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Counterfactual Impact Evaluation of "Work Experience Laureati e Laureate – WELL" (Work Experience for Graduates)

The impact of an ESF-funded intervention in Umbria region, Italy

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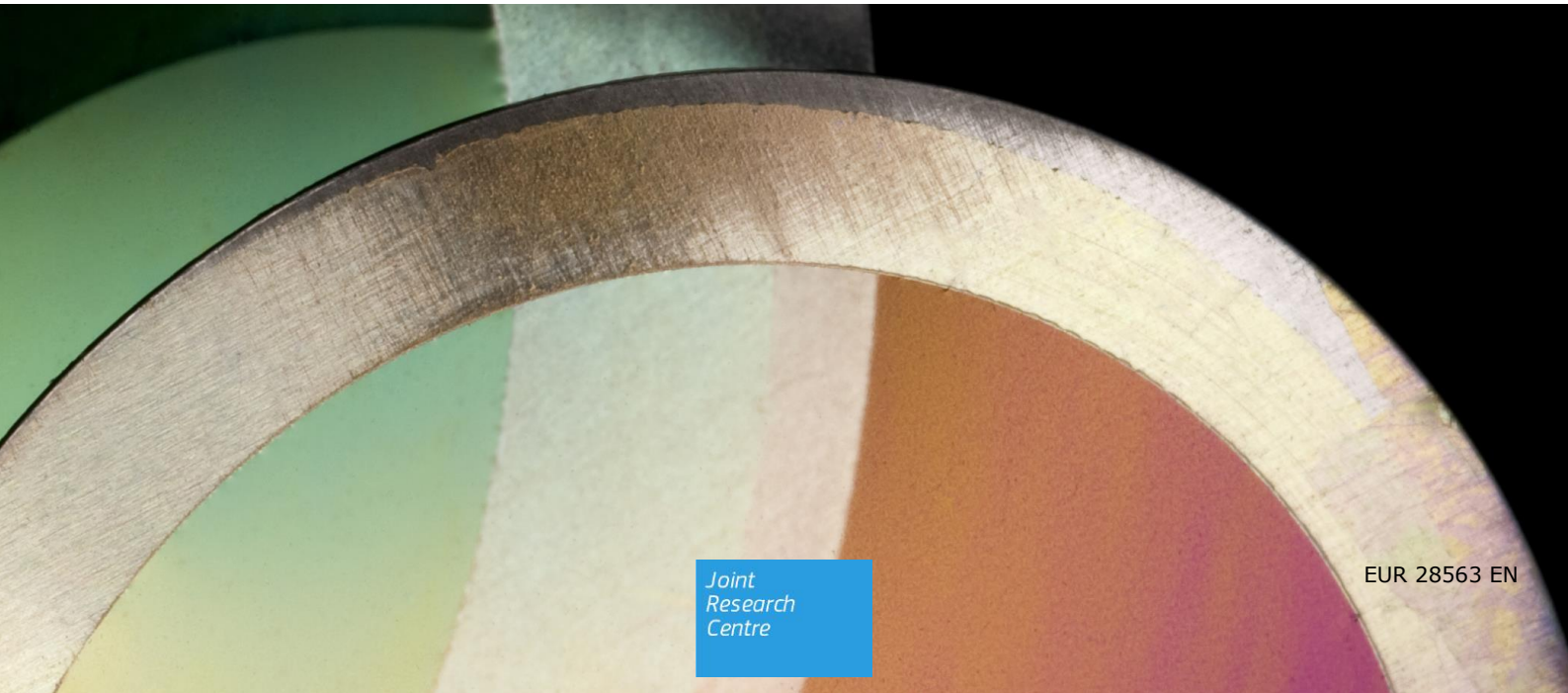

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Foreword

The Counterfactual Impact Evaluation (CIE) of the "Work Experience for Graduates'' (Work Experience Laureati e Laureate, WELL) was carried out within the Data Fitness Initiative, launched in February 2016 by Directorate General Employment, Social Affairs and Inclusion (DG EMPL) and Centre for Research on Impact Evaluation (CRIE) to promote the use of CIE for the assessment of European Social Fund (ESF) interventions. Based on the quality of the data and on the policy relevance of the intervention proposed, in June 2016 this dataset was selected by CRIE to establish a collaboration agreement with the Office of Statistics and Evaluation of Umbria Region (Italy) and work together on the analysis of the programme. This collaboration resulted very fruitful, both for strengthening interactions between the ESF Managing Authorities and the European Commission and in terms of scientific contribution to the evidence on the impact of ESF interventions.

Acknowledgements

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Abstract

The WELL programme was financed by the ESF as part of the 2007-2013 Regional Operational Programme of Umbria Region, Italy. The aim of the programme was to increase the career prospects of unemployed graduates in the region. It consisted of two measures: (i) on-the-job training for unemployed graduates and (ii) wage subsidy to firms and organizations that eventually hired the trainee. The goal of the CIE was to evaluate the effectiveness of the intervention in terms of employability of participants. In doing so, monitoring data of the programme were combined with administrative data from the Compulsory Communication Database (CCD) of the Italian Ministry of Labour, which records total hirings, renewals, transformations, and cessations of labour contracts in the private sector. The analysis was performed by means of propensity score matching. Results indicate that WELL participants are more likely to be employed. This positive effect is measured only for participants who found a job within the region boundaries. However, policy implications are still drawn with caution and require some further crosschecking for potential unobserved factors, since the limited number of variables in the matching impede the full attribution of causality. Therefore, CRIE and Umbria Region agreed on extending the current analysis by including additional data on past labour market experience in the matching procedure, in order to strengthen the comparability of participants and non-participants and hence the identification of causal impact of the intervention.

1 Introduction

This report outlines the Counterfactual Impact Evaluation (CIE) of an intervention implemented in Umbria Region in Italy in 2013 and financed under the European Social Fund (ESF). This exercise has been carried out under the "Data Fitness Initiative for CIE", launched in February 2016 by Directorate General Employment, Social Affairs and Inclusion (DG EMPL) and the Centre for Research on Impact Evaluation (CRIE) to promote the use of CIE for the assessment of ESF interventions and foster collaborations between ESF Managing Authorities and CRIE in this respect. The ESF Managing Authority of Umbria region in Italy proposed to perform a CIE study on the effectiveness of the "Work Experience Laureati e Laureate – WELL" (Work Experience for Graduates) intervention.

In a nutshell the intervention subsidises on-the-job training for unemployed graduates. On the one hand the aim of the WELL intervention was to increase employment among unemployed college graduates. On the other hand it also aimed at promoting innovative capacity and productivity of the participating firms.

To perform the CIE evaluation, CRIE with the support of the Office of Statistics and Evaluation of Umbria combined data from the Regional Monitoring System Database with administrative data regularly collected by the Italian Ministry of Labour, Health, and Social Policies from the local labour offices, i.e. the Compulsory Communication Database (CCD).

As for the evaluation method used, CIE approach involves comparing the outcomes of interest of individuals who participate in the intervention (the "treated group") with those of a group similar in all respects to the treated group (the "comparison/control group"), the only difference being that the comparison/control group does not participate in the intervention. The comparison group provides information on "what would have happened to the individuals subject to the intervention had they not been exposed to it", the counterfactual case.

In this case the treated group is composed of highly educated unemployed who participate in the WELL intervention, whereas the control group is composed of the remaining population of highly educated unemployed living in the Umbria region but who did not take part in the intervention. The outcome variables of interest measured in 2015 are: the probability of being employed in the Umbria region, the probability of being registered as unemployed in Umbria region, or the probability of being part of a residual category. The causal effect of the intervention on the labour market career of participants, the Average Treatment Effect on the Treated (ATT), is computed using propensity score matching method. We selected this method based on the characteristics of the intervention. In particular, since there are no fixed thresholds to define the eligibility criteria we could not use a Regression Discontinuity Design (RDD), and since the individuals in our treated and control group are all unemployed in the pre-intervention period we could not apply a Difference in Differences (DID) methodology. This leaves us with a single choice which is based on matching methods.[1] These methods allow to compare individuals in the treated and control group based on observable characteristics, in order to estimate the effect of the training on employment outcomes.

[1] RDD and DID are the most used methods for evaluating the impact of labour market policies. Another method is known as "Instrumental Variables" which exploits specific sources of variation and often relies on the use of invitation letters to increase participation in the training programme. This method could not be used due to absence of incentives that could change the probability of participation in the intervention.

In Section 5 we provide a thorough explanation of this methodology. According to the estimated results, WELL participants are more likely to be employed in Umbria than non-participants at the end of 2015. However, they are equally likely to be registered as unemployed in the unemployment lists of Umbria labour offices. In addition, participants are less likely to be in the residual category than non-participants. These results should be taken with caution given that the matching is performed on few available characteristics that allow to reduce the selection bias but not necessarily to eliminate it. In Section 7 we discuss extensively possible avenues to address these issues.

The remainder of the report is organized as follows: Section 2 provides a description of the Umbria labour market; Section 3 describes the intervention and the selection procedure. In Section 4 we describe the data used in the analysis, while Section 5 explains the methodology implemented to quantify the impact of the WELL intervention and illustrates the main results. In addition, in Section 6 and 7 we discuss the possible channels behind the results, data limitations and future extensions to improve the quality of the evaluation.

2 Description of Umbria labour market

This section describes the labour market of Umbria region to frame the intervention in the context of this region. The description is based on data from two different and complementary data sources: i) the database of the Italian National Statistical Office (ISTAT) and, ii) the Compulsory Communication Database (CCD) collected by the Italian Ministry of Labour and Social Policy in collaboration with the Regions, the National Institute of Social Security (INPS), the Italian Government Agency for the Insurance against Work-related Injuries (INAIL) and the Prefectures. ISTAT statistics are based on labour force surveys. These surveys are representative of the population of interest and hence provide a broad picture of both the Italian economy as a whole and its regions. By contrast, the CCD consists of data from administrative archives. The impact evaluation of the WELL intervention is based on the use of administrative data from the Compulsory Communication Database (CCD) of the Italian Ministry of Labour, which records total hirings, renewals, transformations, and cessations of labour contracts in the private sector. These data are needed in order to build a good control group. Furthermore, we have the opportunity to rely on the whole population of unemployed graduates at a given date. These data are described in Section 4.

The two data sources are complementary since they use slightly different definitions of employment. In particular, the data collected by the CCD refers to the employee and regular work, excluding self-employment and people working in the underground 7economy, which is instead taken into account in ISTAT data. The combination of both allows to obtain a comprehensive picture of the Italian labour market.

Umbria is a small region located in central Italy. It consists of two provinces (Perugia and Terni) and 92 municipalities, with a total population of about 890,000 inhabitants. Of these, 62.3% are aged 15 to 64, while the labour force aged 15+ amounts to 401,000 persons (see Table 1 and Table 2).

Table 1 - Population by age group on January 2016 in Umbria and Italy

	Population January 2016		
	0-14 years	15-64 years	Total
Umbria	114.858	555.362	891.181
Perugia province	87.536	414.516	662.110

Terni province	27.322	140.846	229.071
Males	59.012	273.363	427.662
Females	55.846	281.999	463.519
Italy	7.709.914	39.013.938	60.665.551
Males	3.743.180	19.582.411	31.209.230
Females	3.966.734	19.431.527	29.456.321

Source: Istat

Table 2 - Population by age group at 1° Jan, 2016 - Umbria and Italy

	Population at 1° Jan, 2016					
	0-24 years	25-29 years	30-34 years	35-39 years	40 years and over	Total
Umbria	193.284	45.406	50.934	58.806	542.751	891.181
Perugia province	146.564	34.310	38.648	44.359	398.229	662.110
Terni province	46.720	11.096	12.286	14.447	144.522	229.071
males	99.466	22.782	25.273	29.178	250.963	427.662
females	93.818	22.624	25.661	29.628	291.788	463.519
Italia	14.199.594	3.260.703	3.537.822	4.080.470	35.586.962	60.665.551
males	6.884.476	1.607.399	1.761.403	2.037.299	18.918.653	31.209.230
females	7.315.118	1.653.304	1.776.419	2.043.171	16.668.309	29.456.321

Source: Istat

2.1 Economic development by sectors of industry

The Italian economy faced serious structural problems that hampered the production system compared to other industrialised countries already in the years preceding the economic crisis, as: the lack of raw materials, especially those of energy; production specialization in export-oriented sectors, where competition from emerging countries contributes to lose significant market share; a productive structure in which small and micro enterprises make up the bulk of economic activity, and consequently the level of productivity and investments in research and innovation is scarce.

In the last three years, the economic context partially recovered the wealth losses observed since the economic crisis in 2008.

The recent recovery started late with respect to the European average situation: "In 2015, Italy's real GDP had fallen back to the early 2000s levels, while the euro area GDP was more than 10% higher".[2]

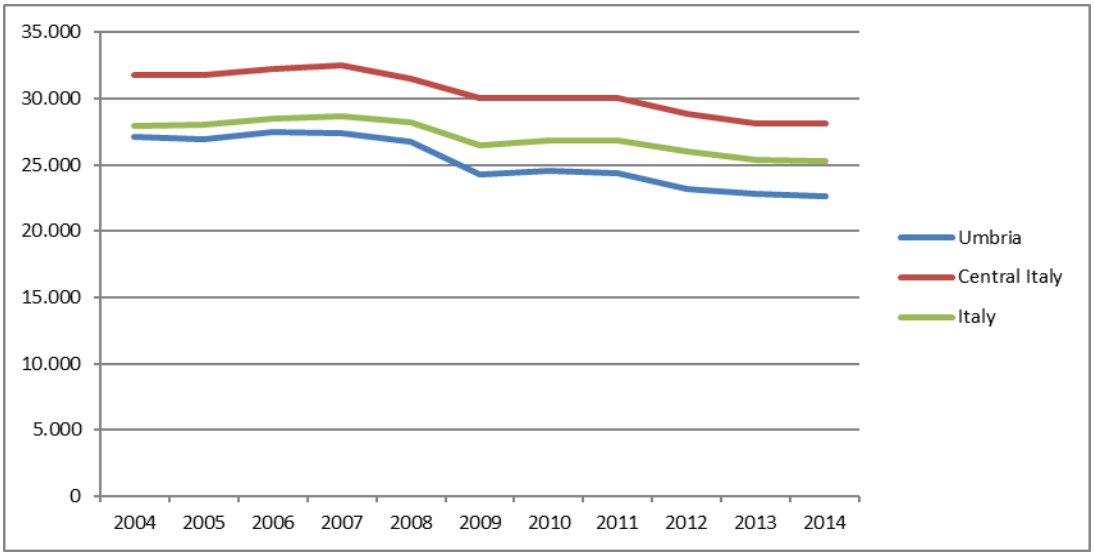
Although there are signs that the reforms undertaken (including in the labour market) are achieving the first positive results, it is still premature to assume that the recovery is stable and lasting.

[2] European Commission, Country Report Italy 2016, executive summary.

There remain many uncertainties about the factors that contributed to the recovery of competitiveness of the country system - including for example the decrease in real terms of oil prices and other energy products - and to the positive expectations of economic agents.

During the crisis the decline of Umbria's per capita GDP was more pronounced than in the rest of the country as shown in Figure 1. In Southern Umbria (province of Terni), the crisis of the steel sector heavily influenced the development of the area, where the largest multinational companies present in the area drastically reduced employment up to one third since the mid-eighties. As for the sector composition, the economic crisis has affected to a greater extent the construction sector and the manufacturing industry, while services - in particular the services offered by public administrations, and more generally market non-tradable sectors - have declined to a lesser extent.

Figure 1 - Gross domestic product per capita *(euro, chained index - base year 2010)*



Source: Istat

Labour market in Umbria and Italy based on ISTAT data

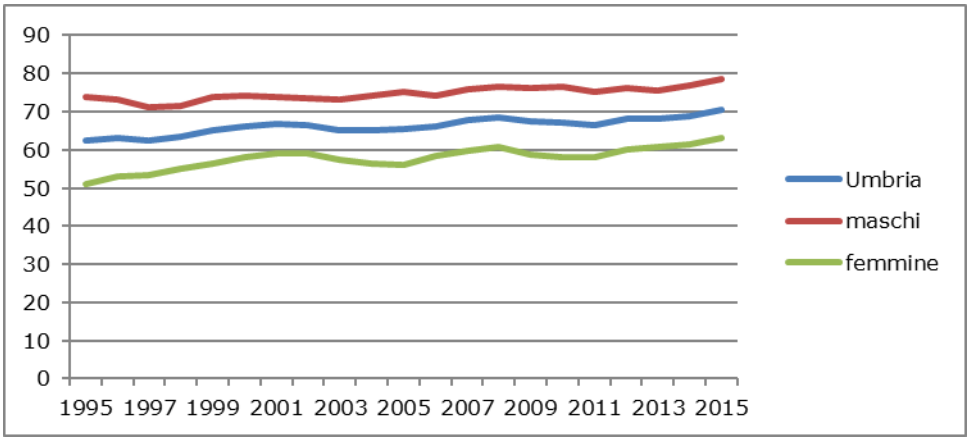
This paragraph describes the Umbria Labour market based on ISTAT data. The main regional labour market indicators reflect the negative trend of the national economic conditions.

As shown in Figures 2 and 3 labour market participation of women is lower compared to males, both in Italy and in Umbria. Figure 2 displays that Umbria's activity rate is slightly higher than the national average, for the entire period considered. Thus, the difference between the regional and the national figure is more marked for women.

Since 2012 the labour force participation has slightly started to increase.

Figure 2 - Labour force participation, total and by gender - Umbria

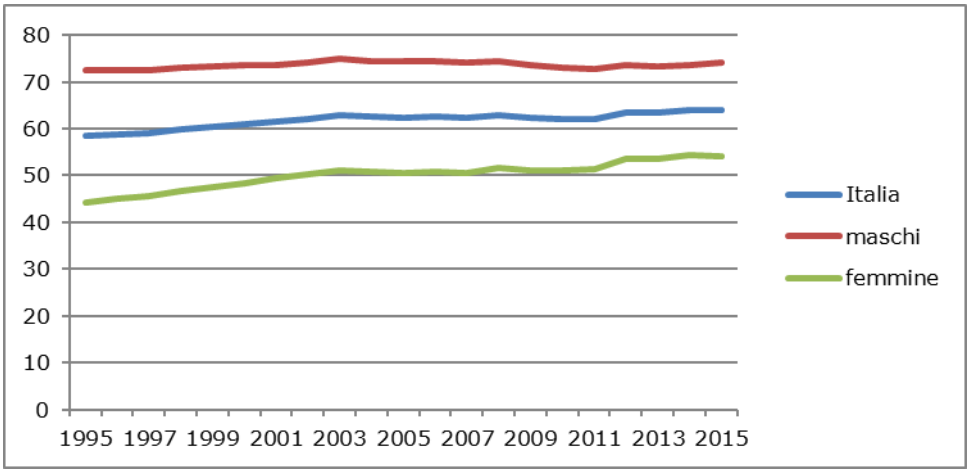
Labour force aged 15-64 over the total population in the corresponding age group 15-64 years (percentage)



Source: Istat – Dipartimento Politiche Sociali

Figure 3 - Labour force participation, total and by gender - Italy

Labour force aged 15-64 over the total population in the corresponding age group 15-64 (percentage)

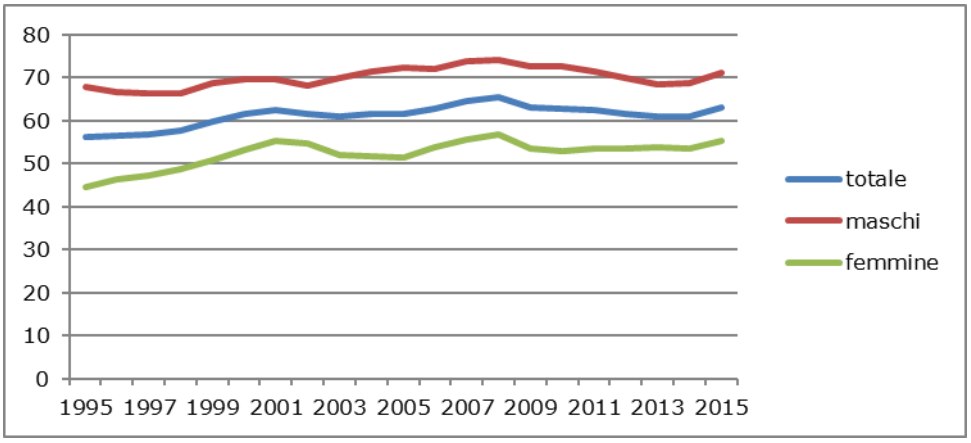


Source: Istat - Dipartimento Politiche Sociali

Similarly, the employment rate for people aged 16-64 in Umbria is higher compared to the Italian average (see Figure 4 and 5). In addition, the employment rate in Umbria increased more compared to the national average between 2014 and 2015 (2.1 percentage points in Umbria as opposed to 0.6 percentage points in Italy).

Figure 4 - Employment rate, total and by gender - Umbria

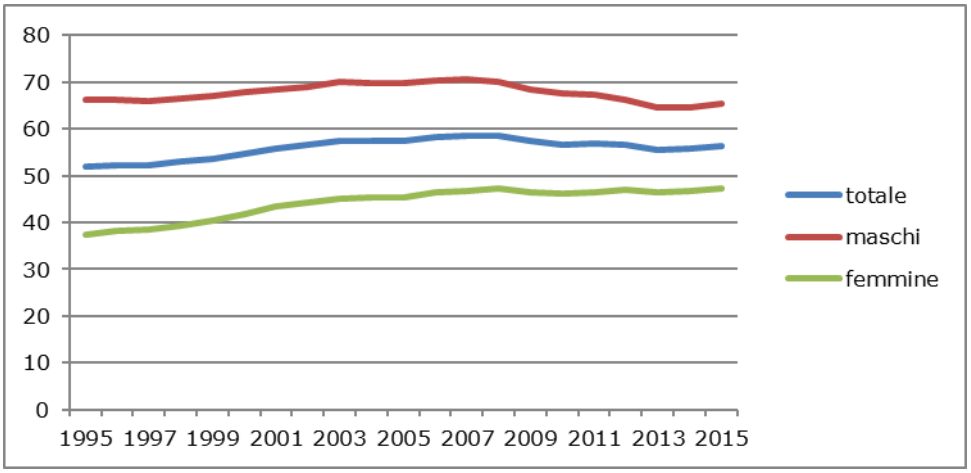
Employed aged 15-64 over the total population in the corresponding age group 15-64 (percentage)



Source: Istat – Dipartimento Politiche Socia

Figure 5 - Employment rate, total and by gender - Italy

Employed aged 15-64 over the total population in the corresponding age group 15-64 years (percentage)



Source: Istat – Dipartimento Politiche Sociali

The trend of the unemployment rate is less easy to read, even if it has the advantage of returning an immediate overall picture of the labour market critical features.

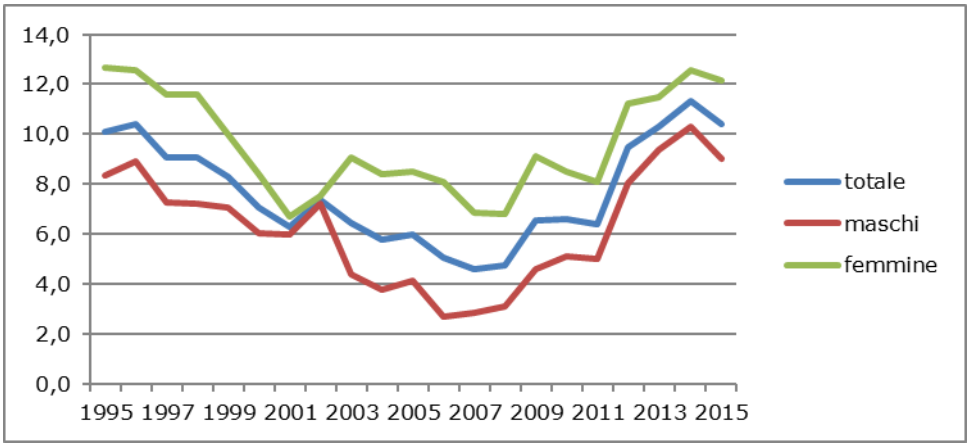
The amount of the unemployed consists in fact of different categories, whose employment status may be further broken down as follows:

- unemployed in the strict sense, that is, people who had a job and lost it;
- people looking for their first job, defined as first-time jobseekers;
- people who were not part of the labour force but have decided to look out in the labour market: for example, students who have finished their cycle of study (or early study abandonment) to search for a job.

The three sets described above are related not only to economic conditions but also to the demographic structure; therefore they are affected by factors that may have counterbalanced trends, even in the short term.

Figure 6 - Unemployment rate, total and by gender - Umbria

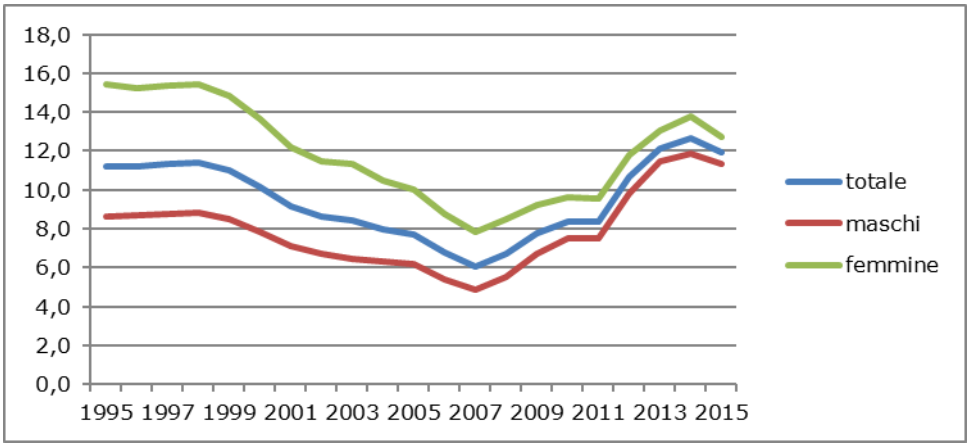
Unemployed aged 15-64 over the total population in the corresponding age group 15-64 (percentage)



Source: Istat – Dipartimento Politiche Sociali

Figure 7 - Unemployment rate, total and by gender - Italy

Unemployed aged 15-64 over the total population in the corresponding age group 15-64 (percentage)



Source: Istat – DPS

Umbria labour market based on CCD data

Below we describe the Umbria labour market based on the administrative CCD data. For Umbria, the latest release of data (2015) shows a positive net balance of around 8,400 recruitments, equal to 6.7% in payroll employment.

This positive figure marks a turnaround from the previous two years, in which the difference between dismissals and hires was about -4,900 in 2014 and - 4,600 in 2013.

In the last year, no sector showed a decrease in employment rate. The latter remains very high in the service sector (especially in education and in the field of hotels and restaurants) followed by the manufacturing and mining industries; in the latter branch the relative growth of 2015 is the most sizeable (+ 17.3%).

Open-ended contracts are the only type of contract which registered a sharp increase; this is to be related to reforms approved in Italy in 2014 (financial law for 2015 and Jobs

Act), the effectiveness of which, however, already seems to be questioned by the most recent analysis.

During 2015 the number of all other types of contract decreased, even for temporary and staff leasing contracts, which instead have shown positive trends in other areas of the country.

A further indicator of the close link between the regional economic environment and the labour market context is the number of workers on the mobility lists. These are workers laid off due to the reduction, transformation or cessation of production activities in the private sectors (note: in 2013, enrolment in mobility lists was possible only for collective dismissals of companies with more than 15 employees). These workers receive incentives to search for a new job, including partial exemptions of social contributions for businesses who hire them.

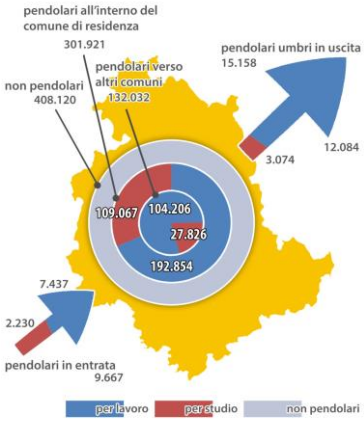
In 2015 the amount of workers enrolled in Umbria mobility lists shrank by over a third compared to 2014, and more than half the figure for 2013. It is hoped that this indicator continues its reduction, and that this could be interpreted as a signal of going beyond the crisis, at least for larger companies.

2.2 Commuting patterns in and out of Umbria

Data on commuting, which are systematically collected from the 1981 general population and housing census, show that over the years the number of those moving daily to the usual place of study or work has increased both within the municipality of residence and to other municipalities. The latest available data refer to the 2011 census; in the last decade, Umbrian commuters have increased more than 13% on average, although the period also includes the periods of the economic crisis and of the rapid growth of the possibilities offered by ICT to work remotely, through i.e. videoconference or accessing on-line archives. As shown in Figure 8, at the regional level, people who commute towards Umbria amount - in the census of 2011 - to 9,667, of which 7,437 are workers; this figure only partly offsets the flow of those moving out daily from the region for work (12,084 people) or study (3,074 people).

Rome and its surroundings are the main destination of Umbrian commuters, with more than a third of outgoing commuters from the region. Of these, the majority comes from Terni and two neighbouring municipalities (Narni and Amelia) and from Orvieto, the latter being connected by railway and by motorway.

Figure 8 - Commuting patterns in Umbria



Starting from the commuting work flows, it is possible to identify infra-regional areas where most productive activities and services are concentrated, therefore offering job and residential opportunities to the population which is settled there. These areas are defined "Local Labour Systems" (LLS) and are identified putting together two or more neighbouring municipalities, in which the level of interaction is maximized using some iterative algorithms (i.e. INTRAMAX technique). The criterion used corresponds to self-restraint on the labour supply side (ratio between the commuting work flows within a LLS and the number of residents employed) and on the labour demand side (ratio between the commuting work flows within a LLS and the number of jobs).

In
Figure 9 the Local Labour Systems of Umbria are illustrated, as calculated with the 2011 general population and housing census.

Figure 9 - Local Labour Systems of Umbria

The analysis of commuting patterns in and out of the region is important to understand to what extent participants may find a job in another region after the training and decide to work outside Umbria. A possibility is that the intervention improves the employability of participants but that the latter find jobs in the neighbouring regions, thereby not fostering Umbria's economy. If this is the case, the intervention would lead to a "brain drain out of Umbria". However, even in this situation, to the extent that participants

keep the residence in Umbria, the fact that they work in other regions would represent only a "partial" brain-drain out of Umbria, since earnings is accounted in the region of residence. In fact, this is the case: none of the individuals in the sample change municipality of residence between 2013 and 2015.

3 Description of the intervention

Within the "Data Fitness Initiative", CRIE selected the proposal submitted by the ESF-Managing Authorities of the Umbria Region. The proposal was to carry out a CIE of the ESF-funded intervention "Work Experience Laureati e Laureate – WELL" (Work Experience for Graduates).

The project was part of the activities of the Regional Operational Programme of Umbria Region. It was implemented under the ESF Ob. 2 2007-2013 Programming Period and within the Annual Regional Plan for interventions in support of the work.

Launched in April 2013 with the financial resources of "employability" axis, WELL had the specific goal of reducing unemployment and strengthening professional qualifications of graduates, raising the quality of their employment status.

More specifically, WELL was designed to promote fully- subsided work experience, with the aim of increasing employment among highly educated individuals and with a higher risk of exclusion from the labour market.

In addition, the possibility to employ highly qualified individuals is expected to be beneficial to the firms. The project WELL, in fact, indirectly also aimed at promoting dissemination of modern and efficient production processes and increase the innovative capacity and productivity of the participating companies.

Employability was strengthened with the provision of wage subsidies to employers that hired the participant at the end of the work experience.

The intervention therefore was characterized by a tightly integrated path consisting of two steps, namely:

- on-the-job training for unemployed graduates.

  The duration of the work experience was six months, with a minimum commitment of 24 hours weekly. A monthly gross salary of €800 was paid to the trainee.

- wage subsidy to firms and organizations that eventually hired the trainee.

  The amount of the subsidy depended on the type of contract. In particular, a trainee hired with a fixed-term contract for at least six months, the subsidy was equal to €2,500; while for an apprenticeship contract the subsidy amounted to €4,000; and finally for an open-ended contract the subsidy could amount to €6,500.

The on-the-job training foresaw a traineeship targeted at the graduate from a tutor responsible of training activities in one or more areas of the organization plus the supply of high-tech tools and support for the educational activities.

The work experience had to be coherent with the activities and work organization of the host company. The training activities enlisted in the project aimed at acquiring knowledge and professional skills correlated to the educational qualification of the

internee, although not merely operative. The provision of incentives to the unemployed and to the firm was granted under the unemployed availability to take up measures that the public services dealing with labour policies consider suitable.

The design of this project was consistent with the objectives set out in the 2007-2013 EU Programming Period, in particular with the European Commission's priorities in favour of sustainable development by strengthening growth, competitiveness, employment and social inclusion.[3] In this respect the project is in line also with the objectives set for the current programming period, in particular with reference to the thematic objective 8 concerning the sustainable promotion of employment and quality and, partially, to the thematic objective 9, which concerns the promotion of social inclusion and the fight against poverty and any kind of discrimination.

3.1 Selection procedure

To evaluate the impact of an intervention on later outcomes it is necessary to have a clear set up of the selection procedure into participation. For instance, we need to know if individuals self-select into treatment, or if there are some pre-defined rules or thresholds that determine participation. In the first case we may for instance apply matching methods, while in the second case we may apply RDD or DID as discussed in Section 1. Hence, depending on the selection procedure the methodology chosen for the evaluation would differ. In the case of WELL we cannot apply the latter so we use matching methods to estimate the impact of participation in the WELL programme on labour market outcomes. This method relies on observable characteristics such as age, education, etc. to control for the possible bias induced by the selection process. We discuss in more details its features in Section 5.

The intervention deemed as beneficiaries unemployed people including also first-time jobseekers or first-entry unemployed, who held a Bachelor or Master degree and resided in Umbria at the time of publication of the notice (May 2013). Moreover, the status of unemployment had to be proven through registration in the public employment offices lists.

Companies and organizations such as associations, foundations, cooperatives and consortia thereof were to have at least one production/work unit in Umbria. Yet, organizations had to have employed at least two permanent employees. Finally, employers had to be in compliance with the workplace security and safety procedures and with specific procedures for employing persons with disabilities (Law no. 68 of 1999).

To avoid the possibility that the intervention would have produced displacement effects, companies applying for the intervention must have not dismissed workers with similar occupational tasks to the ones they were hiring, in the year preceding the submission of the traineeship, or must have not underwent wage guarantee scheme ("cassa integrazione guadagni").

The project WELL was launched in April 2013 and was completed in September 2014.[4]

[3] COUNCIL REGULATION (EC) No 1083/2006 of 11 July 2006 laying down general provisions on the European Regional Development Fund, the European Social Fund and the Cohesion Fund and repealing Regulation (EC) No 1260/1999 - Article 3 – Objectives.
[4] The call was published in the regional internet portal (www.formazionelavoro.regione.umbria.it).

The A application consisted of two parts: the first one was filled by individuals willing to take part in the work experience , while the second part concerned the firm, including notably the possible commitment to employ the trainee at the end of the work experience.

A shortlist of around one hundred available firms was published by Umbria region, to encourage the participation in the intervention. Actually, each participant used his personal network to speed up this preliminary activity.

The applications were examined by the regional department of Labour policies and the eligible applications were ranked according to the following criteria:

- Commitment of the host company to employ the internee at the end of the work experience; depending on the type of job contract:
  - open ended contract (full time and part time) - 5 points
  - fixed-term contract, lasting at least six months - 2 points
  - other types of contract - 1 point
- Applicant with disability, under the rules of Italian national law n° 68/1999 – 1 point;
- Applicant's age:
  - below 29 years old – 2 points
  - 30-39 years old – 3 points
  - 40 years old or over – 4 points
- Innovation activity of the host organization, defined as participation in regional/ national poles or clusters, or ministerial research laboratories – 2 points.

In case of equal scores, the ranking was determined according to the chronological order of the electronic submission of the application.

For both intervention phases, it was scheduled a quota for female applicants, accounting for 50% of the initial amount of financial resources (€1.2 million).

The intervention was very successful in terms of participation. Indeed the number of applications received exceeded MA's expectations. To meet this unforeseen demand, the budget was increased to €3.6 million and all eligible applications were admitted. Consequently, the quota for women proved to be unnecessary.

4 Data

This study combines micro-data on WELL intervention from the Regional Monitoring System Database with administrative data regularly collected by the Italian Ministry of Labour, Health, and Social Policies from the local labour offices, i.e. the Compulsory Communication Database (CCD). The CCD reports information about all hiring, prolongations, transformations, and cessations of labour contracts that private companies and public administrations are obliged to communicate to the labour offices. In addition, it records jobseekers registered at public employment offices. This information system is operated by the Ministry of Labour and Social Policy in cooperation with the Regions, the National Institute of Social Security (INPS), the Italian Government Agency for the Insurance against Work-related Injuries (INAIL) and the Prefectures. Starting in 2008 all the companies operating in the private sector and public administrations are obliged to communicate hiring, prolongations, transformations and cessations of labour contracts,

accessing on-line and entering the data into an information system called precisely "Compulsory Notifications." This information system has been introduced in Italy by Law 27 December 2006 No.296, Art. 1, paragraphs 1180 to 1185, laying down the financial law for 2007.[5]

We have access to the CCD for Umbria[6], which collects information on the universe of working spells and registered unemployment spells. This data has been extracted on July 2013 and December 2015 for all individuals in the sample. Thus, we have information on the individuals before and after the intervention.

We observe a number of individual characteristics measured in July 2013, which are pre-determined with respect to the start of the intervention. In July 2013 all individuals in the population of interest are unemployed graduates. The variables measured in December 2015 refer to the labour market status of the individuals, and for those who are working report also information on the sector of industry, firm and type.

Our study relies on the population of unemployed graduates residing in Umbria, as observed on the day of the deadline for participating in WELL intervention (2 July 2013). Hence, the sample of analysis comprises both participants (treated group) and non-participants (control group). The treated group is represented by the 574 participants in WELL programme that completed the training (out of 682 eligible applicants). The control group is instead represented by the entire population of graduates who, on the deadline for the application are (i) registered as unemployed in the public unemployment offices and (ii) resident in Umbria. This group amounts to 6,950 individuals in 2013.

4.1 Descriptive statistics of WELL and non-WELL participants

The programme received 712 applications, of which 30 not eligible. Of the 682 eligible applicants, 74 renounced to start the work experience and 34 drop-out during the training. 574 graduates successfully completed the work experience.

The high dropout rate may be due to the administrative burden related to the setting up of the traineeship period.

As for step 2 of the intervention, grant subsidies were given to 96 companies and host organizations that recruited 98 trainees who successfully completed step 1. Of these, 13 workers were employed with an open-ended full time contract; 51 were hired with a fixed term/part-time contract and 34 were employed with an apprenticeship contract.

Descriptive statistics of participants and non participants are shown in the tables below (Table 3-6).

[5] The recent efforts and advancements in terms of linkage of administrative and statistical data sources on labour force in Italy are documented in the "Quarterly note on employment trends", jointly published in December 2016 by the Italian Ministry of Labour, Health, and Social Policies, ISTAT, INPS and INAIL.

[6] CRIE and Umbria region would like to thank the Regional Observatory of the Labour Market for granting access to and collecting the data from the Compulsory Communication Database.

Table 3 - Labour market status of WELL participants and non participants in 2013, by gender

	WELL			No WELL		
LM Status 2013	Male	Female	Total	Male	Female	Total
Unemployed	118	261	379	1.548	3.966	5.514
%	31,1	68,9	100,0	28,1	71,9	100,0
Unempl. (first entry)	58	137	195	484	952	1.436
%	29,7	70,3	100,0	33,7	66,3	100,0
Total	176	398	574	2.032	4.918	6.950
%	30,7	69,3	100,0	29,2	70,8	100,0

The population of unemployed, including first-time jobseekers, registered in Umbria at the launching date of WELL intervention consisted of 7.524 individuals. Of these, 574 participated in the intervention. Among WELL participants, the amount of unemployed people who had a job and lost it almost doubled that of unemployed at their first entry in the labour force, i.e. people looking for their first job. In the groups of non participants, instead, the number of unemployed almost quadrupled that of first-time jobseekers. Women were equally represented among WELL participants and non participants (around 70%).

Table 4 - Labour market status of WELL participants and non participants in 2013, by age group

	WELL			No WELL		
	Labour Market Status 2013			Labour Market Status 2013		
Age group	Unemployed	Unempl. (first entry)	Total	Unemployed	Unempl. (first entry)	Total
0-24	26	15	41	161	256	417
%	6,9%	7,7%	7,1%	2,9%	17,8%	6,0%
25-29	168	103	271	1.204	705	1.909
%	44,3%	52,8%	47,2%	21,8%	49,1%	27,5%
30-35	114	51	165	1.793	300	2.093
%	30,1%	26,2%	28,7%	32,5%	20,9%	30,1%
35-40	44	19	63	1.034	77	1.111
%	11,6%	9,7%	11,0%	18,8%	5,4%	16,0%
>40	27	7	34	1.322	98	1.420
%	7,1%	3,6%	5,9%	24,0%	6,8%	20,4%
Total	379	195	574	5.514	1.436	6.950
%	100,0	100,0	100,0	100,0	100,0	100,0

As for the distribution of unemployed with respect to age classes, among the participants there is a higher concentration of youngest age groups (aged 24- and 25-29). In contrast, the oldest groups (age classes 35-40 and 40+) are less represented than in the non participant group. Note the age is calculated at the time of the launching date of WELL, for both participants and not.

Table 5 - Level of study of WELL participants and non participants in 2013, by gender

Level of degree	WELL			No WELL		
	Male	Female	Total	Male	Female	Total
High school				44	125	169
%				2,2	2,5	2,4
Some college				199	502	701
%				9,8	10,2	10,1
Bachelor degree	83	154	237	528	922	1.450
%	37,9	31,2	33,3	26,0	18,8	20,9
Master degree	136	339	475	1.214	3.259	4.473
%	62,1	68,8	66,7	59,7	66,3	64,4
Post-graduate				47	110	157
%				2,3	2,2	2,3
Total	219	493	712	2.032	4.918	6.950
%	100,0	100,0	100,0	100,0	100,0	100,0

As defined in the eligibility criteria of the intervention, WELL participants included unemployed holding at least a bachelor degree. Unemployed resident in Umbria, not participating in the intervention, also included individuals with a high school or college degree. For the sake of comparability of participants and non participants, the latter will not be considered in the following analysis. Among the participants, there was a high concentration of individuals with bachelor degree, whereas the majority of non participants had a master degree.

Table 6 - Field of study of WELL participants and non participants in 2013, by gender

Field of degree	WELL			No WELL		
	Male	Female	Total	Male	Female	Total
Education	8	52	60	46	450	496
%	3,7	10,6	8,5	2,6	10,1	8,0
Humanities and Arts	35	123	158	317	1.341	1.658
%	16,1	25,1	22,3	17,7	30,1	26,6
Social Sciences, Business and Law	77	210	287	599	1.402	2.001
	35,3	42,9	40,5	33,5	31,5	32,1
Science	21	41	62	222	460	682
%	9,6	8,4	8,8	12,4	10,3	10,9

Engineering, Manufacturing and Construction	53	35	88	391	318	709
	24,3	7,1	12,4	21,9	7,1	11,4
Agricultural	10	11	21	82	106	188
%	4,6	2,2	3,0	4,6	2,4	3,0
Health	14	18	32	124	359	483
%	6,4	3,7	4,5	6,9	8,1	7,7
Services				7	17	24
%				0,4	0,4	0,4
Total	218	490	708	1.788	4.453	6.241
%	100,0	100,0	100,0	100,0	100,0	100,0

As shown in Table 6, among the participants there is a predominance of individuals with a degree in social sciences, business and law. In contrast, individuals with a degree in science are less represented than in the group of non participants.

4.2 Outcomes

This study considers the following outcome variables measured in December 2015.

- Employment status indicator: it is an indicator equal to one if the individual is observed as employed in the CCD data of Umbria region, and zero otherwise. Note that this definition is different from the traditional employment rate. In addition to having a regular job, it requires that the job is located in Umbria. Hence, working in a neighbouring region is coded as zero. This definition is not fully satisfactory since it does not allow considering working out of Umbria as a success. However, it represents a relevant outcome variable to the extent that increasing the employment rate within Umbria region is one of the main objectives of the programme. Since the intervention of interest is financed by Umbria region, it becomes of interest assessing the impact within the region.

- Unemployment status indicator: it is an indicator equal to one if the individual is registered as unemployed in the lists of the unemployment offices of Umbria region, and zero otherwise.

- Residual category: it is an indicator equal to one if the individual is neither employed nor unemployed in the CCD data of Umbria region, and zero otherwise. Namely, it contains a number of cases: (i) discouraged workers that are out of the labour market – both within Umbria and in the neighbouring regions; (ii) individuals working in the underground economy; (iii) self-employed workers; (iv) individuals registered as unemployed in unemployment offices of other regions; (v) individuals working in regular jobs in other regions.

In addition to the aforementioned labour market statuses, we consider the type of contract (permanent, temporary or apprenticeship) received by individuals employed in Umbria.

Table 7. Descriptive statistics of outcome variables (2015)						
	treated group		Control group		T-test	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Difference	P-val
Employment indicator in Umbria	0.52	0.50	0.37	0.48	0.16	0.00
Unemployment indicator in Umbria	0.25	0.43	0.22	0.41	0.04	0.06
Residual category	0.23	0.42	0.42	0.49	-0.19	0.00
Permanent contract	0.16	0.37	0.15	0.36	0.01	0.53
Temporary contract	0.17	0.38	0.13	0.34	0.04	0.02
Apprenticeship contract	0.09	0.29	0.02	0.15	0.07	0.00
Obs	550		5,266		5,816	

Table 7 reports descriptive statistics of the outcome variables for the treated and control group. Column (1) and (3) show the average outcomes for treated and control group, respectively. Column (5) shows the difference in the averages by treatment status. Column (6) reports the P-value of the t-test on this difference. P-value equal to less than 0.05 indicates that the corresponding difference in the outcome values is statistically different from zero at 95% confidence level. WELL participants seem to be more advantaged in terms of labour market outcomes. They are more likely to be employed (the difference in employment rate between the two groups is 16%). As for the type of contract, WELL participants are more likely to get a temporary job or apprenticeship, but no significant differences are found for permanent contract.

Nevertheless, we need to be cautious about these comparisons as they may be misleading due to the presence of selection bias.

4.3 Covariates

As explained in Section 4.1, in order to perform the evaluation we need to make the groups of participants and non-participants comparable in terms of observable characteristics such as age, education, gender, etc. Using the two sources of data (data from the intervention and administrative data to construct the control group), we select covariates available for both groups to include in our analysis and check the similarity between participants and non-participants.

Table 8 reports the observable individual characteristics measured in 2013 (before the treatment takes place) for both treated and control units.

Table 8. Descriptive statistics of covariates by treatment status						
	Treated group		Control group		T-test	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Difference	P-val
female	0.69	0.46	0.71	0.45	-0.02	0.29
age_group==0-24	0.07	0.26	0.05	0.21	0.02	0.04
age_group==25-29	0.46	0.50	0.25	0.44	0.20	0.00
age_group==30-35	0.30	0.46	0.31	0.46	-0.01	0.48
age_group==35-40	0.11	0.32	0.18	0.38	-0.06	0.00
age_group==>40	0.06	0.24	0.21	0.41	-0.15	0.00
edufield==Education	0.08	0.27	0.09	0.28	0.00	0.76
edufield==Humanities and Arts	0.24	0.43	0.27	0.44	-0.03	0.11
edufield==Social Sciences, Business and Law	0.39	0.49	0.33	0.47	0.07	0.00
edufield==Science	0.08	0.28	0.11	0.32	-0.03	0.02
edufield==Engineering, Manufacturing and Construction	0.13	0.34	0.12	0.33	0.01	0.50
edufield==Agricultural	0.03	0.16	0.03	0.18	0.00	0.53
edufield==Health	0.04	0.20	0.05	0.22	-0.01	0.49
edulevel==Bachelor degree	0.33	0.47	0.22	0.41	0.11	0.00
edulevel==Master degree	0.67	0.47	0.78	0.41	-0.11	0.00
cod_cpi==Perugia	0.57	0.50	0.50	0.50	0.07	0.00
cod_cpi==Città di Castello	0.10	0.30	0.09	0.29	0.01	0.43
cod_cpi==Foligno	0.15	0.36	0.15	0.36	0.00	0.84
cod_cpi==Terni	0.16	0.37	0.22	0.42	-0.06	0.00
cod_cpi==Orvieto	0.02	0.13	0.03	0.18	-0.02	0.00
prov_res==PG	0.81	0.39	0.74	0.44	0.07	0.00
prov_res==TR	0.19	0.39	0.26	0.44	-0.07	0.00
Obs	550		5,266		5,816	

Column (1) and (3) show the average value for each characteristic for the treated and the control group, respectively. Column (6) reports the P-value of the difference between the average values in columns (1) and (3). We indicate in bold the characteristics in which treated and control units differ in a statistical sense (at the 95 % confidence level). The treated units are on average significantly younger than the control units (54% of the treated are aged less than 29 as opposed to 31% in the control group; conversely, in the treated group the proportion of individuals with at least 30 years old amounts to 17% while in the control group it represents 38%). In addition, a statistically higher proportion of treated units have a degree in Social Sciences, Business and Law (40% in the treated versus 33% in the control group) and have a bachelor degree (34% in the treated group versus 22% in the control group). By contrast, a higher proportion of individuals in the control group have a degree in Science (the difference between the two proportions of 2% is statistically significant at 95% level) and obtained a Master degree (this proportion corresponds to 78% in the control group and to 66% in the treated group). Lastly, treated units are significantly more likely to reside in Perugia, the capital of the region.

5 Counterfactual analysis

5.1 Identification strategy

This analysis aims at evaluating the impact of WELL intervention on the labour market prospects of WELL participants.

As already mentioned, the outcome variables of interest are the probability to be employed in Umbria region (employment status indicator, as collected in Umbria database), the probability to be registered as unemployed in Umbria's unemployment offices (unemployment status indicator, as collected in Umbria database) and the probability to be in the residual category (residual indicator).

We focus on the Average Treatment Effect on the Treated (ATT) which represents the impact of the intervention for the group of participants (Angrist and Pischke, 2008). The ATT is calculated as the difference between the average outcome of the treated group given the treatment and the average outcomes of the treated group in the counterfactual situation in which the treatment did not take place. In this analysis it corresponds to the difference in employment status between the WELL participants (observed in the data) and the WELL participants had the intervention not taken place (counterfactual and hence not observed scenario).

In formula:

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

where D is an indicator equal to one if the treatment takes place and zero otherwise, Y^1 is the individual potential outcome given treatment and Y^0 is the individual potential outcome in the absence of the treatment. Note that for the ATT both potential outcomes refer to the treated group since they are conditioned upon $D = 1$.

The identification problem for the ATT is that $(Y^0|D = 1)$, the potential outcome in the absence of the treatment for the treated group, cannot be observed. Therefore, the identification strategy boils down to finding a proper control group that mimics the counterfactual situation of the treated group in the absence of the treatment. Ideally, we would like to find a group of individuals who did not participate in the WELL programme but who are exactly the same as the treated individuals in all characteristics that affect the outcome of the analysis. Once a suitable control group is available, the identification of the ATT amounts to a simple difference following Eq. (1). The following section describes in details the identification problem.

Other causal parameters can be considered as well, such as the Average Treatment Effect (ATE) and the Average Treatment Effect on the Non-treated (ATNT). The latter measures the effect of the intervention on non-participants (the control units considered in the analysis). By contrast, the former parameter represents a weighted average of the ATNT and the ATT on the relative sample size of treated and control groups. In general, the ATNT and the ATT differ if the treatment effect is heterogeneous and varies along with certain characteristics of participants. If instead the treatment effect is the same across the population of interest, the ATNT and the ATE coincide. The identification of the ATNT boils down to the symmetrical problem of quantifying the ATT, where D is replaced by (1-D) in Eq. (1).

5.2 The identification problem

The ATT amounts to comparing the average of the outcome variable between the treated and the control group (i.e. the employment status). Such comparison would provide an unbiased estimation of the treatment effect if the treated and the control group were comparable. Comparability means that the two groups are identical in all respect but for the treatment status, that is the participation in the intervention under analysis. In case of random assignment of the treatment, the comparability between treated and control group is ensured by construction since, by the law of large numbers, these two groups

have on average the same characteristics. In addition, since the treatment assignment is random, it is orthogonal to both unobservable and observable factors that affect the outcome variable.

Clearly, comparability is not ensured when participation in the intervention is voluntary. Namely, if individuals self-select into the treatment, participation can be correlated with factors that also affect the outcome variables. In our case, individuals choose whether to participate or not in the intervention. To the extent that participation is an individual choice, the assignment into the treatment is not random but rather driven by observable and unobservable individual characteristics. The identification problem arises if the characteristics that determine the treatment participation are also correlated with the outcome variables. In this case the treatment assignment D is endogenous (selection bias problem).

Voluntary participation induces selection bias problem. To make an example, consider the "age" variable. Recent graduates without a job may be more prone to participate in training programmes than older workers without a job because they are at the start of their career; at the same time, firms may be more interested in hiring recent graduates than mature unemployed workers. If age mattered in determining the choice of participation in 2013 and the outcome variables in 2015, then the values in Col (5) of Table 1 would comprise also such effect.

To formalise this idea, the simple difference reported in Column (5) of Table 1 represents the effect of the intervention plus the effect of confounding factors that also induced treated individuals to participate in the intervention (for instance, age). If age was observed, this could be taken into account in the estimation. The methodology which allows washing away properly the confounding effect of age from the estimated treatment effect (matching) is described in the following section.

The identification problem arises when some confounding factors are not observed. An example is motivation. It is possible that treated individuals participate in WELL intervention because they are very much motivated to find a stable job. Such motivation would determine the treatment status but also the likelihood to find a job in 2015. In absence of credible proxies for motivation in the available data, the effect of unobserved motivation will bias the estimated treatment effect. Note that motivation is likely to be a very important factor in the setting of this programme. This is because the target population of the programme bears the burden of finding a firm that is willing to offer a traineeship (which will be financed by the programme). This is going to be a major limitation in the analysis.

According to Table 1, treated units are significantly more likely to be employed in Umbria compared to control units, and significantly less likely to belong to the residual category. By contrast, the probability to be registered as unemployed in Umbria is not statistically different between treated and controls. However, as already mentioned, such comparison is biased. In addition, while there is no difference in the proportion of individuals hired with a permanent contract between treated and controls, the former are significantly more likely to be hired as temporary workers or as apprentices than the controls. As such, this naïve comparison is consistent with the idea that the intervention was successful in increasing the employment rate in Umbria. However, the increase in the employment rate in Umbria may well be - entirely or partially - due to the selection bias, i.e. due to the higher motivation of treated individuals rather than the programme itself. However, this seems not to be compensated by a drop in the unemployment rate but rather by a decrease in the residual category, potentially hiding a detrimental effect on employment spells in neighbouring regions or self-employment.

To recapitulate, since individuals self-select into the treatment, a simple comparison in the average outcomes between treated and controls according to Eq.(1) gives a biased estimate of the ATT. Ideally, one could get rid of the bias if one could control for all characteristics that affect both the outcomes and the selection into the treatment. The propensity score matching method relies on this intuition. This methodology requires the

availability of a large amount of data – ideally all factors that simultaneously affect the participation in the WELL intervention in 2013 as well as the labour market status in 2015. This method is described below.

5.3 Matching

To identify the ATT we rely on the propensity score matching procedure that ensures that the outcomes of treated units are compared with similar control units. We define the following quantities: Y^1 is the potential outcome given the treatment; Y^0 is the potential outcome in absence of the treatment; D is an indicator equal to one if the individual receives the treatment and zero otherwise; X is a set of observable *confounding* characteristics that are correlated both with the selection into the treatment and with the potential outcomes. The identification of the ATT relies on the following assumptions:

a. Conditional Independence Assumption (CIA): $(Y^1, Y^0) \perp \mathrm{D}|\mathrm{X}$
   In words, the potential outcomes are independent from the assignment of treatment conditional on the observable characteristics X. Namely, controlling for all observable characteristics, the participation decision is uncorrelated with the potential outcomes. The extent to which this assumption is reasonable depends on the availability of the data. This assumption will be extensively discussed in the remainder of the section.
b. Stable-Unit-Treatment-Value Assumption (SUTVA): the effect of the treatment on the outcome of one unit does not affect the outcome of another unit (no interference). This may be a quite strong assumption in the context of very large-scale labour market policies since it rules out spillover effects or general equilibrium effects of the treatment that change the behaviour of the control units. For instance, this assumption prevents crowding-out (displacement) effects in local labour markets: namely, if treated units are more likely to find a job due to the intervention, this should not deteriorate the likelihood to find a job of control units. In addition, the intervention should not affect the control units through changes in the general equilibrium of the wage in the labour market. In our case SUTVA is a reasonable assumption since the intervention's target group is quite small (treated units are 574 while control units are 6,950) and hence unlikely to drive general equilibrium or displacement effects.
c. Common Support Assumption: $0 < P(D = 1|X = x) < 1$
   This means that for any given value of the observable characteristics X, the treatment assignment should not be certain. Therefore, for each value of the confounding variables X an individual could be potentially observed as treated or not. This assumption ensures that for each treated individual (with given realisations of variables X) we can find a sufficiently similar individual in the control group, i.e. a control unit that is identical to the treated one in terms of variables X.

Basically, the purpose of the matching procedure is to estimate the ATT by comparing treated units with control units that are similar in terms of observable characteristics – all characteristics that affect both the treatment participation and the outcome variables. Ideally, we would like to compare the outcome value of a treated unit i with the outcome value of a control unit j that is identical to i in terms of a number of characteristics Xs. Finding an exact match for each individual i becomes more and more difficult as the number of Xs characteristics increases (curse of dimensionality problem). However, it has been shown that matching on characteristics Xs is equivalent to define the matches through a propensity score, namely an indicator summarising all information contained in the Xs. Formally, the propensity score is the probability of being assigned to the treatment conditional on the observed characteristics (Bryson, Dorsett and Purdon, 2002).

The propensity score has to be estimated and gives us a value for each individual. Then, propensity score matching procedure amounts to compare treated and control units with

similar value of the propensity score. If the propensity score is correctly estimated, individuals with similar value in the propensity score are also similar in terms of observable confounding factors. This also means that one is comparing treated and control units which are similar in terms of potential counterfactual outcomes. This comes from the CIA replacing X with the propensity score P(X) as shown below:

$$(Y^1, Y^0) \perp \mathrm{D}|\mathrm{P(X)}$$

The selection process into treatment models the probability to be treated as a function of the aforementioned covariates, as follows:

$$\mathrm{P(D = 1) = f(age, gender, edu\_field, edu\_level, employment\_office + e)} \quad (2)$$

The propensity score is a function of individual characteristics such as age and gender. In our context, we also include the available educational variables for the field of study (e.g. science, education, etc.) and the degree of study (bachelor or master). These variables are relevant for explaining the labour market status after participating in the intervention in Umbria region, since the labour market status of the individuals depend on the labour demand's needs in terms of educational background. Similarly, individuals with specific educational profiles may be more or less likely to find a potential firm where to carry out a traineeship, and hence have higher chances to participate in the programme. Lastly, we include the municipality where the individual registers himself/herself as unemployed in Umbria region. This is meant to be a proxy of the local labour market where the unemployed is looking for an occupation (or a potential internship to participate in the WELL intervention). This is relevant to explain both the outcomes and the choice of participation. Given the available data at the time of writing, this is the richest specification possible. We plan to further enrich this specification by adding the distance between the municipality of residence and the location of the unemployment office where the individual registers as unemployed. This will serve as a proxy for the motivation of the individual to find a job. This is particularly relevant in a mountainous region such as Umbria, where connections between municipalities imply rather long commuting time. In addition to this, we foresee to enrich the set of covariates in the propensity score specification even further, by adding information on the past labour market experience of the individuals.[7] Following the routine, the propensity score is estimated through maximum likelihood estimation (Caliendo and Kopeinig, 2008).

5.4 Results

Table 9. Average treatment effect on the treated

ATT	(1) Employed in Umbria	(2) Unemployed in Umbria	(3) Residual category	(4) Permanent contract	(5) Temporary contract	(6) Apprenticeship contract
Linear regression	0.1731***	0.0148	-0.1879***	0.0283*	0.0416***	0.0577***
	(0.0217)	(0.0187)	(0.0219)	(0.0162)	(0.0154)	(0.0077)
NN matching (n=1) with repl.	0.1494***	0.0337	-0.1831***	0.0454	0.0308	0.0290***
	(0.0407)	(0.0330)	(0.0418)	(0.0326)	(0.0225)	(0.0100)
NN matching (n=5) with repl.	0.1265***	0.0417	-0.1683***	0.0089	0.0269	0.0273***
	-0.0301	-0.0324	-0.0331	-0.0172	-0.0202	-0.0078
Observations	5,816	5,816	5,816	5,816	5,816	5,816

Standard errors in parentheses: for matching, robust Abadie-Imbens standard errors, otherwise, conventional standard errors

*** p<0.01, ** p<0.05, * p<0.1

[7] Such avenues are discussed in Section 7 and will be explored when the additional requested data will be available.

Table 9 reports the results on the outcomes variables. Results are based on the same sample as reported in the last row of the Table. This means that for columns 4-6 the outcomes have value zero if one is not employed in Umbria.

Ordinary least squares: why it does not work

The first row reports the coefficient from a naïve linear regression where the outcome variable is regressed on the covariates in the right-hand side of Eq. (2) and the indicator for participation in the intervention D, as follows:

$$y = a + b * D + c * \mathrm{Age}, d * \mathrm{gender}, e * \mathrm{edu}_{\mathrm{field}}, f * \mathrm{edu}_{\mathrm{level}}, g * \mathrm{employment}_{\mathrm{office}} + u \quad (3)$$

The estimated coefficient b amounts to comparing the average of the outcome variable between the treated and the control group, controlling for the individual characteristics on the right-hand side of the equation. Ordinary least squares (OLS) provide an unbiased estimation of the treatment effect (b in Eq.(3)) under two assumptions: (i) the CIA, i.e. the treatment indicator is exogenous controlling for the covariates on the right-hand side of Eq. (3); (ii) functional form assumption, i.e. the true conditional expectations of the outcomes are linear, so that the linear regression function provides a good approximation of the true conditional expectations (Imbens, 2014).

Hence, the linear regression provides biased estimates of the treatment effect if the conditional expectations are not linear and if the covariates distributions are different in the treated and the control groups. The problem of this method is that results are very much affected by observations with extreme values in the covariates. Outliers are precisely the units that are not appropriate as counterfactual images of the treated units.

While it is difficult to assess if true conditional expectations are linear so as to justify the use of linear regressions, it is quite straightforward to check if the covariates distributions differ or not by treatment status. A standard procedure is to test through t-statistic the null hypothesis that the difference in the average covariates between the two groups is equal to zero. These tests are reported in Table 2 above and show that the distributions of age, field of study, level of study and residence are different between the treated and the control groups. This suggests that linear regressions provide biased estimations of the treatment effect because the results will be sensitive to outliers which are not appropriate control units and to the choice of the (linear) specification.

A way to reduce the bias when the covariates distributions are different is to weight the units in the control group so that the average of the covariates of the weighted control group is identical to the average of the covariates in the treated group. The idea behind this approach is that control units that have values of covariates that are far from the values of covariates of the treated units should be given smaller weights, while higher weights should be attributed to control units with values in covariates that are closer to those of the treated units. Another way to do this could be to restrict the comparison to control units whose values of covariates are similar enough to those of the treated groups (so called trimming). This is equivalent to giving weight equal to zero to control units that are too different from the treated units.

Nearest-neighbor matching:

In general, matching boils down to a number of non-parametric approaches (e.g. exact matching, propensity score matching, sub-classification) that apply precisely these solutions: no functional forms are assumed and sort of weighting schemes are used so as to equate the covariates distributions in the treated and control groups. The basic procedure consists of the following steps: (i) to sort all units according to a propensity score that represents the likelihood to participate in the programme, (ii) to compare the average outcomes of treated and control units with similar values of the propensity score and (iii) to average these differences out over the distribution of the propensity score so as to estimate the ATT. Row 2 and 3 of Table 3 report the results from two different types of matching procedures. In both cases, each treated unit is matched with

replacement, which means that each control unit may be used as a match more than once. This improves the comparability between treated and controls, thereby decreasing the estimation bias. In row 2 of Table 3 each treated unit is matched with the control unit with the closest value of the propensity score. In row 3 of Table 3 each treated unit is matched with the 5 closest control units in terms of propensity score. The choice of the number of control units to be used in each match (one as in row 2 versus more than one as in row 3) entails a trade-off between bias and variance. Increasing the number of control units to be assigned in each matching pair tends to increase the bias in the comparison (since each treated unit is compared with control units that may be not as close in terms of propensity score) but it also increases the precision of the estimate. As the table suggests, in this case this choice does not make much difference.

Overall, the comparison between the results in the first row versus those in the second and third row suggests that the matching procedure is not very effective in reducing the bias. This suggests that the selection equation used to estimate the propensity score is not well specified. In other words, even though the matching procedure adjusts the covariates distributions in the two groups so as to make them comparable, it must be that the two groups remain different in terms of unobserved factors that affect both the outcome and the participation in the treatment. Given the current data limitations, one should be cautious in interpreting these results as causal effects of the WELL intervention. Future avenues for improving the analysis will be discussed in the following section.

In the remainder of the section we discuss the possible interpretation of the results – keeping in mind the aforementioned limitations about causal interpretation. Column 1 of Table 3 suggests that WELL participants are more likely to be employed in Umbria than non-participants at the end of 2015. However, they are equally likely to be registered as unemployed in the unemployment lists of Umbria labour offices. In addition, participants are less likely to be in the residual category than non-participants. These results should be taken with caution. First, the fact that the impact on registered unemployment in Umbria is not significant casts doubts on the effectiveness of the programme. Further, the positive effect on the employment rate in Umbria is compensated by a negative effect on the residual category. If the programme was successful in improving the labour market prospects of unemployed graduates, we would expect the positive effect on the employment rate in Umbria to be compensated by a negative effect on the unemployment rate in Umbria. The degree of success of the programme is not clear-cut since on one hand the employment prospects of participants seem to improve, while on the other hand, non-participants are more likely to be in the residual category which may hide employment prospects outside Umbria, or self-employment – i.e. not being necessarily a negative outcome.

6 Discussion of possible channels

The following section discusses possible channels through which the WELL intervention may improve the labour market prospects of participants. Such channels are suggested by the economic theory.

6.1 On-the-job-training channel

The intervention may improve the skills of participants and therefore increase the probability of being employed (in Umbria). Training programs are in fact meant to increase human capital of participants and therefore enhance their employment prospects. In this respect, the on-the-job training activity carried out within WELL could work has a stepping-stone function helping graduates to enter regular employment. However, the recent literature on active labour market policies shows that the on-the-job training programs are not particularly likely to yield positive impacts in the short-run. Because of short-term locking-in effects, the positive impact of training might in fact only materialize in the long run (e.g. Lechner et al. 2004, Card et al. 2010).

6.2 Network channel

The intervention may foster/activate the job search skills of participants and therefore increase the employment rate (in Umbria). Therefore, the positive effect may not necessarily come from the training itself but from the enhancement of job search skills. Furthermore, since participants have to indicate the hosting firm at the moment of the applications, the positive effect of this intervention may also arise from the possibility to get in contact with local firms.

6.3 Fictive traineeships

Participants and firms can agree on setting up fictive traineeships to get funding. To the extent that we find significant impact on the employment status in Umbria, this channel can be ruled out based on the analysis results (as a matter of fact, if fictive traineeships were in place, no positive effect on the probability of being employed in Umbria should be expected).

6.4 Deadweight loss

Deadweight loss is the situation in which participants would have been employed anyway in the firm where they did the training (i.e. the intervention was useless). If this was the case, participants would be employed in the same firm where they did their training. Hence, we can exclude this if we show that many participants find a job in 2015 in different firms compared to where they did the training.

6.5 Selection bias

Due to the participation process, participants are those who managed to find a firm which is willing to offer them an internship that will be funded by the programme. Therefore, participants are by construction more likely to find an internship than eligible non-participants (i.e. because they are more motivated, more skilled, or because they have a larger network); hence, they could be similarly more likely to find a job afterwards. The selection bias prevents to simply compare the average outcomes between treated and control groups since the treated units differ from the control ones in terms of unobserved characteristics that affect the outcomes of interest. As a consequence, the average outcome of the treated is biased by these unobserved characteristics; hence the difference between the latter and the average outcome of the controls is composed of the impact of the intervention and of the impact of these unobserved characteristics. In our case, if WELL participants (the treated group) are on average more motivated to look for a job than the non-participants (control group), the difference of the average employment rate in Umbria between the treated and the control units should/could be attributed to the impact of motivation and to the impact of the programme. If motivation has a positive effect on the employment rate, the selection bias leads to an overestimation of the impact of the intervention. The possibility to exhaustively control for the selection bias depends on the richness of the data and available variables that can be used as proxies for unobserved characteristics as ability and motivation. In our analysis we would need to account for instance for the final mark of each graduate, as it may be considered as a proxy of ability. Unfortunately, such information is not available for the control group based on the CCD administrative data. However, we try to control for as many variables as we can to limit the selection bias.

7 Limitations and future avenues

Conditional on access to additional data:

7.1 Reducing the selection bias

To the extent that selection bias is present, the estimated impact of the intervention is composed of the true impact of the intervention plus the impact of unobserved characteristics that affect both the participation in the intervention and the outcomes of

interest. Therefore, controlling for these unobserved characteristics allows reducing the selection bias, which means hence obtaining estimates that are closer to the true impact of the intervention. Note that the additional information should be provided for both treated and control units.

7.1.1 Past labour market experience

Collecting information on the labour market outcomes prior to participation is important to reduce selection bias, since it reveals important information on the past labour market experience of the individuals, that could be used as (imperfect) proxies of workers' skills and quality. Labour market status of individuals resident in Umbria and contract type could be measured on 31 December 2012, 30 June 2012, 31 December 2011, and 30 June 2011. This extra information could be obtained from the national database of the Compulsory Communication Database (CCD).

7.1.2 Educational career

Collecting data on the educational career of the individuals could allow obtaining information on workers' quality and motivation: the final grade of the degree is a good proxy of student's ability. In addition, the information on the graduation date, combined with the date of enrolment in the university could allow to measure the time they needed to complete their university career, thus providing another proxy of students' ability: students that graduate on time are of better quality and more motivated than students that graduate with delay takes more time to graduate ("studenti fuori corso").

This would allow us to make the unobserved variables observable, reducing the selection bias. In addition, the date of graduation could be used as proxy of the potential first entry in the labour market: the time elapsed between the potential first entry in the labour market and the potential start of the intervention (May 2013), could serve as a proxy for the duration of the period spent in the labour market. This information (graduation date, date of enrolment in university and final grade) could be collected from the "Anagrafe degli studenti" (students' census) of Umbria region, or Almalaurea: this requires putting in contact the person in charge of these databases with the responsible of the CCD database, as the additional information on the educational career should be linked to the current one from CCD using a unique identifier (i.e. the fiscal code).

7.2 Improving the outcome variables

7.2.1 Broader definition of employment rate

We could consider the "national employment rate" in addition to the employment rate in Umbria in order take into account the possibility that some individuals in 2015 may have found a job in the neighbouring regions. Ignoring this possibility may have two effects: on the one hand, if treated individuals find a job in another region because of the intervention, this should be accounted for (the impact of the programme on the employment rate of Umbria would be a lower bound of the impact of the WELL intervention on the overall employment rate). On the other hand, if control units find a job in the neighbouring regions in 2015, this should also be accounted for, since the impact of the intervention would be otherwise overstated. National employment rate could be constructed based on labour market status of all individuals in the sample (on 31 December 2015) in the national database of the CCD.

7.2.2 Longer-term impact

The literature on on-the-job-training suggests that the positive impact of this type of intervention may be displaced in the long term. Since the outcomes of interests are measured on 31 December 2015 and the intervention takes place in the second semester of 2013 lasting on average 6 months, the impact of the intervention is measured around one year after. The analysis would be enriched if the labour market status of the

individuals in the sample was measured on 31 March 2016 (and, possibly, 30 June 2016) from the national database of the CCD.

7.2.3 Occupational mismatch

It is interesting to ask to what extent the intervention is successful (or not) in reducing the occupational mismatch, that is the fact that individuals find jobs that are not pertinent to the field of study. This cannot be currently studied, since the only available information is the ATECO[8] code of the sector of industry of the firm where one is employed. This investigation requires information on the type of occupation that is associated with a job. This information is collected by the CCD based on the International Standard Classification of Occupations (ISCO). For a more complete analysis, this information should be reported from the national database of the CCD. Secondly, the case in which individuals find jobs that require a lower level of education than the one acquired is known in the economic literature as over-education. For the moment being, this cannot be investigated.

8 Conclusion

In this report we described the CIE of the WELL intervention implemented in Umbria Region in Italy in 2013 and financed under the European Social Fund.

The intervention subsidized on-the-job training for unemployed graduates. The aim was twofold: 1) increase employment among unemployed college graduates; 2) promote capacity and productivity of the participating firms. To evaluate the effectiveness of the intervention we looked at the employment status of participants and similar non participants in Umbria in 2015 (two years after the intervention).

The evaluation exercise was performed using different sources of data. Information on participants of WELL was provided by the Regional Monitoring System Database, while information on the comparison group was gathered through the Compulsory Communication Database.

To calculate the causal effect of the intervention on the labour market career of participants, the Average Treatment Effect on the Treated (ATT), we relied on propensity score matching technique.

First results suggest that WELL participants are more likely to be employed in Umbria compared to similar non-participants. However, they are equally likely to be registered as unemployed in the unemployment lists of Umbria labour offices. The impact of the WELL intervention is therefore not clear-cut based on current data. As a matter of fact if the intervention was successful in improving the labour market prospect of participants we should also have observed a decrease in the probability of being unemployed.

To conclude these results should be taken with caution. However, thanks to the first edition in March 2014 a second edition of the project WELL was launched within the 2014-2020 programming period. It was named WELL30 and it focused on a more specific target group, i.e. graduates unemployed aged 30 and over. The launch of this intervention was motivated by the following facts:

[8] Since January 2008 the Italian Institute of Statistics (Istat) has adopted the new ATECO 2007 classification of economic activities. This classification is the national version of the European nomenclature, Nace Rev. 2, published in the Official Journal of 20 December 2006 (Regulation (EC) no 1893/2006 of the European Parliament and of the Council of 20 December 2006).

- the first edition of WELL confirmed to policy makers that in Umbria unemployment is a serious issue, mostly for women and for those who were previously employed and lost their job;
- in April 2014 the regional Youth Guarantee Plan was launched, targeting individuals aged 15-29 years. Consequently, the regional Managing Authority could concentrate its efforts on people older than 30 years.

The ex-post evaluation of WELL30 is not part of this study. Nevertheless, based on the results of our study, it would be an interesting avenue for future research.

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Annex 1. Categories of labour market status

Table 10 - Labour market status of WELL participants and non participants in 2015: aggregation of categories from 8 to 5

WELL participants

Labour Market Status (8 cat.) 2015	Labour Market Status (5 cat.) 2015					
	Unemployed	Unemployed (first entry)	Employed	Internees	Residual category*	Total
Unemployed	104	0	0	0	0	104
Unemployed (first entry)	0	38	0	0	0	38
Precarious (low wage)	0	0	59	0	0	59
Employed	0	0	223	0	0	223
Employed (still in Unempl. list)	0	0	6	0	0	6
Internees	0	0	0	20	0	20
Out of Unempl. list (cancelled)	0	0	0	0	9	9
Out of Unempl. list (other)	0	0	0	0	110	110
Missing	0	0	0	0	5	5
Total	104	38	288	20	124	574

* Residual category: discouraged worker, underground economy, self-employed, registered in other unemployed offices, or employed in other regions

No WELL

Labour Market Status (8 cat.) 2015	Labour Market Status (5 cat.) 2015					
	Unemployed	Unemployed (first entry)	Employed	Internees	Residual category*	Total
Unemployed	1.204	0	0	0	0	1.204
Unemployed (first entry)	0	310	0	0	0	310
Precarious (low wage)	0	0	293	0	0	293
Employed	0	0	2.083	0	0	2.083
Employed (still in Unempl. list)	0	0	37	0	0	37
Internees	0	0	0	103	0	103
Out of Unempl. list (cancelled)	0	0	0	0	210	210
Out of Unempl. list (other)	0	0	0	0	2.707	2.707
Missing	0	0	0	0	3	3
Total	1.204	310	2.413	103	2.920	6.950

* Residual category: discouraged worker, underground economy, self-employed, registered in other unemployed offices, or employed in other regions

Table 10 shows how the categories related to the labour market status in 2015, as measured in the CCD, were re-aggregated in the interest of higher readability of the results. In particular, in the final classification with 5 categories, the two categories of unemployed and unemployed (first entry) are kept separated in order to distinguish between unemployed who had a job and lost it and unemployed at their first entry in the labour force, i.e. looking for their first job. On the other hand, employed defined as precarious because of the low level of wages and employed still registered in the

unemployment list because of the short duration of their contracts were merged with the category of employed. Finally, a residual category was defined to include those individual who were no longer registered in the employment list, being discouraged workers, registered in other unemployed offices out of Umbria region, self-employed, employed in other regions or working in the underground economy.

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