Does training improve skill match?

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Abstract

Training is recognised as a key resource to reduce the gap between required and provided skills and to meet the continuous changes faced by organisations. However, since training efforts involve significant costs and risks for both training providers and recipients, rigorous measures of training capability to improve employees' skill match would provide guidance for a more effective use of available resources. Based on data on employees from the 28 EU countries collected by the CEDEFOP ESJ survey this paper assesses the impact of three measures of training on change in skill match levels by means of a propensity score matching with difference-in-differences approach.
All examined types of training moderate the gap between the initial skill mismatch and the desired target of skill match. However, training received in the 12 months before the survey decreases the overall skill gap by lowering overskilling, whereas cumulative formal training undertaken since start of current job involves a reduction in underskilling.

Keywords – Training, Skill match, Difference-in-differences, Propensity score matching, EJS survey

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Introduction

Change is probably the most striking feature of workplaces in current years. High markets volatility, continuous technological innovation, and frequent re-engineering of organisational processes result in new job contents, changing tasks, and new requirements in terms of skills and competences. The decreasing regulation of labour markets provides an additional source of workplace change by expanding employees' turnover and promoting new forms of labour division and labour organisation.

Change in the workplace has brought in a new attention towards employees' skills, increasingly perceived as a key input to deal with output uncertainty and routine evolution. Employers and policy makers are increasingly aware of the importance of pursuing a balance "in which the skills of the applicants and the requirements of the job fit closely, neither a shortfall nor an oversupply of skills relative to those requirements" (Cappelli, 2015, p.253). Indeed, if a lack of skills risks to compromise the success of labour processes, overskilling may jeopardise future performance by negatively affecting employees' satisfaction and commitment (McGuinness and Sloane , 2011; Mavromaras *et al.*, 2013).

Training is often indicated as the chief solution to improve the match between required and provided skills in a fast-changing environment (Kiss, 2016; European Commission, 2012). However, the costs that training imposes on both employers and employees and the uncertain outcomes of learning processes obstacle higher investments and limit the willingness of involved stakeholders to experiment new training solutions.

Uncertainty about the outcomes of training efforts partly roots in the limited evidence about the effectiveness of training in improving skill levels and reducing skill mismatch. Poor available evidence is probably due to a long-established trend in skill studies. Employees' skills are seldom the outcome variable of models that directly test the returns to training. Past research has shown that training results in higher wages (Bassanini *et al.*, 2007; Brunello, 2001), improved individual productivity (Colombo and Stanca, 2014; De Grip and Sauermann, 2013), better firm performance (Aragón-Sánchez *et al.*, 2003), and higher chance to remain in the labour market in difficult times (Filippetti *et al.*, 2016) or to re-employ after job displacement (Ok and Tergeist, 2003). This evidence complies with the hypothesis that training improves individual skill match, which subsequently translates in better performance and is recognised by means of higher wages or improved opportunities in the labour market. However, a univocal connection is not established and other mechanisms could be at work.

Based on the recently released European Skills and Jobs (EJS) survey developed by CEDEFOP, this paper implements the PSM-DID approach proposed by Abadie (2005) to investigate the impact of training on change in the extent of individual skill mismatch. Taking advantage of the rich set of information on the skills and training experiences of interviewed employees provided by the ESJ survey, the proposed empirical analysis calculates the change in the levels of overall skill mismatch, underskilling, and overskilling due to three different types of training, which include participation in any type of training in the 12 months before the interview, participation in employer-sponsored training undertaken for job-related reasons in the 12 months before the interview, and participation in formal training since start of current job.
The article proceeds as follows. The next section briefly reviews the literature on the relationship between training and skills to outline the need for empirical analysis focused on whether and how training impacts skill mismatch. After presenting the characteristics of the ESJ survey Section 3 illustrates different measures of training provided by the dataset and reports recorded skill mismatch levels and skill mismatch transitions. Section 4 outlines the empirical strategy to measure the average change in skill mismatch experienced by trained employees, whereas Section 5 presents the empirical outcomes. The last section provides some concluding remarks.

2. Literature background

The human capital theory (Becker, 1964) indicates training as one of the drivers that, together with schooling, innate abilities, and individual background shape the stock of skills that affect individual productivity, hence wage (Acemoglu and Autor, 2011). This approach has deeply affected existing empirical research on the antecedents and consequents of training (De Grip and Sauermann, 2012). The former group of studies investigates the determinants of participation in and intensity of training (Brunello 2001; Pischke, 2001; Arulampalam *et al.*, 2004; Bassanini and Ok, 2004; Vignoles *et al.*, 2004). Implicitly assuming that training involves benefits for both firms and employees, this research stream focuses on possible demand-related or supply-related obstacles to point out viable solutions, from training incentives targeted at specific segments of the labour market such as younger employees to training-related tax benefits for firms. The latter group of studies assesses the impact of training on labour market outcomes such as (change in) wage and employability (at individual level) or productivity (at firm/industry level) (Brunello, 2001; Bassanini *et al.*, 2007; Albert *et al.*, 2010; Carneiro *et al.*, 2010). Also in this case empirical studies base on an implicit hypothesis: training is expected to improve labour market outcomes because it improves individual skills, which reflect into higher productivity or better earnings.

The assumption of a positive impact of training on skills has proven difficult to test in empirical studies due to the lack of suitable and reliable measures of skills and skills change (Ferreira Sequeda *et al.*, 2015). The lack of suitable data explains the preference of policy makers for training input (training participation, training intensity, or financial investment in training) rather than training outputs such as learning achieved or improvement in skills level (Sels, 2002). In addition, the difficulty and the cost of providing large scale comprehensive measures of individual skills has long justified the resort to easier to observe proxies such as education for pre-training skill level/human capital, or wage for post-training skill level/human capital.

Nevertheless, the growing availability of large scale surveys focused on training, learning processes, and skills assessment – despite mostly based on subjective skills self-assessment rather than objective skills measurement[1] – has been encouraging efforts to open the "black box" of the relationship between training and skills levels. Based on a firm-level survey concerning the training efforts of a sample of Belgian companies Sels (2002) reports poor correlation between the size of the training effort in financial terms and the quality of training programmes as measured by the attention paid to needs analysis, training design, and effect evaluation, thus suggesting that training efforts do not necessarily correspond to a proportional increase in employees' skills level. Also Felstead *et al.* (2010) stress the need for more insight on the quality of provided training and its impact on quality indicators such the increase in skill levels, the improvement of work practices, post-training wage raise, and increase of well-being at work. The authors provide evidence in favour of a positive relationship between training and learning, which is nevertheless significantly mediated by the type of work organisation practices adopted.

Other studies are more explicitly focused on the impact of training on skills. Green *et al.* (2001) report a positive effect of training on skill provision. However, off-the-job training is associated with more frequent provision of all kinds of skills, whereas on-the-job training increases the supply of problem-solving and team-working skills. De Grip and Sauermann (2012) assess the effects of job-related training on individual performance in a call centre. The authors show that, besides directly affecting the performance of trained employees, training has an indirect positive effect on the productivity of trainees' peers.

[1] A recent exception is provided by on the OECD Survey of Adult Skills (OECD, 2013), developed within the wider Programme for the International Assessment of Adult Competencies, which provides the outcomes of field tests for the assessment of individual proficiency in literacy and numeracy. For 18 out of the 22 participating countries the field tests concerned also problem solving activity in a technology-rich environment. However, also for the PIAAC survey objective skills assessment is limited to the mentioned cognitive skills.

A recent paper by Ferreira Sequeda *et al.* (2015) tackles the relationship between training and skills by testing the impact of training and informal learning on a self-assessed measure of individual skills change. Based on the same European Skills and Jobs survey used in this paper Ferreira Sequeda *et al.* (2015) implement ordered-probit models to document a significant impact of both training and informal learning on skills improvement, especially in the case of initially underskilled employees. However, the proposed outcome (self-assessed change in skills level) is not explicitly connected with job requirements and consequently provides no clue on the effectiveness of training in improving individual performance by aligning or re-aligning required and provided skills. The negative consequences of skill mismatch for employees are well-documented in the literature. If underskilling is associated with a wage penalty compared to equally skilled employees in a matched job (Sgobbi and Suleman, 2013), overskilling also involves job dissatisfaction (Green and Zhu, 2010; Mc Guinnes and Sloane, 2011) and compromises future career development (Mavromas *et al.*, 2013). Given that training is not aimed at a general improvement of individual skills, but at solving skill mismatch between provided skills and (current or prospective) required skills (Ferreira Sequeda *et al.*, 2015), a better understanding of how different types of training impact skill mismatch could provide useful insight for improving the effectiveness and the efficiency of training programmes.

3. Data

The European Skills and Jobs (ESJ) survey, commissioned by the European Centre for the Development of Vocational Training (CEDEFOP), was run by IPSOS in 28 EU Member States between March and June 2014 (IPSOS Mori, 2014; Cedefop, 2015). The ESJ Survey involved national representative samples of individuals in employment aged 24-65 years, for a total of 48,431 interviews. Questionnaire were administered by means of either on-line or telephone interviews, the specific channel depending on the diffusion of ICT skills among sampled population segments and on national penetration rates of Internet connections at households and workplaces. Public use datasets have been released in April 2016.

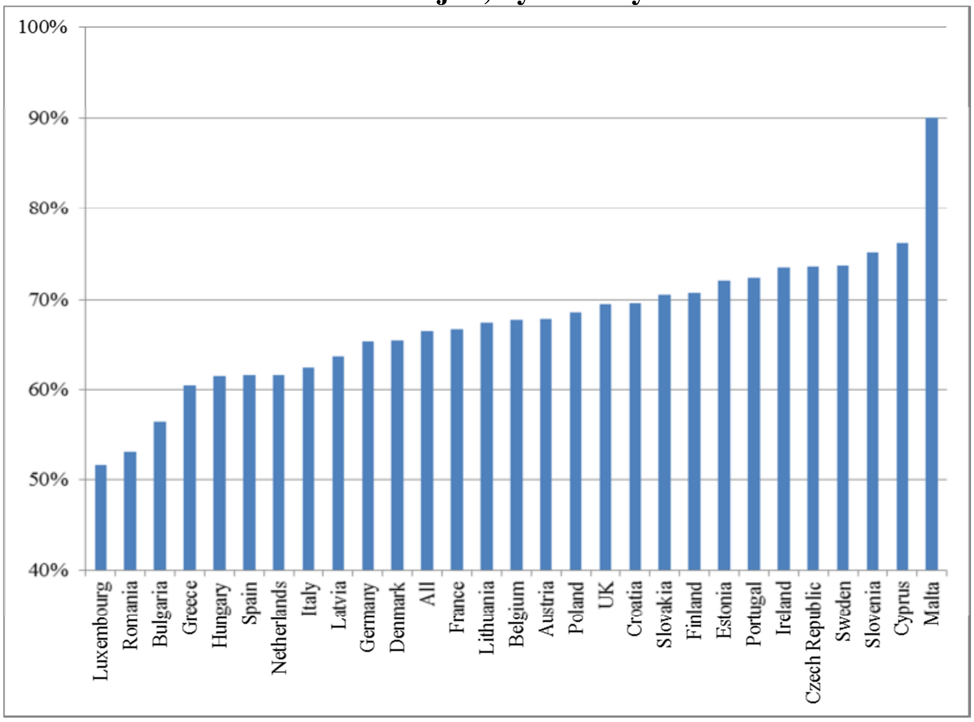
The survey questioned interviewees on their work situation, their present and past jobs, experience in adult education and training, educational path, household background, and perceived proficiency in cognitive and non-cognitive skills. Compared to other international surveys focused on individual skills (e.g., the OECD PIAAC Survey, OECD 2013) the ESJ provides an explicit focus on employed individuals rather than adult population and pays a stronger attention to learning mechanisms and learning paths at the workplace. Examined learning tools concern both formal training (courses and seminars attended both during working hours and outside working hours) and informal training (on-the-job training such as guidance from a supervisor or a co-worker, job rotation, interaction with colleagues, or participation in learning or quality circles). The interview dedicates a section to training and skill change since the beginning of the current job, whereas an additional section focuses on training experiences in the 12 months before the survey. In the latter case it is possible to discriminate between training undertaken for job-related reasons and for other reasons, and between employer-sponsored and non-employer sponsored training.

On average 91.1% of employees report at least one training experience with their current employer, with the lowest figure reported for Romania (83.9%) and the highest for Malta (96.8%). Also when restricting the analysis to formal training, reported participation since start of the current job is still quite frequent and involves on average over 66% of EU-28 employees (Figure 1). If we focus the analysis on the last 12 months before the interview figures gets obviously smaller, yet never smaller than 50% of employees when considering all types of training (Figure 2). However, data in Figure 2 may only partially reflect the extent of the investment in human capital aimed at improving performance at work and career prospects. A more accurate measure is provided by employer-sponsored training undertaken for job-related reasons, which includes training programmes focused on job-related matters whose cost is completely or at least partially covered by one's employer, hence reflecting employer's commitment to training. Participation in employer-sponsored training undertaken for job-related reasons covers a variable share of all training experienced in the 12 months before the survey, from 39% in Greece to 80% in Denmark. It is reported on average by 42.6% of employees, spanning from 23.4% in Greece to 58.2% in the Czech Republic (Figure 3).

Given the focus on employees' learning processes, the ESJ survey provides a suitable testbed to assess the impact of (different types of) training on skill match. However, the choice of an output variable able to assess the quality of skill match is challenging. Assuming that a set of skills in line with job requirements has a positive impact on productivity and that wage measures the value of an employee's marginal productivity, a large literature resorts to monetary earnings as a proxy for skill match (McGuinness, 2006). Based on the ESJ survey the first panel of Table 1 reports the coefficients estimated for three different measures of training with current employer in three OLS regressions where the dependent variable is the logarithm of the gross monthly wage[2].

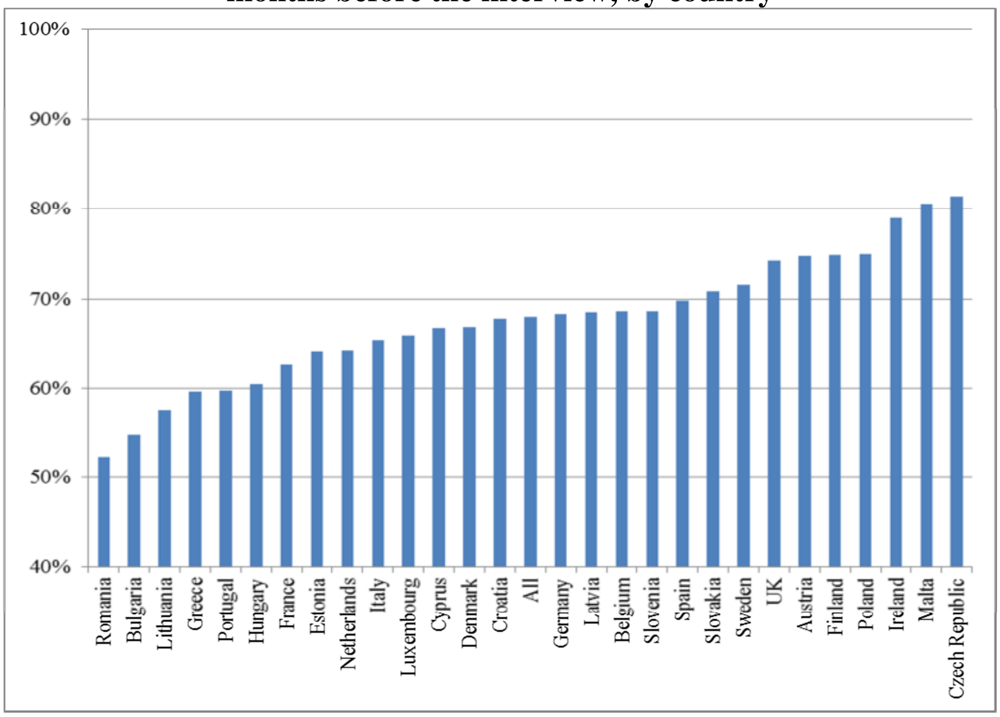
[2] All regressions in this paper exclude observations concerning employees who declared to work without a formal employment contract, employees in armed forces (for whom occupation could not be identified) and interviewees who declared ambiguous occupations, and individuals working less than 15 hours per week.

Figure 1. Share of employees who participated in formal training since start of current job, by country



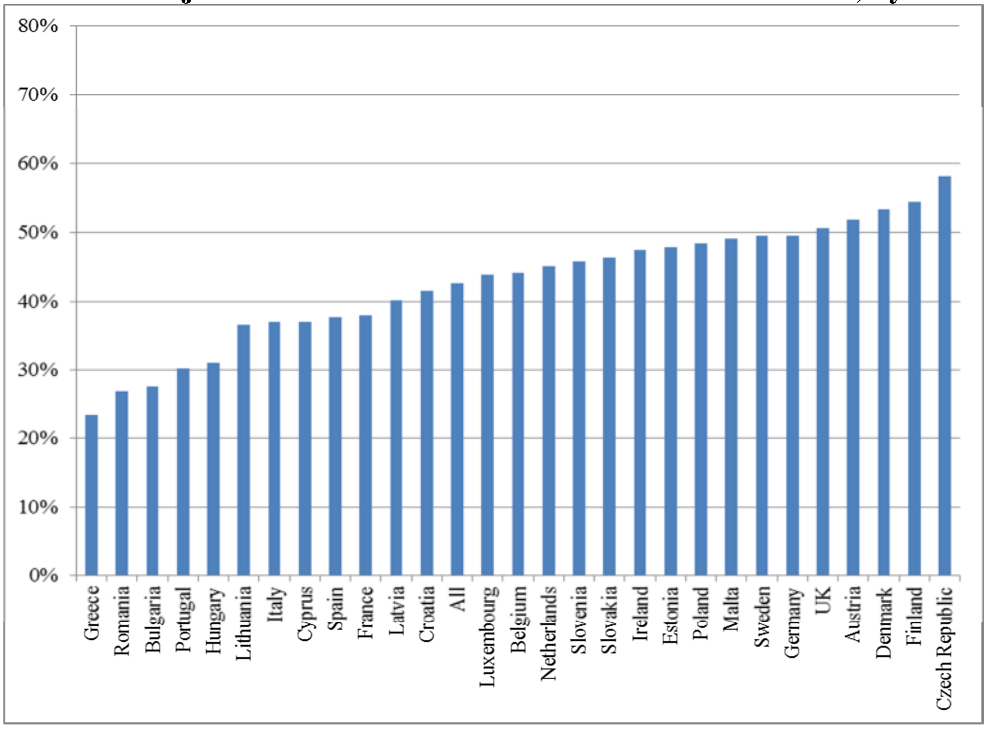
Source: ESJ survey. Weighted observations

Figure 2. Share of employees who participated in any type of training in the 12 months before the interview, by country



Source: ESJ survey. Weighted observations

Figure 3. Share of employees who participated in employer-sponsored training undertaken for job reasons in the 12 months before the interview, by country



Source: ESJ survey. Weighted observations

Reported outcomes support a positive causal relationship between training and wages. After controlling for a large set of additional wage determinants, employees who participated in training in the 12 months before the interview enjoy an average wage premium of 3.6%. However, when overall training splits into employer-sponsored training undertaken for job-related reasons and other types of training, the former coefficient is statistically more significant and the overall wage premium rises to 4.6%. This piece of evidence supports the hypothesis of higher efficiency of training efforts that respond to specific job needs and are regarded worthy to invest in by employers. In line with the results proposed by Ferreira Sequeda *et al.* (2015), if training experience is measured as formal and informal training since start of current job informal training is a stronger and more significant driver of gross monthly wage.

Despite the significant coefficients estimated for different measures of participation in training, criticisms can be made to the choice of assessing the outcome of training by means of wage. Besides on individual skills, hence productivity, wage strongly depends on collective labour agreement schemes, on individual employees' bargaining power, and on the wage policy of the firm. This problem may be overcome by using an outcome variable that more immediately reflects the impact of training on skills. The ESJ survey provides a measure of overall skill proficiency by asking interviewees the following question: "Think about the level of skills needed to do your job as well as possible. How would you rate your own level of skills?". Answer is provided along a 0-100 scale, where 0 indicates need to develop all required skills and 100 denotes full skill endowment. The second panel of Table 1 reports the coefficients estimated for different measures of past training in three OLS regressions where the dependent variable is the above mentioned measure of skill proficiency. Training in the last 12 months before the interview (and, namely, employer-sponsored training) is a significant despite negative driver of self-assessed skill proficiency, whereas training measures that consider the cumulate training experience with current employer do not display significant coefficients. Recent participation in training is associated with a drop in skill proficiency of about 0.39% compared to non-participating employees. It seems that either training programmes, targeted at employees affected by skill shortage, need some time to fully display their impact on skill proficiency, or that participation in training discloses new opportunities of learning and makes trainees re-assess their skill level downwards. Whatever the answer, this outcome outlines a second major problem of cross-sectional outcome measures of training, i.e., the inability to account for correlation between unobservable variables determining participation in training and unobservable variables determining the outcome variable of interest. For instance, unobserved individual characteristics may drive both the probability to participate in training and the subsequent self-assessment of one's skill proficiency. Also, a more proactive employee may have higher chances to get trained and may also perform better in wage bargaining.

The ESJ survey supplies a longitudinal measure of skill match by providing distinct assessments of the alignment between required and provided skills when starting current job and at the time of the interview. To assess current skill match interviewees were asked "Overall, how would you best describe your skills in relation to what is required to do your job?". Employees who answered either "My skills are higher than required by my job" or "Some of my skills are lower than what is required by my job and need to be further developed" were asked to further quantify the severity of their overskilling or underskilling along a 1-5 scale. By rescaling values it is possible to build up a measure of skill mismatch at the time of the interview that ranges between -5 (severe underskilling) and 5 (sever overskilling), whereas 0 signals skill match. In a similar way the question "When you started your job with your current employer, to what extent would you say that your skills were lower than required to do your job at that time?" and the subsequent specifications for past underskilling and past over-skilling allow the identification of a measure of skill mismatch at the beginning of the current job.

Table 1. Impact of training on wage and self-assessed skill proficiency

Output measure (dependent variable)	**Training measures** (independent variables)			
Ln of gross monthly wage		Coeff.	Robust std. error	
	1a) Any training in the 12 months before interview	0.036	0.008	***
	1b) - Employer-sponsored training for job-related reasons in the 12 months before interview	0.046	0.009	***
	- Other type of training in the 12 months before interview	0.020	0.010	*
	1c) - Formal training since start of current job	0.054	0.017	***
	- Informal training since start of current job	0.029	0.017	*
Perceived skill proficiency		Coeff.	Robust std. error	
	2a) Any training in the 12 months before the survey	-0.345	0.215	
	2b) - Employer-sponsored training for job-related reasons in the 12 months before the survey	-0.390	0.229	*
	- Other type of training in the 12 months before interview	-0.274	0.258	
	2c) - Formal training since start of current job	0.301	0.461	
	- Informal training since start of current job	0.174	0.482	

*Logarithm of gross monthly wage in PPP dollars 2008. Perceived proficiency self-assessed along a 1-100 scale. All 6 OLS regressions include additional controls for employee-specific factors (gender, living with children, born in country of residence, 4 binary variables for educational qualification, overeducation and undereducation, attitude towards learning, and 27 dummy variables for country of residence), job-specific factors (tenure, squared tenure, part-time job, fixed-term job, 8 dummy variables for 1-digit occupations, skill match when starting current job, provenience when starting current job, and job learning opportunities) and firm-specific factors (4 binary variables for firm size class and 14 binary variables for industry), and a binary variable for interview mode (on-line or by telephone).Weighted observations. * Statistically significant at the .10 level; *** at the .01 level.*

Table 3 reports the skill (mis)match transitions recorded by the ESJ survey. Slightly over than 50% of sampled employees report no change in their skill mismatch level since start of current job, with 36.4% declaring both past and current skill match. Employees affected by initial underskilling display the most intense rate of skill match transitions. Only 15% of initially underskilled employees still regarded themselves as underskilled at the time of the interview, whereas 64.5% had switched to skill match and 20.6% even declared overskilling when surveyed by IPSOS. In contrast, only 3.6% of initially matched employees switched to underskilling and 25.3% switched to over-skilling. The large majority of employees who declared initial over-skilling still reported over-skilling at the time of the interview (79.7%), while only 18.4% achieved skill match and 1.9% switched to underskilling.

The difference between the absolute values assumed by current and past skill levels as depicted in Table 2 describes increases and decreases in the gap from the ideal situation of skill match and provides an overall measure of change in skill mismatch (D_SkillMatch). Positive values signal a larger final distance from skill match compared to the initial situation, negative values signal gap closure, and null values correspond to no change in the distance from skill match since start of current job[3]. According to the proposed measure, overall change in skill mismatch results from the composition of change in the degree of underskilling and change in the degree of overskilling. Since training may exert a different impact on underskilling compared to overskilling (Ferreira Sequeda *et al.*, 2015), and considering the non-negligible share of observed skill match transitions that involve a switch from underskilling to overskilling (4.8% of observations in Table 2), and vice versa (0.5%), two additional variables focus on changes in levels of underskilling and overskilling, respectively. Variable D_Underskilling is defined as the difference between final and initial absolute levels of underskilling, whereas variable D_Overskilling is the difference between final and initial absolute levels of overskilling (Table 3).

Table 2. Skill match transitions

			Current Skill Match										
			Strong underskilling					Skill match				Strong overskilling	
			-5	-4	-3	-2	-1	0	1	2	3	4	5	Total
Past Skill Match	Strong underskilling	-5	18	20	28	29	39	354	10	14	23	19	40	594
		-4	0	42	58	68	50	658	2	25	53	91	55	1,102
		-3	4	27	147	136	161	1,951	12	71	191	208	93	3,001
		-2	5	5	56	168	140	1,872	24	102	242	196	66	2,876
		-1	1	10	28	62	288	2,003	48	127	223	158	95	3,043
	Skill match	0	31	77	167	231	330	16,443	199	711	1694	2108	1144	23,135
		1	3	0	1	3	6	104	64	54	49	39	49	372
		2	1	0	4	8	14	188	41	237	180	82	30	785
		3	0	3	16	22	23	556	19	144	975	422	161	2,341
		4	1	9	14	20	21	782	12	95	468	1922	636	3,980
	Strong overskilling	5	5	2	11	11	19	457	26	35	232	637	2458	3,893
		Total	69	195	530	758	1,091	25,368	457	1,615	4,330	5,882	4,827	45,122

[3] It has to be noted that the latter situation includes both employees who remain in a condition of skill match, employees who declare the same degree of underskilling or overskilling, and employees who switch from a degree of underskilling/overskilling to the specular degree of overskilling/underskilling.

Table 3. Change in skill mismatch

Variable	Description	N	Min	Max	Mean	Std. Dev.
D_SkillMatch	Difference in levels of skill mismatch at the time of the interview and when starting current job	42,771	-5	5	0.002	2.000
D_Underskilling	Difference in absolute levels of underskilling at the time of the interview and when starting current job	42,856	-5	5	-0.446	1.170
D_Overskilling	Difference in absolute levels of overkilling at the time of the interview and when starting current job	42,937	-5	5	0.448	1.757

Weighted observations

4. Empirical strategy

Given the non-continuous nature of the proposed measures of change in skill match levels, the use of OLS models to estimate the impact of training on the dependent variable is not suitable. Also the use of ordered probit models to estimate the impact of training on the odds of switching from a skill match level to a higher or a lower one is forbidden by the failure of the test of parallel lines, which rejects the hypothesis that the cumulative probability functions of belonging to each different skill mismatch level can be represented by parallel shifted logistic curves.

Propensity score matching with difference-in-differences methods (PSM-DID) provide an alternative approach to assess the impact of training on change in skill mismatch level (Heckman *et al.*, 1997; Blundell and Costa Dias, 2000; Imbens and Wooldridge, 2009; Lechner, 2011). Training can be regarded as a binary treatment expected to impact the match between required and provided skills.

By combining propensity score matching techniques with difference-in-differences approaches, PSM-DID methods match treated individuals with members of a non-treated control group along a set of relevant characteristics (PSM) and double differentiate the outcome variable of interest across treated and untreated individuals and across time (DID). On the one hand, the use of a matching algorithm to compare treated and untreated individuals rules out non-random differences in the distribution of initial characteristics that affect the probability of selection into treatment. On the other hand, difference-in-differences sterilises the effect of non-time variant unobservables and possible time trends unrelated with the treatment by comparing the gains in outcomes achieved by the treated with those of the control group.

However, a number of constraints requirements have to be met to ensure safe application of a PSM-DID approach. First, the conditional independence assumption, or unconfoundedness assumption, requires that, conditional on a set of covariates X that impact the probability of selection into treatment, the expected outcome (or the distribution of outcomes, in a stricter definition) is independent of the treatment status[4] (Lechner, 2011). A wide set of information on treated and untreated individuals before treatment increases the probability of meeting this condition. Second, the overlap assumption requires that for each given value of the X covariates that drive participation in treatment both treated and controls can be observed. In addition, the choice of specific PSM mechanisms may impose further constraints. These reasons make parsimonious approaches such as the one suggested by Abadie (2005) seem preferable. Under the conditional independence assumption and the overlap assumption, Abadie (2005) shows that the average treatment on the treated (ATT) compared to the counterfactual of untreated individuals can be modelled as

$$\tau_{ATT} = E\left\{\frac{(Y_1 - Y_0)}{P(D=1)} * \frac{D - P(D=1|X)}{1 - P(D=1|X)}\right\} \qquad (1)$$

where Y_1 and Y_0 are the outcomes observed for the same individual in two subsequent time periods; D is equal to 1 for individuals exposed to the binary treatment under exam; $P(D = 1)$ is the unconditional probability of treatment in the sample; $P(D = 1|X)$ is the individual propensity score for treatment given a set of X covariates; and $1 - P(D = 1|X)$ is the individual propensity score for no treatment.

A consistent and $\sqrt{N}$-asymptotically normal estimator of the average treatment on the treated for treatment h can be calculated as in (2)

$$\hat{\tau}_{ATT} = \frac{1}{N}\sum_{k=1}^{N}\left\{\frac{(Y_1 - Y_0)}{P(D=1)} * \frac{D - \hat{P}(D=1|X)}{1 - \hat{P}(D=1|X)}\right\} \qquad (2)$$

where N is the number of observed individuals either in treatment or no treatment.

The estimator proposed by Abadie (2005) presents some important advantages over other PSM-DID estimators (e.g., Heckman *et al.*, 1997; Blundell and Costa Dias, 2000). Instead of using a parametric matching mechanism, treated and untreated observations are balanced through a weighting scheme based on propensity scores to treatment, which increase when the values taken by the covariates are over-represented among the treated and vice-versa. In other words, Abadie's estimator increases the weight of untreated observations similar to treated observations along the covariates profile (i.e., untreated observations with high propensity scores) and weights down the outcome gain displayed by untreated observations with low propensity scores.

As the distribution of covariates is balanced between treated and untreated by simply weighting untreated observations through their covariate-based propensity scores, Abadie's parsimonious estimator requires no additional hypothesis on the matching mechanism. As a consequence, post-matching tests of covariate balance between treated

[4] Rosenbaum and Rubin (1983) prove that conditional independence is still valid if controlling for the probability of participating in treatment based on the X covariates, rather than on all specific X covariates.

and control group are not required and no observations are lost due to balancing mechanisms.

5. Empirical outcomes

In line with the empirical strategy outlined in the above section, the estimate of the average impact of training on the skill level of trained employees compared to a counterfactual of untrained interviewees entails two steps. The first step involves the calculation of individual propensity scores to participate in training by means of a binary logistic model (see, e.g., Blundell *et al.*, 2004; Dorsett, 2006). The second step implements the weighting scheme proposed by Abadie (2005) to estimate the average treatment on the treated.

Both steps are replicated for each of the dependent variables identified in Table 3 (change in absolute distance from skill match, D_SkillMatch; change in self-assessed underskilling, D_ Underskilling ; and change in self-assessed overskilling, D_Overskilling). In addition, estimates are replicated for three different measures of training: participation in any type of training in the 12 months before the interview, participation in employer-sponsored training undertaken for job-related reasons in the 12 months before the interview, and participation in formal training since start of current job (see Table 4 for some descriptive statistics).

Definition and descriptive statistics for the covariates used to calculate individual propensity scores to treatments are provided in Table 4. Table 5 reports the marginal effects of the covariates that assess the probability of participating in either any type of recent training (first column), employer-sponsored recent training undertaken for job-related reasons (column 2), and cumulative formal training since start of current job (column 3).

Before commenting on the results of the binary logistic regressions two remarks are important. PSM-DID algorithms have to comply with the overlap assumption, which requires that, given a covariate profile X, each observation has a positive probability to be either treated or untreated. This condition is met for all the 35,941 observations that present jointly non-missing values for both dependent and independent variables. In addition, the conditional independence assumption requires that the covariates chosen to control for selection into treatment actually capture the probability of participating in training. The large set of pre-treatment observable covariates provided by the ESJ survey enhances the chance of controlling for factors that affect the probability of participating in different types of training. As shown in Table 5, the reported estimates display a satisfactory prediction power, with around 70% of cases correctly classified and pseudo R2 between 0.086 and 0.145.

Table 4. The determinants of training: Training measures and training determinants

Dependent variables **Variable**	**Description**	**N**				**%**
Training12	Any training in the 12 months before the interview	43,506				68.3%
Spon_Training12	Job related employer-sponsored training in the 12 months before the interview	43,506				43.4%
Formal_Tr	Any formal training with current employer	43,506				67.2%
Independent variables **Variable**	**Description**	**N**				**%**
ISCED0_1 [a]	No qualification or ISCED 1 qualification	43,506				1.6%
ISCED2	ISCED 2 qualification	43,506				11.3%
ISCED3	ISCED 3 qualification	43,506				36.9%
ISCED4	ISCED 4 qualification	43,506				12.4%
ISCED5_6	ISCED 5 or ISCED 6 qualification	43,506				37.5%
Overeducated	Educational qualification above requirements to get current job	43,506				22.0%
Undereducated	Educational qualification below requirements to get current job	43,506				15.8%
Female	Female employee	43,506				47.8%
Female*Children	Female employee living with children	43,506				20.8%
Native	Born in the country of residence	43,506				90.1%
Part_time	Part time job contract	43,506				13.1%
Fixed_term	Fixed term contract	43,506				12.8%
Past_NotWorking [a]	Not working before starting current job	43,506				4.3%
Past_SameJob	Same job before starting current job	43,506				11.3%
Past_SimilarJob	Similar job before starting current job	43,506				26.4%
Past_DifferentJob	Different job before starting current job	43,506				34.2%
Past_Unemployed	Unemployed before starting current job	43,506				13.1%
Past_Student	Student before starting current job	43,506				10.8%
		N	**Min**	**Max**	**Mean**	**Std. Dev.**
Learning_attitude	Self-assessed interest in learning	43,334	0	10	7.56	2.27
Tenure	Tenure with current employer in years	43,368	1	50	10.47	9.24
SqTenure	Squared tenure with current employer	43,368	1	2,500	195.14	313.39
Past_SkillMatch	Self-assessed skill match level when started current job	42,950	-5	5	0.41	2.35
Learning_opp	Mean of three self-assessed measures of the learning opportunities when beginning current job	43,506	0	10	6.69	2.26
Dynamic_job	Self-assessed measure of the probability that skills will get obsolete in the next 5 years	41,567	0	10	3.85	3.10

[a] *Reference category*

In general terms, most covariates display the expected impact on the probability of participating in training. Among employee-specific factors, educational qualifications are always significant determinants of training and their marginal effects steadily grow from ISCED level 2 to ISCED levels 5 and 6 compared to the reference category of no qualification or ISCED level 1 qualification. Also the coefficients of the binary variables that signal overeducation and undereducation compared to the educational qualification required to get the job at the time of the interview display the expected signs (McGuinness, 2006), with lower probability of receiving training for overeducated employees compared to matched ones (with the lowest marginal value of -5.2% in the case of employer-sponsored training) and a higher probability of about 4% for undereducated employees.

Female employees suffer no penalisation compared to male colleagues in the probability of having received any type of training in the recent past. However, focus on employer-sponsored training undertaken for job-related reasons entails a small but significant penalisation (-1.5%), which increases to -2.6% in the case of formal training since start of current job. Living with own children entails no penalisation for female employees and even a small positive impact in the case of formal training since start of current job[5]. As in the case of female employees, immigrated workers and native workers have the same probability of receiving some training in the 12 months before the interview, but the latter have a significant advantage (+2.5%) in the case of formal training since start of current job.

The attitude towards learning exerts a strong impact on all the three examined measures of training. This variable reflects the agreement with the statement “I enjoy learning for its own sake” and its value ranges between 0 (strong disagreement) and 10 (strong agreement). Compared to an employee who declares null interest in learning, the increase in the probability to participate in training for most motivated employees ranges between 7% (recent training and cumulative formal training since start of current job) and 8% (employer-sponsored training).

When significant, the marginal effects associated with tenure display positive linear and negative quadratic effects. Part-time contracts and fixed-term contracts are generally associated with a lower probability to participate in training, with the highest penalties recorded in the case of employer sponsored training (-1.9% for part-time contracts and -6.7% for fixed-term ones).

[5] However, the ESJ survey provides no information about the age class of children living with interviewed employees.

Table 5. Determinants of participation in training

Dependent variable	Any training in the 12 months before interview			Employer-sponsored training for job-related reasons in the 12 months before interview			Formal training since start of current job		
	dy/dx	Delta-method Std. Err		dy/dx	Delta-method Std. Err		dy/dx	Delta-method Std. Err	
ISCED2	0,048	0,026	*	0,092	0,034	***	0,079	0,027	***
ISCED3	0,085	0,025	***	0,131	0,033	***	0,136	0,026	***
ISCED4	0,114	0,026	***	0,162	0,034	***	0,182	0,027	***
ISCED5_6	0,145	0,026	***	0,190	0,034	***	0,209	0,027	***
Overeducated	-0,013	0,007	*	-0,052	0,007	***	-0,029	0,007	***
Undereducated	0,030	0,009	***	0,041	0,010	***	0,038	0,009	***
Female	-0,004	0,007		-0,015	0,007	**	-0,026	0,007	***
Female*Children	-0,001	0,008		0,006	0,009		0,014	0,008	*
Native	0,008	0,009		0,012	0,010		0,025	0,009	***
Learning_attitude	0,007	0,001	***	0,008	0,001	***	0,007	0,001	***
Tenure	-0,001	0,001		0,004	0,001	***	0,014	0,001	***
SqTenure	-1,4E-08	2,8E-05		-1,3E-04	3,0E-05	***	-2,5E-04	2,7E-05	***
Part_time	-0,010	0,009		-0,019	0,009	**	0,000	0,008	
Fixed_term	-0,025	0,009	***	-0,067	0,010	***	-0,049	0,008	***
Past_SkillMatch	-0,009	0,001	***	-0,013	0,001	***	-0,009	0,001	***
Learning_opp	0,020	0,001	***	0,028	0,001	***	0,018	0,001	***
Dynamic_job	0,002	0,001	*	0,001	0,001		0,000	0,001	
Past_SameJob	0,003	0,016		-0,024	0,017		0,032	0,016	**
Past_SimilarJob	0,009	0,015		0,004	0,016		0,029	0,015	**
Past_DifferentJob	0,009	0,015		-0,001	0,016		0,029	0,014	**
Past_Unemployed	-0,032	0,016	**	-0,057	0,017	***	-0,020	0,015	
Past_Student	-0,010	0,017		-0,016	0,017		0,041	0,016	**
Pseudo R2	0.091			0.086				0.145	
Correctly predicted cases	73.50%			63.9%				75.3%	

Probit Models (Marginal Effects). 35,941 weighted observations.
All regressions include a binary variable for interview mode (on-line or by telephone) and fixed-effects for 1-digit occupation, firm size class, industry, and country
Statistically significant at the .10 level; ** at the .05 level; * at the .01 level.*

In line with past studies (Verhaest and Omey, 2006) the level of skill match at the beginning of current job is always a strongly significant determinant of selection into training. Compared to an employee who reports initial skill match the probability of receiving training for an employee who reports strong underskilling when starting current job (i.e., a value of -5 for variable Past_SkillMatch) is 4.5% higher in the case of any type of recent training and cumulative formal training, and 6.5% higher in the case of recent employer-sponsored training[6]. Also variable Learning_opp exerts a strong

[6] The opposite is true for employers who declare strong initial overskilling. In this case, the probability of receiving training are 4% lower in the case of any type of recent training, 6% lower in the case of recent

impact on the estimated propensity to training. This variable reflects interviewees' motivation to develop their skills when starting their current job and is built as the average agreements with following items in a 1-10 scale: "The job suited your qualifications and skills", "You wanted to gain some work experience", and "The job offered good career progression/career development". The estimated marginal effects show that, compared to a poorly motivated employee, for most motivated individuals the chance to participate in training is 20% higher in the case of any type of recent training, 28% higher in the case of recent employer-sponsored training, and 18% higher in the case of cumulative formal training. Positive values of the coefficients displayed by variable Dynamic_job are expected to reflect the need for continuous learning and skill updating in a dynamic environment. However, calculated coefficients display very small effects, weakly significant only in the case of any type of recent training.

The last set of marginal effects displayed in Table 5 concerns employees' situation before starting the current job. The reference group consists of individuals neither in the labour force nor studying before taking their current employment contract. Unemployment before current job is the only past situation associated with a negative propensity to recent training, either employer-sponsored or not. The picture is reversed in the case of cumulative formal training. The probability of receiving formal training for employees who get their job after a spell of unemployment does not significantly differ from that experienced by the reference category (people not working before the current job), whereas other groups enjoy a comparative advantage. The probability of selection into formal training is significantly higher for former students, while the coefficients associated with progressively more diversified past jobs are not statistically different.

Table 6 reports the estimates of the impact of training on the skill match level of trained employees according to Abadie's (2005) approach. All standard errors are bootstrapped with 500 repetitions[7]. The three panels of Table 6 focus on the three different treatments examined so far. For each treatment the PSM-DID estimates assess the impact on the three different outcomes outlined in Table 3, i.e., change in total skill mismatch, change in underskilling, and change in overskilling.

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employer-sponsored training, and 13% lower in the case of cumulative formal training compared to an initially matched employee.

[7] Some recent contributions point out the limits of bootstrapping to assess the confidence interval of average treatment effects with propensity score matching. Abadie and Imbens (2008) show that the standard bootstrap fails to provide asymptotically valid standard errors in the popular case of nearest-neighbor matching estimators with replacement and a fixed number of neighbors. However, the authors report that bootstrap provides valid inference in case of asymptotically linear estimators, as in the case of the present analysis. Abadie and Imbens (2016) raise further attention to the sources of bias due to fact that prior to matching propensity score itself is the result of an estimation process.

The first two panels of Table 6 show very similar results. The significant and negative impact of training in the last 12 months on overall skill change signals a that both general training and employer-sponsored training generate a decrease in the distance from the optimum target of skill match. However, when overall skill change is split between change in underskilling and change in overskilling only the latter displays a negative and significant coefficient. When accounting for the different distribution of initial characteristics between treated and non-treated employees, unobserved heterogeneity, and time-trends unrelated with treatment, it becomes apparent that the reduction in underskilling observed in Table 2 is not the result of recent training actions. Training in the 12 months before the interview seems more effective in reducing perceived overskilling, probably by enabling horizontal and vertical moves within the organisation. In general terms, the similar results displayed by the first two panels of Table 6 in terms of size, sign, and statistical significance of the estimated coefficients suggest that employers are no more effective that other involved players (employees and institutions) in targeting their training efforts to a better skill match.

Table 6. PSM-DID estimates of change in skill mismatch for trained employees

	Observed differential	Bootstrap std. error	Z	
Any training in the 12 months before the interview				
Change in total skill mismatch	-0.113	0.031	-3.54	***
Change in underskilling	-0.014	0.016	-0.83	
Change in overskilling	-0.100	0.025	-4.06	***
Employer-sponsored training for job reasons in the 12 months before the interview				
Change in total skill mismatch	-0.102	0.045	-4.13	***
Change in underskilling	-0.010	0.012	-0.87	
Change in overskilling	-0.092	0.020	-4.53	***
Any formal training since start of current job				
Change in total skill mismatch	-0.075	0.033	-2.26	**
Change in underskilling	-0.083	0.018	-4.70	***
Change in overskilling	0.007	0.029	0.26	

**** p< 00.01; ** p< 00.05; 37,964 observations*

The third panel of Table 6, which concerns the average change in skill mismatch for employees who undertook formal training since start of their current job, presents a different picture. The impact of cumulative formal training on change in total skill match still displays an average (small) reduction in the observed mismatch. However, this variation is due to a change in underskilling rather than overskilling. This outcome suggests that formal training can be an effective tool to recover from an initial skill gap. However, the full effects of a training action unfold over time.

As a final remark, it has to be noted that, also when significant, the size of the estimated consequences of training on skill change is comparatively small. Considering that all outcome variables vary in a range between -5 and 5, observed average effects account at most for 1 percent of observed values.

6. Discussion and conclusions

Training is recognised as a key resource to moderate the gap between required and provided skills and to meet the continuous changes faced by organisations. However, since training efforts involve significant costs and risks for both training providers and training recipients, rigorous measures of training capability to improve the alignment between required and supplied skills would provide guidance for a more effective use of available training resources. Based on data on employees from the 28 EU countries collected by the ESJ survey this paper has assessed the impact of three measures of training on change in skill match levels.

In general terms, all examined types of training reduce the gap between the initial skill mismatch and the desired target of skill match. However, training received in the 12 months before the survey decreases the overall skill gap by lowering overskilling, whereas the cumulative formal training undertaken since start of current job involves a reduction in underskilling.

The proposed results have significant implications for training actions aimed at improving the alignment between required and provided skills in the labour market and the associated supportive policy measures. By showing that training impacts overskilling in the short term and underskilling in the long term the estimates in Table 8 suggest that training should be a constant presence in working life to ensure the reduction of skill mismatch. However, the analysis of propensity to training also shows that “atypical careers” including frequent change of employer (e.g., due to fixed-term contracts), possible unemployment spells between jobs, or part-time employment significantly reduce the opportunity to participate in training, especially in the case of employer-sponsored initiatives. This finding stresses the importance of identifying tools and solutions to encourage the continuity of training along the working life of all types of employees. At the same time, it also puts forward the issue of who among workers, employers, or institutional players should carry the costs of training employees in atypical jobs. This problem is also connected to the second major finding proposed by this paper, i.e., the poor difference in outcomes when the treatment is any recent training and in the case of recent employer-sponsored training undertaken for job-related reasons. Coupled with the provided evidence on the more selective access to the latter type of training, this finding suggests that employers may concentrate training effort on employees in standard career paths irrespective of individual development potential. Before undertaking initiatives to substitute employers in training provision for “atypical employees”, policy makers may focus on improving employers’ capability to identify the training needs and development potential of their employees

As a final remark, some important caveats constrain the results obtained so far and point out the direction of future improvements. The outcome variables provided by the ESJ survey before and after treatment have discrete nature and vary within a comparably limited range. Given the small changes in skill mismatch levels calculated by the implemented PSM-DID approach, results should be interpreted as trends rather than actual measures of skill increase or decrease.

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