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EDUCATION, TRAINING AND EMPLOYMENT OUTCOMES. EVIDENCE FOR ITALY

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ABSTRACT

This paper aims at analysing the relationship existing between education and training and at evaluating the impact of training programmes on youth employment outcomes in Italy. The analysis is based on a Isfol cohort survey collecting information on individuals aged 21 and 31 years old. In addition to personal and household information, a specific section of the questionnaire is dedicated to training with detailed information about the attended programmes.

The results exclude that training is a substitute for formal education since education, especially technical or professional, positively affects the probability to participate in training courses. As regards employment outcomes, training has a positive effect on youth employment chances and decreases the need for informal channels, such as family or social networks, to find a job.

KEYWORDS: Education; Training; Labour market.

JEL: J23 - J24 - I29

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1. Introduction

Human capital investment is a key public policy due to its impact on individual and collective well-being, on economic growth and on social mobility in presence of notable market failures. In particular, these policies should involve young people providing them skills and competences useful for their entry and staying in the labor market.

Training represents, together with formal education, a primary source of human capital and, thereby, an important area of public intervention. As declared by the Council of the European Union (2001) “Education and training are a structural means by which society can help its citizens to have equitable access to prosperity, democratic decision-making and individual socio-cultural development” and human capital improvement and accessibility represent key issues in the European Union policy agenda.

Given the relevance of this matter, it is crucial to analyze and evaluate with rigorous methodologies the efficacy of these policies focusing on the characteristics of people involved and on their outcomes in terms of skills acquisition and employment.

In Italy each year quite one million of people, that is 4% of the labour force, is involved in training activities (Isfol, 2005). The higher quota of training is supplied by Training Agencies (36%), followed by associations and non profit organizations (16%). Local authorities, such as Regions and Provinces and Municipalities provide 12% of training courses and the remaining part is organized by schools, Universities, firms organizations.

State-sponsored training system in Italy is organized in three main intervention programmes. Firstly, the European Social Fund (FSE) co-finances training programmes organized by public and private training centres and firms. These programmes aim at improving base-skills in order to increase workers employment chances and are addressed to youths in search of first employment, long term unemployed, disadvantaged subjects and women. Secondly the so-called Integrated Superior Training (FIS) is addressed to youth with an high-school degree to provide them additional professional competences demanded by firms. Finally there are programmes specifically devoted to employed (Lifelong Learning Programmes) that can attend the courses autonomously or in consequence of firms proposals. These courses aim in particular at providing workers with new competencies allowing them to face industrial transformations and the evolution of production systems.

This paper aims at investigating the relationship between training, education and employment outcomes in Italy from several perspectives.

Firstly, we investigate the decision to attend a general training program, both state-sponsored and market provided focusing in particular on the role played by formal education in this choice.

Once individuals who typically attend training courses are identified, we analyze the impact of training, always controlling for educational levels and several other individual and context characteristics, on different outcomes related to youth employment condition. Firstly we question training effectiveness, that is if participating in training courses positively affects young people employment chances. Secondly, we investigate if training participation reduces the need for informal channels, such as personal or family networks, to find a job. The hypothesis that here we want to test is that training strengthens workers' power in the labor market and, at the same time, provides some additional "formal" channels to contact potential employers. Thirdly, restricting our analysis only to employed people, we want to study if participating in training allows to obtain better jobs in terms of wage and "selfrealization". Concerning the first issue, training is a source, together with formal education and learning by doing, of human capital and, consequently, of productivity. According to the Mincerian view this should be recognized by the labor market through higher wages. In conclusion we focus on the effect of training on the probability to obtain a better match between the skills and competencies acquired within the whole educational process and the skills and competences required by the job.

The paper is organized as follows. Paragraph 2 presents a brief review of the empirical literature with a focus on the results concerning Italy. Paragraph 3 describes the empirical strategy used to identify the effect of training. Paragraph 4 describes the data set and provides descriptive statistics. Paragraph 5 presents the results of the analysis of the relationship between education and training and of the effect of training on employment. Finally paragraph 6 concludes.

2. Literature review

Most of the empirical literature on the relationship between training and formal education (see for example Brunello, 2001 and Ariga and Brunello, 2006) shows that education and training are complement in human capital formation, that is the more people are educated the more they tend to participate in training programs. Distinguishing between off-the-job and on-the-job training, Ariga and Brunello (2006) in particular find that only off-the-job training is a complement for formal education, whereas more educated workers are less probably involved in firm-provided training activities. It is interesting to investigate if these findings remain true for the young people composing our sample that have just completed (or are still completing) their formal education.

The investigation of the effect of training on employment outcomes represents the focus of several studies. It is important to observe, as well explained by Heckman *and al*. (1999), that the robustness of policies evaluation results strictly depends on the quality of the data which, for the Italian training system, is quite low (Rettore *and al*., 2002). The main methodological critical feature of the investigations on the Italian training system outcomes is the lack of a complete information. For instance Croce and Montanini (1997), in order to overcome the lack of systematic information about trained outcomes, try to contact them a long time after the end of the program with a very low response rate that implicates an inevitable attrition bias in the results. Centra *and al*. (2000) and Comi *and al*.(2002) create a "control group" to be compared with the "treated group" by using a different data set (the Labour Force Survey) with evident problems of information comparability between the two groups. The information availability problem is instead cleverly solved by Laudisa (2000) through the availability of information on the non admitted to a state-sponsored training course, even if the analysis has to be limited only to individuals that are very close to the acceptance threshold. With a different perspective, Tattara and Valentini (2005) use information from the Italian Social Security System (INPS) archives of two Italian provinces to estimate the average employment gain for firms from training on the job contracts (Contratti di Formazione Lavoro-CFL). Having information about firms that entered in a CFL program (treated) and firms that did not (non treated), they use a difference in difference propensity score matching and find a positive effect of these programs on youth employment.

Our paper aims at improving the analysis of the impact of training programs together with formal education in several ways. Firstly, since we have the possibility to exploit the same information for treated and non treated we are quite confident on the robustness of our analyses. Secondly, as we have information not only about the interviewed but also about their families, we can explicitly consider the effect of family background that is crucial in human capital investment decisions (see for example Checchi, 2003). Finally, thanks to the richness of our dataset we are able to establish the effect of training and education not only on youth employment conditions, but also on some qualitative features of the achieved jobs. Since job quality is a crucial issue in the current policy debate, we can provide with our investigation some further elements of analysis.

3. Empirical strategy

The main problem to cope with when analyzing the impact of a policy is to correctly distinguish its effect from the effect of observable and unobservable individual or context characteristics.

Since it is not possible to observe simultaneously the outcome of a person involved in a program and the outcome of the same person if not involved, there is a typical selection bias problem since people participating in a program are probably different from people that do not participate. As observed by Heckman and al., "the fundamental aspect of the programme evaluation problem is that one cannot simultaneously observe the same person in a programme and out of it" (Heckman, Smith and Clements, 1997), hence a different strategy has to be implemented.

In our analysis we adopt two different methodologies that are the most appropriate, in our opinion, to deal with cross-sectional data in presence of selection bias (see for example Tattara and Valentini, 2005).

Firstly, we estimate the impact of training through a non parametric methodology represented by the propensity score matching estimator (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1998a and 1998b; Dehejia, 2005). This estimator allows for the selection bias by assuming that selection depends on observable characteristics. Given this assumption, selection bias can be managed by comparing (matching) individuals that are as similar as possible in these characteristics. This methodology, known as "covariates matching", has the advantage of being very accurate since it takes account of every single relevant individual characteristic. The disadvantage is clear: in the presence of a high number of characteristics that have to be compared, it is difficult to implement it from a computational point of view. The propensity score matching estimator allows to overcome this difficulty by reducing the multidimensionality problem throughout the estimation of the conditional (to observable characteristics) probabilities to take the treatment.

We then estimate the Average Treatment effect on Treated (ATT) as follows:

$$ATT = E_{Pr|T=1} \{E[(O_{1i} \mid T_i =1, Pr(\mathbf{X_i})]- E[(O_{0i} \mid T_i =0, Pr(\mathbf{X_i})]\} \qquad (1)$$

where O_{ji} is the outcome of individual i (for instance employed or unemployed), j is 1 if individual i is treated and 0 otherwise, T_i is the treatment dummy that assume the value 1 if individual i takes the treatment, 0 otherwise and $Pr(\mathbf{X})$ is the propensity score of the treatment, that is the probability to get the treatment conditioning on a vector **X** of observable variables.

The average treatment effect on treated, i.e. the average difference between the outcomes of the treated and the outcomes of the same individuals if not treated, is then computed according to three estimators[1]. The first one is the "best matching" estimator where each treated is compared with the most similar in terms of propensity score. The advantage of this estimator is clear, since it allows to match each trained with a sort of "twin". The main disadvantage is that a lot of information is not exploited (all the controls that are not the "best"), but it could also occur that the "best" control is in any case different from the treated because no restriction is imposed on the distance between the two propensity scores. With the aim of exploiting the whole available information and to test for the robustness of the results, we also present the results of a "kernel matching" estimator where each treated is compared to an observation that is the weighted average of all controls. Finally, to check the robustness of our estimates we also report the results of the "stratification" estimator which compares the outcome of each treated with the outcomes of all controls inside the same propensity score block, that is with the controls that have the same (in average) observed characteristics.

In order to test the robustness of our results we also use a parametric approach represented by a control function estimator (Heckman and Robb, 1985; Larsson, 2003) that allows to exploit more information, especially when we investigate some feature of the individual's job. We then estimate the following equation:

$$\Pr(O_i = 1) = \Pr(L_i \geq 0) = \Phi(\beta_0 + \beta_1 \mathbf{Z}_i + \beta_2 \mathbf{X}_i + \beta_3 T_i) \qquad (2)$$

where L_i is a latent function of a constant β_0, a vector of covariates $\mathbf{Z}_i$, of the treatment dummy T_i and of $\mathbf{X}_i$, the vector of observable characteristics affecting the probability to get the treatment. Finally $\Phi(.)$ is the standard normal cumulative density function. Using this specification we assume that the potential selection bias, arising because of a correlation between T_i and the *unobservables* affecting the outcome, can be eliminated if we add in the estimation the vector of covariates affecting the probability to take the treatment.

Although even this approach rests on the assumption that selection is on observables, these estimates can improve our comprehension of training effects by introducing in the analysis the covariates of the outcome regressions together with the covariates of the selection process.

[1] On this see Becker and Ichino, 2002. The reported results are obtained by using the "pscore" ado file developed by Becker and Ichino with Stata.

As previously noted, both the adopted estimation techniques give unbiased results only if the characteristics affecting the probability to be involved in a program (policy) are observable. Instead, if the selection in the treatment depends on unobservable characteristics, that is if there are some relevant differences between “treated” and “non treated” affecting both their probability to be involved in a program and their outcomes, the resulting estimates are biased. Heckman, Ichimura and Todd (1997), however, argue that selection on unobservable characteristics is strongly reduced in presence of two conditions: firstly, if the same questionnaire is submitted to both treated and controls, that is if the same information is available for both groups; secondly, if the observational units share the same economic environment. As we emphasize in the next paragraph we are rather confident that our data set allows to satisfy both these conditions.

4. The data

The data used in this paper are drawn from the Isfol “Young People Education and Employment Survey (YPEES)” collecting information on 6532 individuals aged 21 (3456) and 31 years (2896) at the moment of interview (end of 2004 and beginning 2005) and that are representative of the whole Italian population in these two cohorts. The questionnaire provides a wide set of information: personnel information, family characteristics, education choices and outcomes, employment conditions, job features. A section of the questionnaire is then specifically devoted to training and contains information on the number and type of training programmes attended and on their perceived quality.

As regards the conditions that should limit, according to Heckman and al. (1997) the possibility of selection on unobservables[2] and the consequent bias in estimations, the nature of our data set certainly satisfies the first one because for both treated and non treated we have the same information. The second condition (same environment conditions for treated and non treated) is only in part satisfied since the individuals were interviewed at the same time but live in geographical areas that have very different labor market conditions. In order to be more confident about the common economic environment, in the propensity score estimates we add for each individual the provincial unemployment rate of his birth cohort as a proxy for the labor market context.

Considering the whole sample, 1389 individuals (29%) attended training programs according to the Isfol definition that includes state-sponsored and market or firm provided

[2] See previous paragraph.

courses. This percentage is the same for the two cohorts signalling a major unwillingness to attend training in the younger cohort.

Since the main aim of this paper is to investigate the effect of training on several employment outcomes, we limit our analysis to training programs not provided by the company or the employer. The exclusion of these courses, that are obviously attended after having obtained a job, arises for two main reasons. Firstly, when we analyse the probability of obtaining a job or the channels exploited to get it, it is meaningless to include between the characteristics affecting these outcomes the participation in a training programme that temporally follows the hiring. But also as regards the investigation of the jobs' qualitative features (wage satisfaction, selfrealization, matching between skills required and owned), introducing information about training provided by the employer obviously entails a potential endogeneity bias. After this exclusion the number of trained individuals slightly decreases at 1255, the 26% of the whole sample.

As regards our first investigation, aiming at estimating the relationship between formal education and training, we consider the whole sample so as to detect the impact of all possible education degrees (compulsory, vocational and upper secondary school and university degrees) on the probability to get a training course.

Afterwards, in order to investigate the impact of training on employment outcomes we consider, within the whole data set, only respondents declaring that their prevailing employment condition is: employed, in redundancy fund (CIG) or in mobility, unemployed or in seek of first job. We then exclude all full time students, housewives and other "non actives" that generally include well-off persons, but also people that are preparing for a competitive examination. Within this restricted data set we then further bound our analysis to the 21 years old. The 31 years olds are excluded from the analysis of the impact of training on employment outcomes since we are not able to establish exactly when the training course has been attended and when exactly they got their first job. In our opinion this could strongly bias in an unpredictable way the results.

The relevant (for our analysis) characteristics of the treated and of the control groups are reported in table 1. Since in the following empirical analyses we will utilize both the whole (21 and 31 years old) and the restricted sample (only 21-years old), we present these descriptive statistics for both samples. In exposing the these statistics, we always distinguish between who completed a training programme ("treated" in the terminology of the adopted empirical strategy) and the others ("controls").

[TABLE 1 AROUND HERE]

Treated and controls do not substantially differ regarding personal information (gender, area of residence and dimension of the city of residence). The two groups instead strongly differ as regards their education level since treated have a lower probability to stop at the end of compulsory school. Treated are then more unwilling to choice professional or technical tracks instead of general tracks (licei) at upper secondary school. As regards the reported final marks, the performances of the controls are a little better compared to the trained. The remarkable no answer rate on this question (especially as regards lower secondary school) is explicitly taken into account in the following analysis. With regard to dropouts, trained present little less failures during the secondary schools, and university[3]. Finally, there are not remarkable differences between the two groups as regards the distribution of failures during school.

With regard to the investigated outcomes, table 2 provide their distribution, still distinguishing between treated and controls. Since in the investigation of these outcomes we restrict the sample to the younger cohort, the reported figures refer only to them.

[TABLE 2 AROUND HERE]

Concerning employment conditions, for the sake of simplicity, we distinguish two main situations: 1) employed, also including those workers in redundancy funds (CIG) or in mobility[4]; 2) unemployed, including those seeking their first job.

From the reported data it could be argued that treated have a higher (6 percentage point) probability to be employed. Concluding from this first evidence that training programmes have some positive effects on the employment chance would clearly be a mistake, since there can be a typical selection bias problem: trained, perhaps, could be more "attractive" workers independently from their participation to a training programme. The matching estimator allows to single out the net effect of the training.

With regard to the second examined issue, we distinguish the channels utilized to find the current job in "formal" and "informal". Formal channels include ads in newspapers or on the internet, CVs sent to employers, competitive examinations, services offered by training centres, public or private jobcentres, stages or other work experiences. Informal channels are represented by every form of signalling from relatives, friends or other people. Table 2 shows that controls use these informal channels more often than trainees (45.5% vs. 37%).

[3] Our sample excludes, by construction, the full time students. The reported dropout percentages concerns only part- time students, i.e. students that declare also an employment condition.
[4] None of the trainees is in CIG or in mobility, while 8 controls (1.21%) are in this condition.

The interest for this last outcome lies in the idea (to be verified) that attending a training course should reduce the necessity to rely on household or social relationships to enter in the labour market, since these courses often give the possibility of contacting firms or employers directly.

Finally, as regards i.e. job “goodness” indicators, the questionnaire contains a large amount of information on the (perceived) job quality. For our purpose, we focus on three sources of information: wage satisfaction, general selfrealization and adequacy of the acquired skills with respect to the job, which have the advantage of summarizing jobs’ economical and general features[5]. Table 2 reports that treated and controls do not differ according to wage satisfaction, while treated feel in average more “selfrealized” and also are more confident about the adequacy of their own skills.

5. Results

5.1 Training and formal education

Table 3 reports the results of two probit estimation of the participation both in a general and in a state-sponsored training program. Having a whatever degree higher than compulsory education significantly increases the probability to attend training courses. As regards the effect of specific educational tracks attended during the high school, we find that individuals with a vocational or technical track (Istituti tecnici and professionali) have a higher probability to get training compared the others (Licei). Finally, individuals that dropped out during upper secondary school are more unwilling to complete their skills and competences acquisition by means of training courses.

[TABLE 3 AROUND HERE]

According to the previous estimates, table 4 then provides the estimated probability to access to training programmes by education level, type of track attended and events occurring during the educational career.

[TABLE 4 AROUND HERE]

[5] These indicators are developed according to the answers to this question: “Are you satisfied about the following features of your current job?” where the examined features are Wage, Selfrealization and Adequacy of your skills to the current job. The possible answers are four : Yes, much; Yes, enough; Not much; Not at all.

Over the whole sample, the probability to participate in general training courses is 26.8% and in a state sponsored training programs is 16.7%. In both cases, we observe that these probabilities strongly decreases for low educated individuals with a compulsory degree (respectively to 18% and 14%). On the contrary, for individuals with a three or five-years vocational degree the estimated probabilities are quite higher, respectively 36% and 25%. Finally, individuals who dropped out during university are more probably involved in training programmes, especially if state-sponsored.

From these figures it appears that it is not possible to establish a clear relationship between formal education and training. While we can exclude that training is a substitute for formal education, since less educated individuals do not attempt to fill their skills gaps by attending extra-school courses, we cannot conclude that training is a complement for education. Indeed we observe that training participation does not linearly increase with education, but it is particularly high for medium-high educated individuals, especially if they have a professional educational track. This evidence could have two main opposite explications: these individuals could consider the skills and competencies acquired at school too poor to enter the labour market or, on the contrary, since they typically acquire at school very specific skills, they could be more able in finding and exploiting useful training programmes.

5.2 Training and employment outcomes

Tables 5, 6 and 7 report the ATT effects of differently defined training programs for which propensity score estimates of the probability to participate in training satisfy the balancing hypothesis. This hypothesis states that the conditional distribution of **X** in (1) conditional to the balancing function, that is the propensity score, is independent from the treatment[6] (Rosenbaum and Rubin, 1983).

[TABLE 5, 6 AND 7 AROUND HERE]

As regards employment condition we find a positive effect both of general and state-sponsored training according to kernel and stratification estimators, while best matching estimator does not detect any significant effect. According to kernel and stratification estimator which, as previously emphasized, exploit the whole available information on controls, the trained have a 5% higher probability than the control to be employed at the

[6] The specification satisfying the balancing hypothesis that here we do not report differs from the one in table 2 in two ways: firstly because we insert new dummies for the city dimension unifying some of the previous ones; secondly, because we add dummies also for the lower secondary school final mark.

moment of the interview. In order to further investigate this not very robust result we restrict our definition of training programmes, by estimating the effect of courses that go on at least for 100 hours, excluding then about 40% of the treated (table 6). Since we cannot establish and measure the quality of the courses, with this limitation we aim at eliminating at least programs that seems too short to provide a real skills improvement. With this restriction we effectively find a higher and even robust effect of training on employment chances: having attended a long-lasting training program increases the probability to be employed by around 7%.

Concerning the use of informal channels in finding the current job, the results are instead very robust. We find a statistically significant negative effect of training (both general and state-sponsored) on the use of social or family networks to successfully enter the labour market. In particular, having participated in a general training would decrease this probability by 6% to 9% depending on the estimator; but when we restrict the analysis to the long lasting courses or to the state-sponsored programmes the probability decreases by 10% or more.

With regard to the analysis of job quality, we report the estimated average training effect on the probability of earning a satisfactory wage, where satisfaction is self-defined by the interviewee. The estimated effect is always negative and also statistically robust in table 5 and 6 according to kernel and stratification estimator. This result deserves a greater attention. Since training increases the human capital level and, as a consequence, the individual productivity we would expect, following the standard microeconomic approach, a wage increase. A possible explanation could be a shorter tenure of the trainees, since the participation in a training programme generally postpones entering into the labour market. An alternative explanation lies on the possibility that, since we are analysing a variable that is the result of an individual perception, people that participated in a training programme doing a costly investment, expect higher wages and are, as a consequence, less satisfied about the actual salary.

With regard to the second job quality indicator, that is self-realization related to the job, we find a positive and statistically significant impact only of state-sponsored training which participation would increase the probability to get a more satisfying job from 6% to 11% depending on the estimator. If we consider self-realization as an indicator of the conformity of the job to individual expectations and ambitions, the interpretation of this result can be that only state-sponsored training increases the probability to have good matches between labour demand and offer.

As regards the third objective, we still find a robust positive result only for state-sponsored training. Having completed this kind of training programme increases by about 7% the probability of considering the acquired skills adequate to one's job.

Even if propensity score matching is easy to implement and very intuitive, it presents some important problematic features: firstly the selection process has to be correctly defined so as to single out all the relevant observables characteristics affecting the choice to attend the treatment; secondly, as previous analysis highlight, results may vary depending on the estimator and, as a consequence, on the exploited information. The advantage of this approach is that it is not necessary to specify the outcome functions, that are instead exploited within the "control function" methodology.

5.3. Robustness check

In order to test the robustness of the obtained results and to give answers to some of the questions left open we present the results obtained through the control function methodology briefly presented in par. 3. For every outcome we then estimate a probit function where the covariates are represented, according to equation (2), by:

a) variables affecting the selection process, that is $\mathbf{X_i}$;

b) variables affecting the outcome ($\mathbf{Z_i}$), that vary according to the outcome and that, in some cases, partially coincide with $\mathbf{X_i}$**;**

c) the treatment dummy ($\mathbf{T_i}$) where we distinguish the participation in a general training programme from the participation in a public training programme.

Table 8 reports the marginal effect of the probit estimates of employment probability. According to previous analyses, we estimate the effect of general training program (column I), of state-sponsored training programs (column II) and of long-lasting training programs (column III). We control for several context characteristics (area of residence, dimension of the city of residence, provincial unemployment rates), for the whole individual educational path (higher degree attained, type of educational track, final marks at lower and upper secondary school, failures and drop outs) and for previous working experiences (internships). We also add an indicator for the length of staying in the labour market, proxied by the (ln) of the difference between the age at the moment of interview (21 years) and the age at the moment of the conclusion of formal education.

[TABLE 8 AROUND HERE]

These estimates confirm the positive effect on employment of training. In particular, general training increases employment chances by about 8%, state-sponsored training by more than 8% and long lasting training programs by 11%. Besides, these effects which are always statistically significant at 1%, are a higher than the ones estimated by propensity score estimators.

(TO BE COMPLETED)

6. Concluding remarks

The aim of this paper is to investigate several features of training courses for youth in Italy. Training, together with education, represents a major source of human capital and should then increase the employment chances of new entrants in the labour market. The relation between education received at school and training is crucial: training courses can be perceived and exploited as complements or as substitutes of formal education. In the first case, training does not fill the skill gaps of the low educated people and becomes a further source of inequality (together with parental background and social relationships) in human capital attainments.

The strong assumption of our analysis is that selection bias, occurring in non experimental studies, is due to observable characteristics, since the nature of the data-set allows to strongly reduce the selection on unobservables. Given this assumption, we estimate the average treatment effect on treated through the propensity score matching estimator and, in order to test the robustness of the results, through the control function approach. Both these methodologies gives unbiased results when selection is on observables.

This paper provides some robust results on the relationships between education, training and employment outcomes of the young.

Firstly, the decision to participate in training programmes for the youth in Italy is positively affected by the education level, in particular if the acquired education is technical or professional. Since training programmes generally provide skills and competences that are easily exploitable in the labour market, this is a signal that training can be considered, in line with the empirical literature on this issue, as a complement of formal education.

As regards labour market impacts of training, we find a positive effect on youth employment chances, that is particularly relevant for long-lasting training courses. Another interesting result is that having attended a training programme of whichever type and duration, decreases the need to rely on informal channels such as family and social relationships to find a job. This result can be interpreted in a twofold sense. Training, increasing the skills of the youth, make them more competitive in the labour market and "attractive" for the employers. This interpretation is supported by the previous result on the higher employment chances of the trained. But training courses, independently from the provided skills, could also represent a source of information on the more effective ways to find a job or, also, could help the matching between workers and employment.

The other results on the effect of training on some job quality features are less strong, but we generally find a positive impact of state-sponsored training.

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APPENDIX

Table 1 Characteristics of treated and controls (in %)

	Whole sample		Only 21 years old	
	Treated	Controls	Treated	Controls
Obs.	1255	3422	636	1590
Personal information				
Female	48.61	45.27	48.27	46.73
North West	25.50	24.78	25.63	22.20
North East	23.27	23.20	22.33	23.21
Centre	23.67	22.97	22.64	22.26
South	15.94	17.91	17.14	18.81
Islands	11.63	11.13	12.26	13.52
<5000	20.56	19.64	20.60	18.24
5000-20000	24.46	26.39	23.58	27.04
20000-50000	17.69	19.05	19.18	21.13
50000-250000	21.51	17.86	20.60	18.74
Over 250000	15.78	17.07	16.04	14.84
Highest education degree				
Compulsory school	17.37	29.46	18.40	25.53
Vocational school	14.18	9.29	15.88	9.50
Upper sec. school	55.94	48.16	65.09	64.09
University diploma	12.51	13.09	0.63	0.88
Lower secondary school final mark				
Sufficiente (Pass)	16.65	18.00	17.77	19.18
Buono (Good)	21.91	19.64	22.64	23.84
Distinto (Very good)	5.90	7.86	5.50	8.74
Ottimo (Excellent)	8.61	7.74	7.23	8.30
No answer	46.69	44.77	46.86	38.99
High or vocational school				
Liceo	18.96	21.01	20.13	24.65
Professionals	24.14	17.15	28.62	17.92
Technical/Commercial	29.64	21.30	27.52	24.34
Others	7.09	5.08	5.66	5.79
No answer	3.11	6.31	0.47	2.33
Upper secondary school final mark				
60-70	19.52	13.94	21.07	18.05
70-80	13.15	12.19	11.48	15.41
80-90	10.92	10.14	7.55	10.38
90-100	12.51	10.58	15.41	12.08
No answer	12.27	14.32	10.22	9.06
Dropouts				
During upper sec. school	8.45	9.99	8.18	11.19
During university	8.21	6.25	3.93	5.16
Fails				
One or more	19.20	17.83	18.71	21.19

Table 2 Outcomes by treated and controls (in %)

Outcomes		Treated	Controls
Employment condition	Employed	61.95	55.41
Use of informal channels	Yes	37.06	45.52
Satisfied for the wage	Much or enough	67.26	68.56
Selfrealization	Much or enough	70.05	65.72
Adequacy of the skills	Much or enough	85.03	80.82

Table 3 Education and training

	General training	State sponsored training
Vocational school	.504***	.295**
	(.104)	(.120)
Upper secondary school	.437***	.173
	(.090)	(.106)
University degree	.549***	.378***
	(.100)	(.118)
Technical track	.316***	.285***
	(.059)	(.073)
Professional track	.277***	.343***
	(.070)	(.084)
Other tracks	.292***	.357***
	(.091)	(.108)
Fail	-.168***	-.194***
	(.056)	(.068)
Dropout upper sec.	.341***	.268***
	(.086)	(.094)
Dropout university	.123	.218**
	(.081)	(.096)
OBS.	4677	4109
PSEUDO R^2	*0.032*	*0.033*

**significant at 5%; ***significant at 1%.
We also control for other personal characteristics such as gender, age, area of residence (North West, North East, Centre, South or Islands), dimension of the city of residence (<5.000, 5.000-20.000 20.000-50000, >50.000), high school final mark and provincial unemployment rate.

Table 4 Estimated probability to attend training programs

	Obs	Estimated probability to attend a general training program	Obs	Estimated probability to attend a state-sponsored training program
Overall	4677	.268 (.085)	4109	.167 (.0628)
Educational level				
Compulsory school (Scuola media inferiore)	1155	.179 (.050)	1097	.136 (.041)
Vocational school (Istituti professionali)	496	.359 (.053)	426	. 253 (.056)
Upper secondary school (Scuola media superiore)	2350	.298 (.068)	1993	. 173 (.063)
University	605	.259 (.057)	523	. 142 (.053)
High school track				
General	957	.238 (.0376)	834	. 132 (.036)
Professional	890	.338 (.054)	906	.196 (.057)
Technical	1101	.340 (.059)	760	.228 (.063)
Other	263	.338 (.054)	225	.228 (.066)
Other events				
Drop outs during upper sec. school	448	.235 (.027)	416	.176 (.032)
Drop outs during university	317	.325 (.074)	270	.21 (.075)
Failures	851	.284 (.064)	731	.167 (.060)

Standard deviation in parentheses.

Table 5 Average treatment effect on treated (treatment: general training programmes)

Matching strategy	Treated	Controls	Average effect	Std. Err.
		Employment		
Kernel	636	1570	0.046***	0.019
Best matching	636	554	0.02	0.031
Stratification	636	1570	0.051***	0.025
		Use of informal channels		
Best matching	394	304	-0.087**	0.05
Kernel	394	865	-0.062*	0.037
Stratification	394	865	-0.057**	0.031
		Wage satisfaction		
Best matching	394	304	-0.020	0.041
Kernel	394	865	-0.009	0.033
Stratification	394	865	-0.012	0.029
		Self-realization		
Best matching	394	304	0.011	0.04
Kernel	394	865	0.043	0.033
Stratification	394	865	0.038	0.034
		Adequacy of the skills		
Best matching	394	304	0.041	0.032
Kernel	394	865	0.035*	0.021
Stratification	394	865	0.041*	0.025

* significant at 10%; **significant at 5%; ***significant at 1%.
The sample is restricted to the 21-years old. We exclude from the analysis individuals who attended a firm-provided training programmes.

Table 6 Average treatment effect on treated (treatment: state-sponsored training programmes)

Matching strategy	Treated	Controls	Average effect	Std. Err.
		Employment		
Best matching	372	341	-0.004	0.04
Kernel	372	1572	0.048**	0.027
Stratification	372	1572	0.045**	0.027
		Use of informal channels		
Best matching	239	202	-0.096**	0.049
Kernel	239	867	-0.112***	0.033
Stratification	239	867	-0.116***	0.035
		Wage satisfaction		
Best matching	239	202	0.024	0.051
Kernel	239	867	-0.066***	0.03
Stratification	239	867	-0.076**	0.035
		Self-realization		
Best matching	239	202	0.110**	0.052
Kernel	239	867	0.110**	0.051
Stratification	239	867	0.062**	0.032
		Adequacy of the skills		
Best matching	239	202	0.075**	0.045
Kernel	239	867	0.063***	0.022
Stratification	239	867	0.063***	0.026

* significant at 10%; **significant at 5%; ***significant at 1%.
The sample is restricted to the 21-years old. We exclude from the analysis individuals who attended a non state-sponsored training program..

Table 7 Average treatment effect on treated (treatment: long lasting general training programmes•)

Matching strategy	Treated	Controls	Average effect	Std. Err.
		Employment		
Kernel	351	1582	0.075***	0.027
Best matching	636	554	0.071*	0.045
Stratification	636	1582	0.066***	0.025
		Use of informal channels		
Best matching	234	185	-0.119***	0.037
Kernel	234	864	-0.100***	0.049
Stratification	234	864	-0.115***	0.035
		Wage satisfaction		
Best matching	234	185	-0.030	0.060
Kernel	234	864	-0.054*	0.036
Stratification	234	864	-0.068**	0.035
		Self-realization		
Best matching	234	185	0.127	0.050
Kernel	234	864	0.018***	0.034
Stratification	234	864	0.012	0.035
		Adequacy of the skills		
Best matching	234	185	0.033	0.044
Kernel	234	864	0.033	0.043
Stratification	234	864	-0.003	0.027

* significant at 10%; **significant at 5%; ***significant at 1%.

• Long lasting training programmes: 100 hours or more programmes.

The sample is restricted to the 21-years old. We exclude from the analysis individuals who attended firm-provided training programmes and who attended short-duration training programs (less than 100 hours)

Table 8 Employment estimation (marginal effects; t values in parentheses)

	II	**III**	**III**
FEM	-.038	-.038	-.035
	(.025)	(.025)	(.025)
NORTH EAST	.008	.007	.004
	(.036)	(.036)	(.036)
CENTRE	-.091**	-.093**	-.085**
	(.037)	(.037)	(.037)
SOUTH	-.339***	-.343***	-.336***
	(.05)	(.050)	(.050)
ISLANDS	-.402***	-.405***	-.406***
	(.055)	(.055)	(.055)
<20.000	.096***	.097***	.092***
	(.031)	(.031)	(.03)
>50.000	.020	.022	.018
	(.032)	(.032)	(.032)
UNEMPL	-.003*	-.003	-.002
	(.002)	(.001)	(.001)
LABOURMKT	.099***	.099***	.101***
	(.036)	(.035)	(.035)
VOCAT. SCH.	-.26**	-.254***	-.251***
	(.066)	(.067)	(.067)
UPP.SEC.SCH.	-.23***	-.224***	-.228***
	(.053)	(.054)	(.053)
GOOD	.026	.0275	.025

	(.037)	(.037)	(.037)
VERY GOOD	-.002	-.003	.002
	(.0526)	(.052)	(.052)
EXCELLENT	-.130**	-.130**	-.130**
	(.056)	(.056)	(.056)
NA_LOWSEC	.036	.033	.0342
	(.037)	(.037)	(.037)
70-80	-.096**	-.100**	-.093**
	(.041)	(.041)	(.041)
80-90	-.176***	-.178***	-.178**
	(.048)	(.048)	(.048)
90-100	-.139***	-.136***	-.138***
	(.046)	(.046)	(.046)
NA_HIGHSEC	-.075	-.066	-.060
	(.053)	(.053)	(.053)
TECHNICAL	.168***	.169***	.171***
	(.030)	(.03)	(.030)
PROFESS	.178***	.176***	.177
	(.037)	(.037)	(.037)
OTHERS	.095*	.091*	.099**
	(.050)	(.051)	(.05)
FAIL	-.060*	-.061*	-.060*
	(.035)	(.035)	(.035)
DROPOUT SEC.	-.004	-.003	-.001
	(.052)	(.052)	(.052)
DROPOUT UNI.	.184*	.182***	.182***
	(.054)	(.054)	(.054)
INTERNSHIP	-.04	-.039	-.043
	(.028)	(.028)	(.028)
GENERAL TRAINING	.078***		
	(.0271)		
PUBLIC TRAINING		.084***	
		(.0321)	
LONG GENERAL TRAINING			.109***
			(.032)
Observations	2027	2027	2027
Pseudo R^2	0.1702	0.1697	0.171

*significant at 10%; **significant at 5%; ***significant at 1%.
I: General training programs
II: general training programs with control for labour market presence length
I: State-sponsored training programs
II: State-sponsored training programs with control for labour market presence length