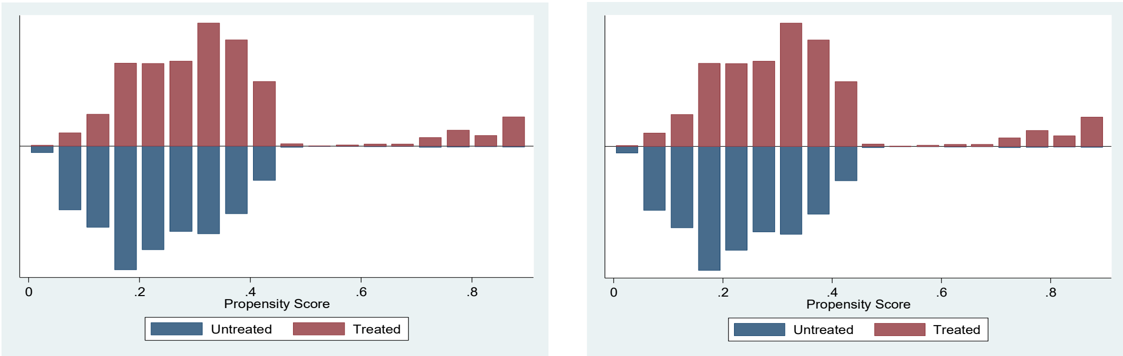
Table 9. Impact of PIPOL by sector of intership

Manufacturing	Probit	0,2108*** (0,2266)
	ATT	0,1976*** (0,2555)
Buildings sector	Probit	0,1459*** (0,0436)
	ATT	0,1462*** (0,0447)
Services	Probit	0,1057*** (0,0135)
	ATT	0,1093*** (0,0175)

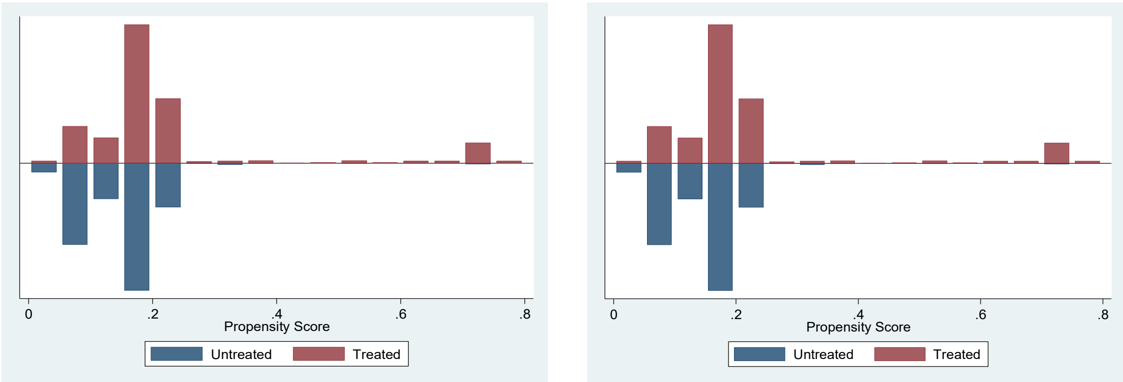
Note: See notes under table 3
Source: our elaborations.

Figure 1. Common support in PSM estimates, with 5 observations (sx) and 15 (observations). Variable: employed at january 2018

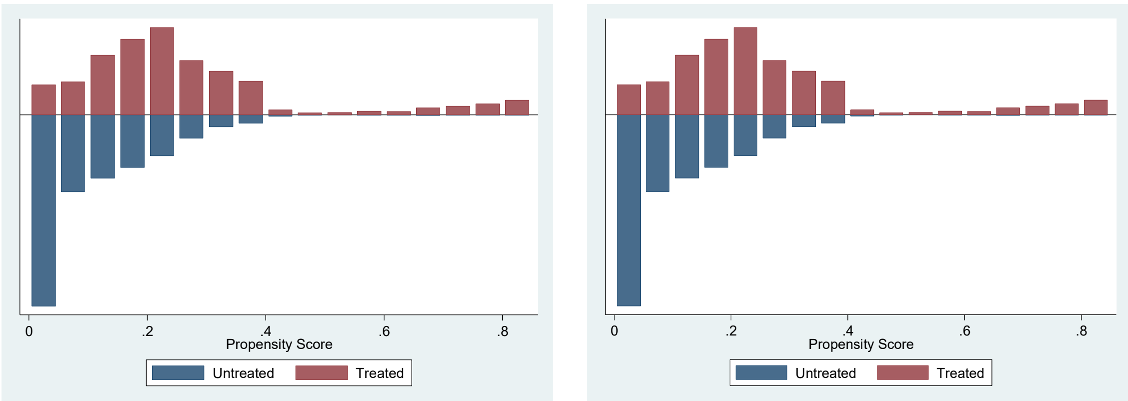
PIPOL



Training

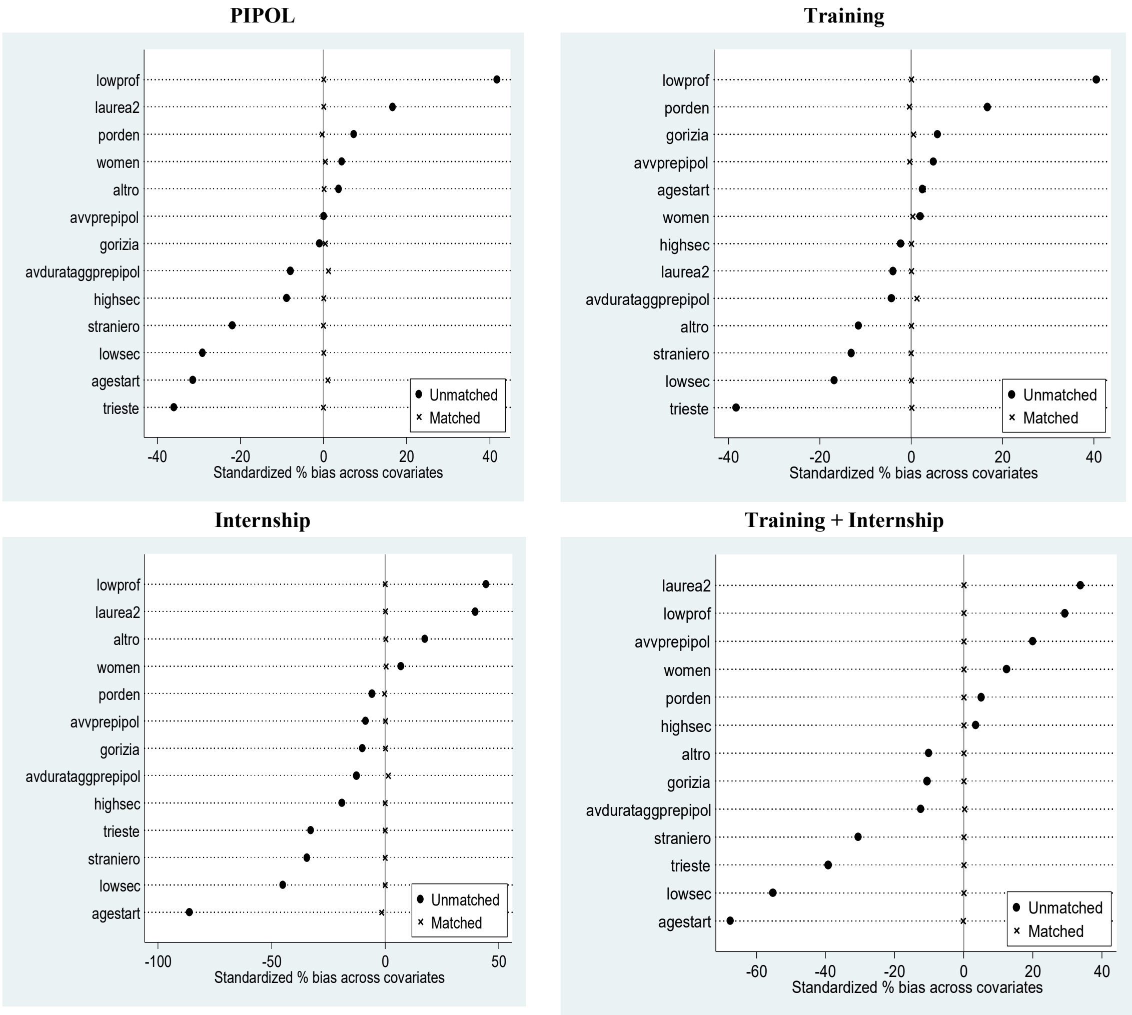


Internship



Source: our elaboration

Figure 2. Results of Mahalanobis matching for different groups and for the variable "employed at January 2018"



Source: our elaboration.