WORK-RELATED LEARNING AND SKILLS DEVELOPMENT IN EUROPE: DOES INITIAL SKILLS MISMATCH MATTER?

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Abstract

Although human capital theory has considered training and on-the-job informal learning as productive investments that further improve workers' skills, this has hardly been directly tested in the empirical literature. In this paper, we analyse to what extent training and informal learning on-the-job are related to employees' skills development. We consider the heterogeneity of this relationship with regard to the employees' initial skills mismatch. Using unique data from the recent *Cedefop European Skills Survey* for 28 countries, we find that employees who participated in training or informal learning show a higher improvement of their skills than those who did not. Informal learning appears to be more important to increase workers' skills than training participation. Moreover, both informal learning and training appear to be most beneficial for skills improvement among under-skilled workers and least for those who are over-skilled for their job. For over-skilled workers, job-related learning seems to be more functional to offset skills depreciation and maintain their skills level rather than to foster skills accumulation.

JEL-Codes: J24, M53

Keywords: training, informal learning, skills development, skills mismatch, human capital.

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1. INTRODUCTION

In order to deal with the challenges of rising global competition, the European Union has set itself goals with respect to formal training and informal learning in the workplace to 'acquire and develop new skills throughout the lifetime of individuals' (European Commission 2010:16). The idea that work-related learning improves workers' skills is in line with the human capital theory (Mincer 1962, 1968; Becker 1964; Heckman 1976). However, due to a lack of data on skills improvement, the assumption that on-the-job human capital accumulation indeed fosters workers' skills development has rarely been directly tested. Instead, most studies have focused on the role of job-related training on wages and productivity (Acemoglu and Pischke 1999; Blundel *et al.*1999; Leuven 2005; Leuven and Oosterbeek 2008; Görlitz 2011; O'Connell and Byrne 2012).

In this paper, we analyse to what extent work-related learning is related to the skills development of workers in 28 European countries. We distinguish between training participation and informal learning on-the-job. Moreover, we allow for heterogeneity in the relation between work-related learning and skills development by workers' initial skill mismatch.

The *European Skills Survey* shows that at the start of a job a significant proportion of the labour force in Europe has skills that either exceed the skill demands or are insufficient to perform their job adequately: 24 percent of all workers report that some of their skills were initially lower than what was required in their job and 25 percent report that their skills were initially higher than required in their job. Workers who are underskilled probably need training or informal learning on-the-job in order to perform at an adequate level. Workers who are overskilled are likely to have other reasons to engage in job-related learning such as keeping their skills up-to-date, which might not reveal skills improvement as such. Due to the difference in the underlying reasons for job-related learning, it is expected that mismatched workers' participation in job-related learning results in a different degree of skills development compared to workers whose skills fully match with the skills demands in their job.

For this study we use a unique dataset on more than 37,000 employees of the *European Skills Survey*, conducted in 2014 by the European Centre for the Development of Vocational Training (Cedefop). This survey is one of the first surveys in which different types of job-related learning as well as employees' skills development and mismatch are measured. We contribute to the literature in two ways. First, we provide empirical evidence to the theoretical relation between the different forms of learning and workers' skills development which has until now been a 'black box' in the empirical human capital literature. Second, we are the first to examine the heterogeneous effects of training and informal learning on-the-job on skills development with respect to workers' initial skill mismatch. Thereby, we find differences between under-skilled and over-skilled workers in the impact of investments in training and informal learning on skills development.

We find that employees who are involved in training and informal learning show a higher improvement of their skills. Informal learning appears to be more important to increase workers' skills than training participation. This holds for both the matched workers and the mismatched workers. However, training and informal learning seem to be most efficient for skills improvement among the under-skilled and least among the over-skilled employees.

The remainder of the paper is structured as follows. Section 2 discusses the relevant literature. Section 3 describes the dataset the definitions of skills development and skills mismatch as well as the other variables used in the analyses. Section 4 describes the estimation method we use -ordered probit models with interaction effects- and explains how results should be interpreted. The results are presented in Section 5. Section 6 concludes.

2. RELATED LITERATURE

2.1 Human capital investments and skills development

Human capital theory has considered on-the-job learning as an investment that increases workers' productivity and wages, via the accumulation of skills (Mincer 1962, 1968; Becker 1962; Heckman 1976). However, due to a lack of data, this skill accumulation has hardly been tested in empirical studies. First, at the individual level, most literature deals with the relation between training and wages, as hard measures of individual productivity are rare (Acemoglu and Pischke 1999; Blundel *et al.*1999; Leuven 2005; Leuven and Oosterbeek 2008; Görlitz 2011; O'Connell and Byrne 2012). One exception is a study by De Grip and Sauermann (2012) who have assessed the effects of job-related training on individual performance, by means of a field experiment. Second, at the firm level, most studies focus on the relation between average training participation and firm productivity as measured by value added (Boothby *et al.*2010; Sepulveda, 2010; Dearden et.al 2006; Barrett and O'Connell 2001; Bartel 2000, 1994; Lowenstein and Spletzer 1998). Third, although Mincer (1974) claimed that informal learning may constitute the essential part and the major productivity investments within the workplace; due to data limitations and the assumption in standard models that experience absorbs the work-related learning effect, there is hardly any empirical evidence that informal learning on-the-job is indeed positively related to wages and productivity. Levitt *et al.* (2012) and Destré *et al.* (2008) have respectively shown that learning by-doing and learning from others is significantly important to explain workers' earnings as well as firm productivity. However, the empirical question whether training and informal learning affect performance via skills, or whether the performance increase is due to other factors still remains (De Grip and Sauermann 2013).

There is one exception. Green *et al.* (2001) analysed training on and off-the-job as a determinant of skills supply. Using the *British Skills Survey*, they found that whereas off-the-job-training is a determinant of all types of skills included in their analysis except team working, on-the-job training contributes to workers' problem-solving and team-working skills. However, Green *et al.* (2001)

measure tasks rather than skills by using information on the importance of workers' particular job activities as dependent variable. Furthermore, their skills measure refers only to one point in time, which does not allow analysing workers' skills development over time. Moreover, due to lack of data, they cannot explore the contribution of informal learning. Hence, having measures of training participation and informal learning as well as skills changes enables us to some extent to open the 'black box' on the transfer of lifelong learning to the workplace in economic literature (De Corte 2003; De Grip and Sauermann 2013).

2.2 Skills mismatch and human capital investments

Research on job mismatch has mostly concentrated on the wage outcomes of overeducation (see McGuinness, 2006; Chevalier, 2003; Di Pietro and Urwin, 2006; Dolton and Silles, 2008; Dolton and Vignoles, 2000; Hartog, 2000; Kiker et al., 1997; Groot, 1996). More recently in the literature there has been a shift in emphasis from overeducation to skills mismatches (McGuinness and Byrne, 2014; Mavromaras and McGuinness, 2012; McGuinness and Sloane, 2011; Mavromaras et al., 2012, 2010, 2009; O'Leary et. al, 2009; McGuinness and Wooden, 2009; Chevalier and Lindley, 2009; Green and Zhu, 2010; McGuinness and Bennett, 2007). These studies have shown that over-education and over-skilling refer to different phenomena, and that overeducation may not fully capture the extent to which an individual's skills are utilised at work. Educational attainment does not incorporate any measure of ability[1] or skills acquired through employment while the job entry requirements are imprecise to measure the skill content of the job. Thus, measuring workers'skills mismatch might solve these difficulties by requesting individuals to compare the actual skill requirement of their job with their own skills either acquired by initial education, training, informal learning or related to their general ability. Although susceptible to measurement error due to subjective bias, skills mismatch is still considered as a more adequate and potentially more robust measure of skills under and over-utilisation than educational mismatch (Mavromaras and McGuinness, 2012).

Studies on human capital accumulation of workers have only emphasised the role of training in reducing educational mismatch. Search and matching theory considers training as a supplement to education in the way that it bridges the gap between generic skills acquired through schooling and specific skills required at the workplace (Arulampalam *et al.*2004; Acemoglu and Pischke 1999; Baldwin and Johnson, 1995). In consequence, training contributes to the adjustment between the workers' potential productivity and the productivity ceiling of the job in which they are employed (Blazquez and Jansen, 2008). In this regard, empirical studies have found that over-(under-)educated workers participate less (more) often in training than those who are well matched, and that training not only has a function of investment in human capital but also ameliorates the disadvantages associated with the job-educational mismatches (Messinis and Olekalns, 2007; Van Smoorenburg and Van der

[1] It has been argued that overeducated workers are likely of lower ability and, therefore, that the wage penalty may be explained to a large extent by this unobserved heterogeneity (Green et al.; 1999, Sloane et al., 1999; Groot, 1996). This supports the idea that employers learn about the productive abilities of overeducated employees and pay them lower wages.

Velden, 2000). That is, training contributes not only to close the gap between actual and required education of undereducated workers through the acquisition of new skills, but also offsets the depreciation and facilitates the restoration of human capital, especially in the case of overeducated and older workers, and employees that experience job-technological innovations or job-career interruptions. Messinis and Olekalns (2008) found that training participation relates to substantial wage benefits for undereducated workers in relation to their co-workers with higher education, but also that training enables overeducated workers to reduce the wage penalty associated with the mismatch. Yet again, the question whether the contribution of training and informal learning to workers' skills improvement differs by their initial mismatch status has not been analysed in the empirical literature.

3. DATA AND DESCRIPTIVE ANALYSES

3.1 Data and sample

We use data from the *European Skills Survey*, conducted in 2014 by Cedefop in 28 European countries. It was based on a representative sample of the 24 to 65 working population in each of the participant countries and administered either online or by telephone to 48,676 individuals.[2] This is a unique dataset that measures employees' change in skills accumulation as well as change in skills mismatch over years of tenure with the same employer. Comparable measures are not available in any other large scale dataset. Furthermore, this survey provides rich information on both the incidence of training and the intensity of informal learning in the workplace, in addition to other individual, job and employer characteristics. We restricted our analyses to full-time employees[3], leaving us with a sample of 37,177 individuals. Table A1 in the appendix shows the distribution of the sample by country.

3.2 Variables and descriptive analyses

Table A2 in the appendix shows the main descriptive statistics of the variables included in our analysis.

3.2.1 Dependent variable

Our main outcome variable, workers' skills development is based on the self-assessed change in skills[4] since the start of their current job. It is derived from the following question: *'Compared to when you started your job with your current employer, would you say your skills have now improved, worsened or stayed the same? Please use a scale of 0 to 10 where 0 means your skills have worsened a lot, 5 means they have stayed the same and 10 means they have improved a lot'*. The response rate to this question was 98 percent, only 2 percent of employees stated to have current skills not comparable to those they had before or not to know the answer to the question. The mean reported skills development is 7.77 with a standard deviation of 1.77. Table 2 shows the distribution of this variable. As shown in

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[2] See Ipsos MORI (2014) for further details about validation of data.
[3] We consider full-time employees those who reported a minimum of 35 working hours a week.
[4] Skills were defined for the respondents to the survey as 'all of the knowledge, abilities, and competences that you have gained as part of your education and also during the time you have been working'.

the table, approximately 86 percent of individuals in the sample report that their skills have improved (scores 6-10) whereas 14 percent indicate that their skills have stayed the same (score 5) or have worsened (scores 1-4).

Table 2. Distribution of skills development

Skills change	Percent
My skills have worsened a lot (0)	0.2
1	0.2
2	0.5
3	0.8
4	1.3
My skills have stayed the same (5)	10.9
6	7.5
7	16.9
8	25.0
9	17.1
My skills have improved a lot (10)	19.7

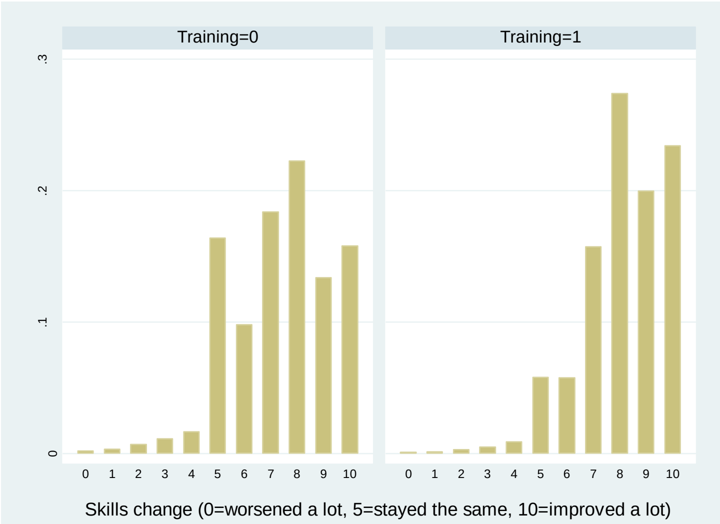
3.2.2 Explanatory variables

First, we distinguish two types of work-related learning: training and informal learning on-the-job. Second, we distinguish between workers who experienced a mismatch at the start of their current job and those who did not.

- Training is a dummy variable that takes the value 1 if the employee has participated in training courses since the start of the current job and 0 otherwise. It is based on the question: *Since you started your job with your current employer, have you attended training courses (work-based, classroom based and online)?* As this question has only been asked to those who reported to have experienced a positive skills development, we impute the information on training participation in the last 12 months for those whose skills declined.[5] Table A2 shows that 62 percent of all employees in our sample have participated in training courses at least once since they started their current job, while 57 percent did so during the last 12 months. Among the latter we observe that 44 percent followed their training during working hours while 22 percent followed it outside working hours. As shown in Graph 1, the density distribution of employees' development of skills shifts to the right when workers participate in training. This already indicates a positive relation between training participation and skills development.

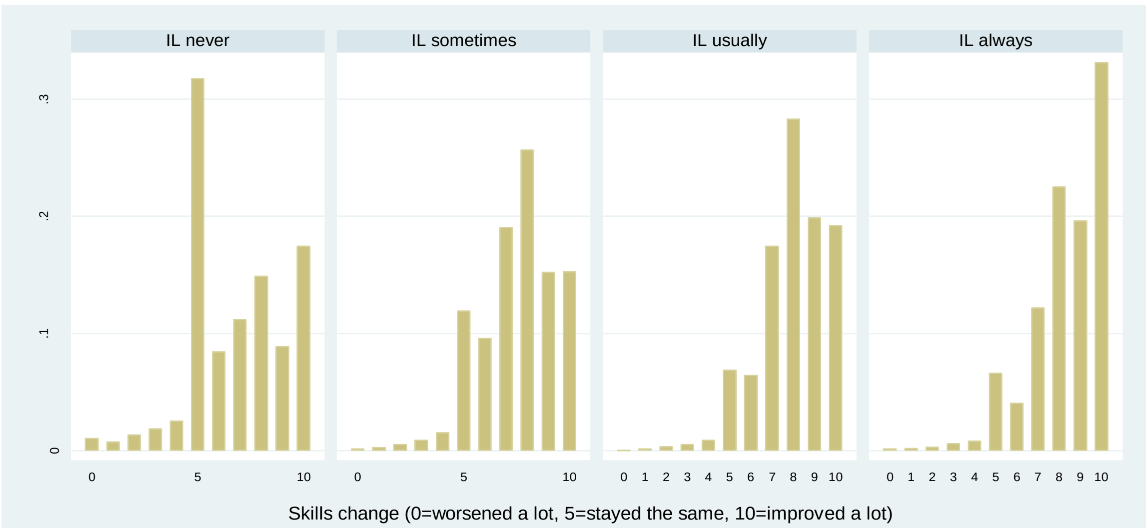
[5] 81 percent of workers, who answered both questions on training participation since the start of their job and during the last 12 months, participated at least once in training during their tenure with the current employer. Workers' answers to the two questions on training are highly positively correlated (0.64).

Graph 1. Skills development distribution by training participation



○ Informal learning (IL) is measured by a categorical variable derived from the question: *How often, if at all, does your job involve learning new things?* Respondents could answer '*never, sometimes, usually, and always*'. Table A2 shows that 55 percent of all full-time employees in our sample stated to learn informally usually or always at work whereas only 4 percent said they never learn anything on-the-job. Importantly, as shown in Graph 2, the density distribution of skills improvement concentrates more to the right when workers are more often involved in informal learning. This gives some first evidence that informal learning is also positively related to skills development of workers. In additional analyses, we differentiate three types of informal learning by including dummy variables for 1) learning from colleagues and supervisors, 2) learning by trial and error, 3) learning from self-study.[6]

Graph 2. Skills development distribution by frequency of informal learning



[6] These variables are based on the question: *Since you started your job with your current employer, have you done any of the following to improve or acquire new skills? a) Your supervisor taught you on-the-job, b) You learned by interacting with colleagues at work, c) You learned at work through trial and error, and d) You learned by yourself (e.g. with the aid of manuals, books, videos or on-line materials*). Respondents could indicate as many of these informal leaning types as applicable.

○ Initial job-skills match status is a categorical variable that takes three different values (initially well-matched, initially under-skilled, initially over-skilled) corresponding to the three possible responses to the question: *When you started your job with your current employer, overall, how would you best describe your skills in relation to what was required to do your job at that time? a) My skills were matched to what was required by my job, b) Some of my skills were lower than what was required by my job and needed to be further developed), or c) My skills were higher than required by my job.* In our sample, 51 percent of all full-time employees stated to have a good skills match at the start of their jobs while 24 percent considered themselves initially under-skilled and 25 percent initially over-skilled. As shown in Graph 3, the distribution of skills development differs between the three different groups in favour of these employees who were initially under-skilled. We also observe significant differences in the mean value of the variable skills development by skills mismatch status, which is 7.81 for the well-matched, 8.41 for the under-skilled and, and 7.15 for the over-skilled. This suggests that workers who start a job with fewer skills than required have the largest skills progress when gaining years of tenure.

Graph 3. Skills development distribution by initial job-skills match status

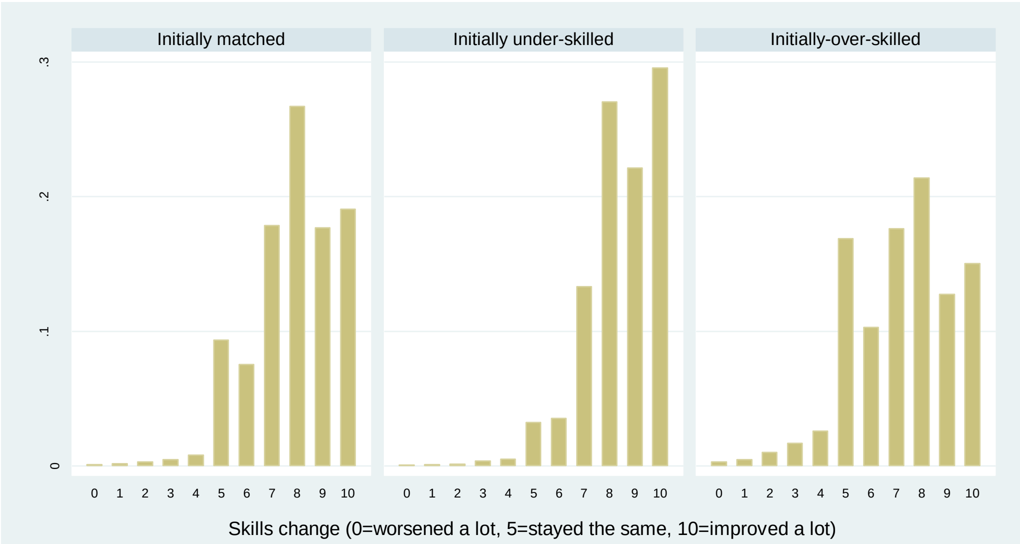
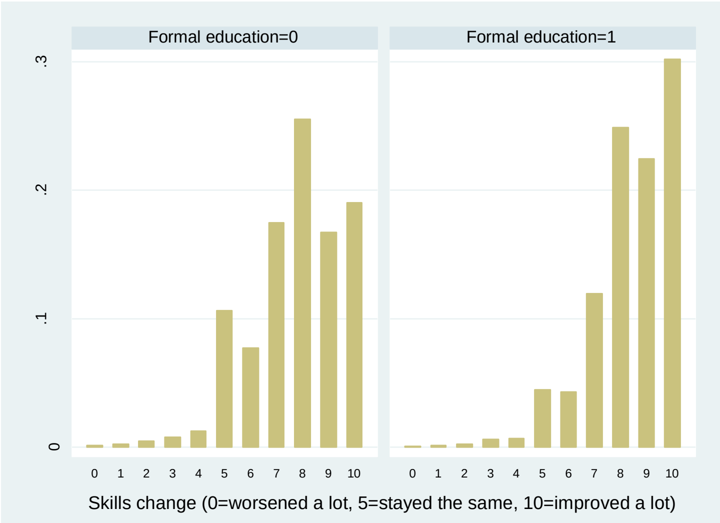


Table A2 shows some other differences between the initially under-skilled and over-skilled workers. In the group of employees who claimed to be initially over-skilled there is a slightly higher proportion of males, higher educated individuals and, workers with temporary contracts and fewer years of tenure. In addition, among professionals, technicians and crafts or related trades occupations there is a higher percentage of under-skilled workers whereas over-skilled workers represent a higher share in the sales and transportation industries. It is worth mentioning that there is no difference in workers' age between the three skills match groups (m= 42, s.d. = 9.8) nor in the size of the firm where they are employed.

- *Control variables:*

First, we explicitly include the participation in formal education which has led to a higher degree while working for the current employer as a control variable in our model. This variable measures human capital investments in the form of schooling rather than job-related learning. Formal education is a dummy variable of participation in formal educational programmes resulting in a higher or different educational degree while working for the current employer. We constructed this variable by imputing the value 1 for those who achieved their highest level of education in a year after they started to work with their current employer and 0 otherwise. As shown in Table A2, 14 percent of all employees in our sample participated in formal education while working for their current employer. Graph 4 shows that skills development is larger for this group.

Graph 4. Skills development distribution by participation in formal education



Second, the questionnaire contains information about individual, current job and firm characteristics. As suggested by human capital theory, we control for age, gender, educational level (low, middle and high), firm tenure, type of contract (permanent, fixed-term temporary, agency temporary and no formal contract), occupation (nine ISCO 1-digit categories), industry (ten ISIC 1-digit categories), firm size (five categories), and country dummies. In addition, we include a dummy variable that indicates whether the survey has been answered by telephone.

4. ESTIMATION METHOD

To estimate the relationship between employees' job-related learning and skills development we use ordered probit models. The fact that responses to our dependent variable are concentrated at some categories suggests that the meaning of certain categories is more expansive than others. In this case, OLS estimation is likely to give misleading results (Winship and Mare, 1984; Long, 1997). Therefore, we consider the self-reported measure of individuals' skills change as an ordinal structure in which the distances between the categories are unknown and allowed to be unequal.

Let SD_i denote an observable ordinal variable coded from 0 to 10 on the basis of responses to the individual skills change question described in the previous section. These choices are modelled based on an unobservable latent continuous variable (SD_i^*) that can be expressed as a function of a set of observable factors (Z_i) and unobservable factors (u_i) using the following linear relationship:

$$\begin{aligned} SD_i^* &= \boldsymbol{Z}_i'\boldsymbol{\beta} + u_i \\ &= \boldsymbol{\gamma}'X_i + \delta L_i + \zeta ISM_i + \psi(L_i * ISM_i) + u_i \end{aligned} \qquad (1)$$

where X is a vector of covariates composed by worker and firm characteristics along with a set of country dummies, L is a vector of participation in training and informal learning variables, *ISM* is an indicator of the initial job-skills match, and u_i~$N(0, 1)$. The existence of a set of *K-1* ordered threshold parameters is also assumed such that the individual responds category k if and only if $SD_i^* \epsilon \left[\theta_{k-1,}\theta_k\right]$. In general terms we can write: $Prob(SD_i = k \mid \boldsymbol{Z}_i) = \Phi(\theta_k - \boldsymbol{Z}_i'\boldsymbol{\beta}) - \Phi(\theta_{k-1} - \boldsymbol{Z}_i'\boldsymbol{\beta})$ *for* $k = 0, \ldots K$ where $\Phi(\cdot)$ denotes the cumulative distribution function of u_i for the standard normal. The first and the final intervals are open-ended, so for $k = 0$, $\Phi(\theta_{k-1}) = \Phi(-\infty) = 0$ and for $k = 10$, $\Phi(\theta_k) = \Phi(+\infty) = 1$. The regression parameters $\gamma, \delta, \zeta, \psi$ and the *K-1* threshold parameters are obtained by maximising the log likelihood function subject to $\theta_k > \theta_{k-1}$ for all k. We use a robust clustered estimator of variance to allow for intragroup correlation at the country level (Wooldridge, 2010).

As described above, in our analysis we consider interactions between the learning variables *L* (training, informal learning and formal education) and the employee's initial skills match *ISM*. As Karaca-Mandic *et al.*(2011), Greene (2010) and Norton *et al.*(2004) have shown, the interpretation of interaction terms in linear models does not extend to nonlinear models. Basically, the interaction effect in nonlinear models cannot be evaluated by looking at the sign, magnitude, or statistical significance of the coefficient on the interaction term (Ai and Norton, 2003). For nonlinear models that include interactions between categorical variables as we have in this paper, the interaction effect becomes the following discrete double difference:

$$\begin{aligned} \frac{\Delta^2\Phi(\boldsymbol{Z}'\boldsymbol{\beta})}{\Delta L * \Delta ISM} &= \frac{\Delta\{\Phi[\delta + \zeta ISM + \psi(L * ISM) + \boldsymbol{\gamma}'X] - \Phi[\zeta ISM + \boldsymbol{\gamma}'X]}{\Delta ISM} \\ &= \Phi(\delta + \zeta + \psi + \boldsymbol{\gamma}'X) - \Phi(\delta + \boldsymbol{\gamma}'X) - \Phi(\zeta + \boldsymbol{\gamma}'X) + \Phi(\boldsymbol{\gamma}'X)^2 \end{aligned} \qquad (2)$$

Some implications need to be taken into account. First, the interaction effects in nonlinear models are conditional on the independent variables. Second, since there are two additive terms that can be each positive or negative, the interaction effects may have opposite signs for different observations and, therefore, the sign of ψ does not always reflect the sign of the interaction effects. Third, even if ψ is zero, the interaction effects could be nonzero. Finally, the statistical significance tests of the interaction terms need to be associated with the entire double difference (Karaca-Mandic et al., 2011; Greene, 2010; Norton et al., 2004). Taking these implications into account, we compute and report, as suggested by Long and Freese (2014) and Karaca-Mandic *et al.*(2011), full interaction marginal effects (cross-differences) and its statistical significance by different groups to correctly interpret our results.

5. ESTIMATION RESULTS

5.1 Work-related learning and skills development

In Table 3 we estimate two ordered probit regressions for skills development.[7] The first specification gives the coefficients without the interaction terms between the learning variables and the initial skills mismatch status and the second specification includes these interactions. To see whether there is heterogeneity in the relation between job-related learning and skills development, we include interaction terms in column (2).[8] In general, we also observe that the estimated threshold parameters are not equally spread out, implying that the meanings of certain categories is more expansive than others (specifically those corresponding to categories 5 and 6, and 9 and 10) and, therefore, that nonlinear estimations are more accurate.

Table 3. Ordered probit coefficients for skills development

Skills change	(1) Oprobit	(2) Oprobit with interactions
Training	0.3154***	0.3127***
	(0.0218)	(0.0221)
IL sometimes	0.3284***	0.3026***
	(0.0576)	(0.0618)
IL usually	0.5515***	0.4972***
	(0.0644)	(0.0692)
IL always	0.7993***	0.7487***
	(0.0702)	(0.0741)
Formal education	0.1550***	0.1412***
	(0.0204)	(0.0283)
Under-skilled	0.3243***	0.5281***
	(0.0153)	(0.0769)
Over-skilled	-0.2496***	-0.4564***
	(0.0243)	(0.0839)
Training courses # Under-skilled		-0.0358
		(0.0232)
Training courses # Over-skilled		0.0561***
		(0.0202)
IL sometimes # Under-skilled		-0.1599**
		(0.0773)
IL sometimes # Over-skilled		0.1136
		(0.0801)
IL usually # Under-skilled		-0.1512**
		(0.0746)
IL usually # Over-skilled		0.2170***
		(0.0799)

[7] T-tests of differences between the 10 cut points obtained from the ordered models were all significant at 95 percent of confidence. Therefore, we kept the 0-10 scale original structure of the dependent variable to estimate our models.

[8] Specification (2) seems to be the most favourable one for two reasons. First, the likelihood-ratio test (LR chi^2 = 61.45) evaluated at 10 degrees of freedom is highly significant (Prob>chi^2 = 0.0000) suggesting that the effect of the interaction terms on skills development identification is significant. Second, the difference of 63.6 points in the BIC statistic between the two models provides strong support for the second model.

	(1)	(2)
IL always # Under-skilled		-0.1704**
		(0.0809)
IL always # Over-skilled		0.2184**
		(0.0907)
Formal education # Under-skilled		-0.0270
		(0.0326)
Formal education # Over-skilled		0.1032**
		(0.0430)
Age	-0.0084***	-0.0084***
	(0.0015)	(0.0015)
Female	0.2091***	0.2095***
	(0.0178)	(0.0176)
Intermediate level education	-0.0669***	-0.0629**
	(0.0247)	(0.0247)
High level education	-0.2039***	-0.1979***
	(0.0293)	(0.0295)
Years of tenure	0.0218***	0.0218***
	(0.0015)	(0.0015)
Temporary contract	-0.1237***	-0.1228***
	(0.0162)	(0.0156)
Agency contract	-0.2625***	-0.2625***
	(0.0743)	(0.0735)
No formal contract	-0.0232	-0.0274
	(0.0513)	(0.0494)
Telephone (interviewed)	0.1162***	0.1119***
	(0.0411)	(0.0409)
Other controls	yes	yes
cut1	-2.6580*** (0.1176)	-2.7025*** (0.1150)
cut2	-2.3398*** (0.1163)	-2.3835*** (0.1143)
cut3	-2.0414*** (0.1165)	-2.0844*** (0.1149)
cut4	-1.7786*** (0.1146)	-1.8210*** (0.1147)
cut5	-1.5274*** (0.1125)	-1.5692*** (0.1134)
cut6	-0.6782*** (0.1002)	-0.7168*** (0.1022)
cut7	-0.3388*** (0.1076)	-0.3762*** (0.1088)
cut8	0.2349** (0.1150)	0.2085** (0.1006)
cut9	0.9661*** (0.1178)	0.9299*** (0.1194)
cut10	1.5415*** (0.1305)	1.5051*** (0.1317)
Pseudo R2	0.562	0.579
BIC-stat	7531.7	7595.3
N	37177	37177

The dependent variable *skills change* is measured by 11 ordinal categories from 0 to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Other controls include occupation, industry, firm size and country dummies. Standard errors clustered at country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimation results presented in Table 3 suggest that both participation in training and informal learning positively contribute to employees' skills development. This is in line with the expectations from human capital theory and our descriptive evidence. Yet, the coefficients from ordered models are not directly interpretable as we can only infer from the signs of the coefficients how an explanatory variable is related to the probability of the end categories (Greene, 2012; Wooldridge, 2010). As suggested by Long and Freese (2014) and Long (1997), we therefore provide in Table 4 the marginal effects of the estimates in column (2) of Table 3. To facilitate the interpretation, we computed the marginal effects in four categories: worsened skills (0-4), no or hardly any change in skills (5-6), intermediate improvement of skills (7-8), and high improvement of skills (9-10).[9]

[9] According to Long and Freese (2014), having more than two outcomes creates the challenge to summarise the effects of the independent variables in a way that fully reflects key substantive processes without overwhelming and distracting detail. We computed marginal effects in the mentioned four categories based on the criteria that the probabilities in the same group were of the same sign and similar size.

Table 4. Average marginal effects of estimates in Table 3 Column (2)

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Training	-0.0191***	-0.0627***	-0.0231***	0.1050***
	(0.0013)	(0.0043)	(0.0026)	(0.0074)
IL sometimes	-0.0310***	-0.0627***	0.0105***	0.0832***
	(0.0067)	(0.0111)	(0.0040)	(0.0157)
IL usually	-0.0449***	-0.1081***	-0.0049	0.1579***
	(0.0072)	(0.0123)	(0.0034)	(0.0176)
IL always	-0.0541***	-0.1516***	-0.0416***	0.2473***
	(0.0073)	(0.0126)	(0.0049)	(0.0201)
Formal education	-0.0091***	-0.0309***	-0.0147***	0.0547***
	(0.0010)	(0.0036)	(0.0031)	(0.0072)
Under-skilled	-0.0135***	-0.0612***	-0.0452***	0.1199***
	(0.0012)	(0.0028)	(0.0028)	(0.0057)
Over-skilled	0.0190***	0.0517***	0.0050***	-0.0758***
	(0.0020)	(0.0054)	(0.0017)	(0.0070)
Age	0.0005***	0.0016***	0.0008***	-0.0028***
	(0.0001)	(0.0003)	(0.0001)	(0.0005)
Female	-0.0113***	-0.0394***	-0.0212***	0.0719***
	(0.0012)	(0.0036)	(0.0016)	(0.0061)
Intermediate level education	0.0031***	0.0114**	0.0074**	-0.0218**
	(0.0012)	(0.0044)	(0.0030)	(0.0086)
High level education	0.0109***	0.0371***	0.0195***	-0.0675***
	(0.0017)	(0.0055)	(0.0031)	(0.0100)
Years of tenure	-0.0012***	-0.0041***	-0.0020***	0.0074***
	(0.0001)	(0.0003)	(0.0002)	(0.0005)
Temp contract	0.0074***	0.0239***	0.0100***	-0.0413***
	(0.0011)	(0.0034)	(0.0010)	(0.0053)
Agency contract	0.0179***	0.0524***	0.0158***	-0.0860***
	(0.0060)	(0.0157)	(0.0015)	(0.0229)
No formal contract	0.0015	0.0052	0.0026	-0.0093
	(0.0028)	(0.0095)	(0.0045)	(0.0168)
Telephone	-0.0059***	-0.0209***	-0.0117**	0.0385***
	(0.0020)	(0.0076)	(0.0046)	(0.0142)

This table shows average marginal effects computed based on the ordered probit specification (2) in Table 3. The dependent variable *skills change* is measured by 11 ordinal categories from 0 to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Marginal effects on skills change are grouped in four categories: worsened (0-4), no or hardly any change (5-6), intermediate improvement (7-8), and high improvement (9-10). The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As we observe in Table 4, the impact of most explanatory variables on the probability of high improvement of skills is crucial in the way that it is offset by the distinctive probabilities of being in the other categories 0 to 8. The marginal effects confirm our descriptive results that the probability of high improvement of skills is larger for employees who participate in training and informal learning. Workers who participated in training are on average 10.5 percentage points more likely of highly improving their skills than those who did not participate in any training course. Likewise, participation in training reduces the odds of experiencing skills worsening and stagnation by 1.9 and 6.3 percentage points, respectively. Also employees' involvement in informal learning raises the probability of improving their skills. For instance, the likelihood of a high improvement of skills is 27, 18 and 11 percentage points larger for workers who are respectively always, usually and sometimes learning informally on-the-job in comparison with those who never get involved in informal learning in their job. The marginal effects show that informal learning seems to be more important for increasing the probability of highly improving employees' skills than training participation.

Moreover, we find that the initial skill mismatch significantly explains workers' skills development over time. We find that initially under-skilled workers develop their skills more than those who started in a job that well-matched their skills. On the contrary, over-skilled workers are more likely to experience skills worsening (by 1.9 percentage points) and stagnation (by 5.2 percentage points) than well-matched employees, which confirms the evidence on skill depreciation shown in De Grip *et al.*(2008).

In terms of the other covariates in our model, we find that the marginal probability of workers' skills development over time decreases with age and is lower for employees who are more educated, and for those who have temporary or agency contracts instead of permanent contracts. Conversely, it increases with participation in formal education, years of tenure (which compensates the negative effect of age by approximately 2.5 times), and tends to be higher for female employees and for those who answered the survey by phone. Other controls indicate that high skills development is less likely for individuals employed in low-skilled occupations and for those employed in large firms with more than 500 employees.

5.2 Heterogeneous effects by initial skills mismatch status

As explained in Section 4, the interpretation of interaction terms in linear models does not extend to nonlinear models; therefore we compute marginal effects and statistical significance by different initial skills mismatch statuses of workers to understand the heterogeneous effects of training and informal learning on skills development in relation to the initial skill match. Two types of heterogeneous effects can be analysed with the interaction terms. First, the difference in skills development between those who have been engaged in learning and those who do not within the same initial job-skills match group, and second, the difference between the three skills mismatch statuses regarding the benefit of training and informal learning for skills development. The tables 5 and 6 show these results, respectively.

Table 5 shows that the findings of Table 4 that participation in both training and informal learning contribute to a large extent to the probability of high skill development hold for all workers, independent of their initial skill mismatch. Compared to workers with the same initial skill mismatch status, those who participate in training or informal learning are more likely to improve their skills considerably than those who have not been involved in any learning activity. Most remarkably, also among initially over-skilled employees, training courses and informal learning seem to contribute to their skills development. For instance, over-skilled workers who participate in training or state that they are always engaged in informal learning are respectively 11 and 28 percentage points more likely to highly develop their skills than over-skilled workers who do not participate in training or are never engaged in informal learning on-the-job. This might be because over-skilled employees that invest in the development of their human capital acquire new skills that are different from the ones they have previously accumulated (e.g. non-technical or non-cognitive skills) or functional to offset skills depreciation. The latter explanation could be inferred from the significantly greater marginal effects for over-skilled workers in the categories 5-6 (i.e. more or less stable skills) in all types of learning.

Table 5. Marginal effects of investments in learning by initial job-skills match group

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Training courses				
Match	-0.0169***	-0.0649***	-0.0269***	0.1087***
	(0.0015)	(0.0046)	(0.0024)	(0.0075)
Under-skilled	-0.0068***	-0.0410***	-0.0466***	0.0943***
	(0.0011)	(0.0068)	(0.0071)	(0.0146)
Over-skilled	-0.0317***	-0.0815***	0.0000	0.1131***
	(0.0025)	(0.0058)	(0.0026)	(0.0074)
IL sometimes				
Match	-0.0257***	-0.0690***	0.0014	0.0933***
	(0.0067)	(0.0140)	(0.0036)	(0.0172)
Under-skilled	-0.0057	-0.0273	-0.0193**	0.0523*
	(0.0039)	(0.0169)	(0.0098)	(0.0306)
Over-skilled	-0.0598***	-0.0889***	0.0500***	0.0987***
	(0.0143)	(0.0141)	(0.0137)	(0.0152)
IL usually				
Match	-0.0363***	-0.1099***	-0.0147***	0.1609***
	(0.0072)	(0.0152)	(0.0033)	(0.0199)
Under-skilled	-0.0113***	-0.0612***	-0.0564***	0.1288***
	(0.0038)	(0.0161)	(0.0097)	(0.0291)
Over-skilled	-0.0852***	-0.1559***	0.0508***	0.1903***
	(0.0151)	(0.0157)	(0.0137)	(0.0172)
IL always				
Match	-0.0453***	-0.1555***	-0.0529***	0.2537***
	(0.0074)	(0.0155)	(0.0044)	(0.0220)
Under-skilled	-0.0152***	-0.0920***	-0.1087***	0.2159***
	(0.0040)	(0.0180)	(0.0138)	(0.0349)
Over-skilled	-0.0987***	-0.2075***	0.0277**	0.2785***
	(0.0153)	(0.0165)	(0.0102)	(0.0212)
Formal education				
Match	-0.0067***	-0.0275***	-0.0159***	0.0501***
	(0.0014)	(0.0053)	(0.0035)	(0.0101)
Under-skilled	-0.0027***	-0.0173***	-0.0226***	0.0425***
	(0.0007)	(0.0047)	(0.0066)	(0.0120)
Over-skilled	-0.0173***	-0.0510***	-0.0113***	0.0797***
	(0.0021)	(0.0067)	(0.0024)	(0.0104)

This table shows average marginal effects computed based on the ordered probit specification (2) in Table 3. The dependent variable *skills change* is measured by 11 ordinal categories from 0 to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Marginal effects on skills change are grouped in four categories: worsened (0-4), no or hardly any change (5-6), intermediate improvement (7-8), and high improvement (9-10). The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 shows the differences in skills development of workers who have been involved in training and/or informal learning between the three skill mismatch groups. It shows a clear distinction in the efficiency of the different types of learning for workers' skills development between under-skilled and over-skilled employees. In comparison with those who started in a job that matched their skills, initially under-skilled workers appear to benefit most from both training and informal learning whereas those who were initially over-skilled benefit the least. For instance, under-skilled employees who participated in training or are always learning informally on-the-job are respectively 13 and 15.6

percentage points more likely to be in the two highest categories of skills development than well-matched workers with similar learning investments. For under-skilled workers the positive influence of having a job above their skills level which is probably more demanding makes learning on-the-job more favourable for their skills development. This might be related to a larger interest in maintaining their jobs and richer learning opportunities at work (De Grip et al., 2008).

Conversely, over-skilled employees who participated in training are on average 7.5 percentage points less likely to developing their skills than similar workers in a well-matching job. This means that trained over-skilled employees are more likely to experience skills depreciation and stagnation than well-matched workers, by approximately 1.3 and 4.6 percentage points, respectively. This also holds for informal learning. Compared to well-matched workers with similar learning investments, over-skilled employees who report that they always learn informally in their job are 6.3 percentage points less likely to improve their skills and are more likely to experience skills worsening and stagnation, by approximately 0.5 and 3.1 percentage points, respectively. However, as mentioned earlier, the more often over-skilled workers are engaged in informal learning, the lower the probability of skills worsening and stagnation. For over-skilled workers the fact of having a job below their skills not only negatively affects their learning participation but also makes training and informal learning on-the-job much less beneficial for their skills development than for those who are employed in a well-matching job. This again suggests that learning investments of over-skilled workers prevent skills depreciation instead of fostering skills accumulation.

Table 6. Marginal effects between the initial job-skills match groups

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
UNDER-SKILLED				
Training courses	-0.0193***	-0.0762***	-0.0343***	0.1298***
	(0.0019)	(0.0050)	(0.0044)	(0.0102)
IL sometimes	-0.0164***	-0.0668***	-0.0322***	0.1154***
	(0.0016)	(0.0033)	(0.0023)	(0.0062)
IL usually	-0.0113***	-0.0598***	-0.0532***	0.1243***
	(0.0012)	(0.0046)	(0.0044)	(0.0092)
IL always	-0.0364***	-0.1085***	-0.0115	0.1564***
	(0.0061)	(0.0152)	(0.0113)	(0.0253)
Formal education	-0.0099***	-0.0523***	-0.0516***	0.1138***
	(0.0009)	(0.0043)	(0.0048)	(0.0090)
OVER-SKILLED				
Trained	0.0126***	0.0461***	0.0166***	-0.0753***
	(0.0014)	(0.0048)	(0.0019)	(0.0070)
IL sometimes	0.0263***	0.0670***	-0.0047**	-0.0887***
	(0.0032)	(0.0082)	(0.0023)	(0.0093)
IL usually	0.0115***	0.0409***	0.0143***	-0.0667***
	(0.0016)	(0.0053)	(0.0020)	(0.0081)
IL always	0.0051***	0.0309***	0.0273***	-0.0633***
	(0.0015)	(0.0067)	(0.0045)	(0.0123)
Formal education	0.0092***	0.0312***	0.0104***	-0.0509***
	(0.0020)	(0.0068)	(0.0039)	(0.0121)

This table shows average marginal effects computed based on the ordered probit specification (2) in Table 3. The dependent variable *skills change* is measured by 11 ordinal categories from 0 to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Marginal effects on skills change are grouped in four categories: worsened (0-4), no or hardly any change (5-6), intermediate improvement (7-8), and high improvement (9-10). The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 What types of job-related learning matter the most for skills development?

5.3.1 Two types of training

In this section we analyse whether training participation during or outside working hours is more important for workers' skills development. We run the same regression as specification (2) in Table 3 but instead of the single training participation variable we include two separate variables for training during and outside regular working hours.[10]

Results in Panel 1 of Table 7 show that training undertaken in working hours is, in general, more beneficial for workers' skills development than training outside working hours. Panel 2 shows that this holds within each skill-match group. However, among the over-skilled workers the difference between the marginal effects of training during and outside working hours is much lower than in the other two skill mismatch groups. This suggests that training outside working hours is probably more important for over-skilled workers to retain or improve their skills for possible future jobs. Panel 3 shows that in comparison to well-matched workers, both training during and training outside regular working hours are equally more beneficial for under-skilled workers. For over-skilled employees, however, both types of training are less beneficial, although they are important to maintain their skills level. Training during working hours seems to contribute slightly more to this skills maintenance of over-skilled workers than training outside working hours.

Table 7. Marginal effects of training during and outside working hours

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
1. AME				
Training in working hours	-0.0119***	-0.0400***	-0.0176***	0.0695***
	(0.0008)	(0.0026)	(0.0019)	(0.0048)
Training outside working hours	-0.0072***	-0.0227***	-0.0088***	0.0387***
	(0.0006)	(0.0022)	(0.0013)	(0.0036)
2.AME within the same initial job-skill match group				
Training in working hours				
Match	-0.0103***	-0.0406***	-0.0201***	0.0710***
	(0.0010)	(0.0033)	(0.0021)	(0.0059)
Under-skilled	-0.0041***	-0.0254***	-0.0315***	0.0609***
	(0.0005)	(0.0032)	(0.0038)	(0.0073)
Over-skilled	-0.0201***	-0.0539***	-0.0043**	0.0783***
	(0.0018)	(0.0050)	(0.0018)	(0.0072)
Training outside working hours				
Match	-0.0049***	-0.0194***	-0.0102***	0.0345***
	(0.0006)	(0.0028)	(0.0019)	(0.0052)
Under-skilled	-0.0019***	-0.0117***	-0.0148***	0.0283***
	(0.0005)	(0.0032)	(0.0042)	(0.0079)
Over-skilled	-0.0145***	-0.0401***	-0.0058***	0.0604***
	(0.0018)	(0.0062)	(0.0022)	(0.0096)
3.AME between the initial job-skill match groups				
UNDER-SKILLED				
Training in working hours	-0.0101***	-0.0543***	-0.0543***	0.1187***
	(0.0009)	(0.0027)	(0.0030)	(0.0055)
Training outside working hours	-0.0113***	-0.0566***	-0.0513***	0.1192***
	(0.0015)	(0.0056)	(0.0053)	(0.0118)

[10] We use the same sample as in our main results (37,177 observations).

OVER-SKILLED				
Training in working hours	0.0133***	0.0457***	0.0147***	-0.0738***
	(0.0018)	(0.0059)	(0.0022)	(0.0090)
Training outside working hours	0.0115***	0.0366***	0.0094***	-0.0575***
	(0.0027)	(0.0085)	(0.0027)	(0.0133)

This table shows average marginal effects computed based on an ordered probit regression similar to specification (2) in Table 3 that includes two separate variables for training during and outside regular working hours instead of the single training participation variable. The dependent variable *skills change* is measured by 11 ordinal categories from 0 to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Marginal effects on skills change are grouped in four categories: worsened (0-4), no or hardly any change (5-6), intermediate improvement (7-8), and high improvement (9-10). The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Three types of informal learning

In this section, we analyse whether there are any differences in the relevance of different types of informal learning on-the-job for workers' skills development. We run the same regression as in Table 3 Column (2) but now include three dummy variables on informal learning to account for i) informal learning from others (co-workers and supervisors), ii) informal learning by trial and error, and iii) informal leaning by self-study. Since the question for the different types of informal learning was only asked to those who reported a positive skills change (i.e., categories 6-10), we here only use a sample of 31,954 observations.

Panel 1 of Table 8 shows that informal learning from others and by self-study equally contribute to the positive skills development of workers whereas the contribution of learning by trial and error seems to be slightly lower. A possible explanation for this is the possible higher cost of mistakes when workers learn by trial and error in comparison with the other two types of informal learning. This would make the skills benefits of learning by self-study or from colleagues and supervisors to be larger. Panel 2 shows that these results only hold for well-matched employees. Within the group of under-skilled workers, learning by self-study is clearly more beneficial than learning from others for their skills improvement, while there does not seem to be any significant difference in skills progress between those who are involved in learning by trial and error and those who are not. In contrast, for the skills improvement of over-skilled workers, informal learning from colleagues and supervisors appears to be more important than learning by trial and error, whereas learning by self-study does not seem to make any significant contribution.[11] Panel 3 shows again that in comparison to the well-matched workers with similar informal learning participation, under-skilled workers benefit more from all three types of informal learning while over-skilled benefit less.

[11] Note, however, that we cannot make any inference regarding skills maintenance or decline in this section due to the sample truncation.

Table 8. Marginal effects of different types of informal learning

Skills change	6	7	8	9	10
1. AME level					
IL from others	-0.0118***	-0.0139***	-0.0043***	0.0068***	0.0232***
	(0.0028)	(0.0031)	(0.0011)	(0.0016)	(0.0053)
IL by trial and error	-0.0073***	-0.0082***	-0.0020*	0.0044***	0.0131***
	(0.0016)	(0.0021)	(0.0011)	(0.0010)	(0.0037)
IL by self-study	-0.0094***	-0.0130***	-0.0060***	0.0052***	0.0233***
	(0.0024)	(0.0027)	(0.0010)	(0.0016)	(0.0042)
2.AME within the same initial skill-match group					
IL FROM OTHERS					
Match	-0.0110***	-0.0126***	-0.0031***	0.0067***	0.0200***
	(0.0039)	(0.0042)	(0.0010)	(0.0024)	(0.0066)
Under-skilled	-0.0096***	-0.0156***	-0.0093***	0.0050***	0.0295***
	(0.0036)	(0.0054)	(0.0031)	(0.0018)	(0.0102)
Over-skilled	-0.0157***	-0.0156***	-0.0018***	0.0096***	0.0235***
	(0.0048)	(0.0045)	(0.0006)	(0.0030)	(0.0066)
IL BY TRIAL AND ERROR					
Match	-0.0084***	-0.0098***	-0.0026***	0.0051**	0.0157***
	(0.0031)	(0.0037)	(0.0010)	(0.0020)	(0.0057)
Under-skilled	-0.0020	-0.0034	-0.0021	0.0010	0.0066
	(0.0027)	(0.0044)	(0.0028)	(0.0013)	(0.0085)
Over-skilled	-0.0103**	-0.0106**	-0.0015**	0.0063**	0.0161**
	(0.0047)	(0.0047)	(0.0007)	(0.0028)	(0.0071)
IL BY SELF-STUDY					
Match	-0.0118***	-0.0138***	-0.0038***	0.0072***	0.0221***
	(0.0036)	(0.0042)	(0.0011)	(0.0023)	(0.0067)
Under-skilled	-0.0132***	-0.0220***	-0.0138***	0.0067***	0.0423***
	(0.0026)	(0.0050)	(0.0032)	(0.0019)	(0.0091)
Over-skilled	-0.0010	-0.0010	-0.0002	0.0006	0.0015
	(0.0045)	(0.0047)	(0.0007)	(0.0027)	(0.0071)
2.AME between the initial skill-match groups					
UNDER-SKILLED					
IL from others	-0.0327***	-0.0457***	-0.0208***	0.0187***	0.0805***
	(0.0025)	(0.0031)	(0.0019)	(0.0016)	(0.0061)
IL by trial and error	-0.0304***	-0.0426***	-0.0194***	0.0174***	0.0751***
	(0.0029)	(0.0031)	(0.0019)	(0.0017)	(0.0063)
IL by self-study	-0.0336***	-0.0489***	-0.0240***	0.0190***	0.0875***
	(0.0030)	(0.0047)	(0.0026)	(0.0024)	(0.0078)
OVER-SKILLED					
IL from others	0.0122***	0.0144***	0.0038***	-0.0076***	-0.0228***
	(0.0039)	(0.0038)	(0.0009)	(0.0022)	(0.0059)
IL by trial and error	0.0125***	0.0147***	0.0039***	-0.0078***	-0.0233***
	(0.0043)	(0.0044)	(0.0009)	(0.0026)	(0.0067)
IL by self-study	0.0183***	0.0207***	0.0047***	-0.0114***	-0.0324***
	(0.0050)	(0.0049)	(0.0009)	(0.0030)	(0.0075)

This table shows average marginal effects computed based on an ordered probit regression similar to specification (2) in Table 3 that includes three dummy variables to account for the three different types of informal learning. Since the question for the different types of informal learning was only asked to those who reported a positive skills change, the dependent variable *skills change* in this regression only takes values from 6 to10. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. CONCLUSIONS

In this paper, we have analysed to what extent training and informal learning on-the-job are related to the skills development of workers in 28 European countries. Consistent with the expectations from human capital theory, we found that employees who are involved in training and informal learning show a higher improvement of their skills. In line with Mincer's (1974) claim, we also found that informal learning seems to be more important to improve workers' skills than training participation.

We have also analysed the heterogeneity in the relationship between job-related learning and skills development in regard to workers' initial skill mismatch. First, our results showed that compared to workers with the same initial skill mismatch status, those who participate in training or informal learning are more likely to considerably improve their skills than those who have not been involved in any learning activity. Second, in comparison with those who started in a job that matched their skills, under-skilled workers appear to benefit most from training as well as informal learning whereas those who are over-skilled benefit the least. For under-skilled workers, the positive influence of having a job above their skills level makes job-related learning more favourable for their skills development. This might be related to a larger interest in maintaining their jobs and richer learning opportunities at work (De Grip *et al*., 2008). A plausible reason for that is that investments in learning of under-skilled workers contribute to close the gap between their actual skills and skills required at the workplace (Arulampalam *et al.*2004). In contrast, for over-skilled workers, having a job below their skills level not only negatively affects their learning participation but also makes training and informal learning on-the-job much less beneficial for their skills development compared to workers with a well-matching job. However, this is because learning investments of over-skilled workers are more functional to offset skills depreciation and maintaining their skills level rather than to foster skills accumulation. This result confirms De Grip (2006) and De Grip and van Loo's (2002) suggestion that adults' human capital accumulation may be a key mitigating factor counteracting skill obsolescence.

Last, we have analysed whether there are any differences in the relevance of different types of training and informal learning for workers' skills development related to their initial skills mismatch status. Our results first showed that, among the well-matched and under-skilled employees, training undertaken during working hours is far more beneficial for their skills development than training outside regular working hours. Among over-skilled workers, however, the difference between the influence of training during and outside working hours on a worker's skills improvement is rather small. In addition, training during working hours seems to contribute slightly more to the skills maintenance of over-skilled workers than training outside working hours. All in all, this suggests that training outside working hours is probably more important for over-skilled workers than for those who are well-matched or under-skilled in their job. In this way over-skilled workers might keep their skills not used at work up-to-date or improve their skills for possible future jobs.

In regard to the different types of informal learning, we found that for workers in well-matching jobs informal learning from others and by self-study equally contribute to the positive skills development of workers whereas the contribution of learning by trial and error seems to be slightly lower. A possible explanation for this is the likely higher cost of mistaking when learning by trial and error in comparison with the other two types of informal learning. This would make the skills benefits of learning by self-study or from colleagues and supervisors to be larger. Within the group of under-skilled workers, learning by self-study is more beneficial than learning from others for their skills improvement, while there does not seem to be any significant difference in skills progress between those who are involved in learning by trial and error and those who are not. In contrast, for the skills improvement of over-skilled workers, informal learning from colleagues and supervisors appears to be more important than learning by trial and error, whereas learning by self-study does not seem to make any significant contribution.

Concluding, we find significant evidence of heterogeneity in the role of training and informal learning on skills development with respect to workers' initial skills mismatch status. Knowledge about these heterogeneities is crucial to make efficient decisions on workers' human capital investments, given that lifelong learning and skills development of workers have been said to be central for economic progress and productivity (World Economic Forum, 2014). In that sense, optimal learning investments could also contribute to reduce the missadjustment between the workers' potential productivity and the optimal productivity of their jobs, created by skills mismatch in the labour market.

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APPENDIX

Table A1. Distribution of the sample

Country	***Obs.***	***% Sample***	***Initial match***	***Initially under-skilled***	***Initially over-skilled***
Germany (DE)	2,920	7.85	51.82	19.01	29.18
France (FR)	3,088	8.31	50.68	23.83	25.49
United Kingdom (UK)	2,822	7.59	41.74	23.99	34.27
Sweden (SE)	738	1.99	57.45	18.83	23.72
Italy (IT)	2,271	6.11	53.46	20.65	25.89
Greece (GR)	1,449	3.9	41.75	19.88	38.37
Czech Republic (CZ)	1,272	3.42	48.66	32.94	18.40
Poland (PL)	3,157	8.49	50.99	21.48	27.53
Netherlands (NL)	818	2.2	57.21	20.17	22.62
Denmark (DK)	690	1.86	52.17	24.00	23.83
Hungary (HU)	1,276	3.43	54.46	21.87	23.67
Spain (ES)	2,893	7.78	51.09	17.66	31.25
Austria (AT)	723	1.94	43.43	22.96	33.61
Belgium (BE)	1,001	2.69	52.55	20.18	27.27
Ireland (IE)	747	2.01	42.84	26.77	30.39
Slovakia (SK)	834	2.24	41.85	35.97	22.18
Finland (FI)	1,575	4.24	43.81	28.95	27.24
Portugal (PT)	1,280	3.44	57.73	23.98	18.29
Estonia (EE)	848	2.28	48.35	41.04	10.61
Romania (RO)	1,299	3.49	59.50	25.64	14.86
Lithuania (LT)	824	2.22	49.87	38.96	11.17
Cyprus (CY)	396	1.07	45.96	29.04	25.00
Slovenia (SI)	852	2.29	60.45	18.54	21.01
Bulgaria (BG)	881	2.37	55.73	27.01	17.26
Latvia (LV)	808	2.17	52.60	36.76	10.64
Luxembourg (LU)	420	1.13	73.57	11.43	15.00
Malta (MT)	408	1.1	57.60	28.92	13.48
Croatia (HR)	887	2.39	57.05	22.32	20.63
TOTAL	37,177	100	50.90	23.90	25.20

Table A2. Descriptive statistics 1

	ALL		***INITIAL WELL-MATCHED (51%)***		***INITIAL UNDER-SKILLED (24%)***		***INITIAL OVER-SKILLED (25%)***	
	Obs.	***Mean***	***Obs.***	***Mean***	***Obs.***	***Mean***	***Obs.***	***Mean***
Training (during tenure)	37177	0.62	18924	0.61	8886	0.70	9367	0.58
Training 12 months	37177	0.57	18924	0.56	8886	0.60	9367	0.55
Training in working hours	37177	0.44	18924	0.43	8886	0.49	9367	0.43
Training out. working hours	37177	0.22	18924	0.22	8886	0.20	9367	0.22
IL never	37177	0.04	18924	0.04	8886	0.02	9367	0.05
IL sometimes	37177	0.41	18924	0.40	8886	0.38	9367	0.45
IL usually	37177	0.33	18924	0.34	8886	0.36	9367	0.30
IL always	37177	0.22	18924	0.22	8886	0.23	9367	0.20
IL from others	31954	0.77	16459	0.76	8450	0.86	7045	0.72
IL by trial and error	31954	0.61	16459	0.58	8450	0.70	7045	0.58
IL by self-study	31954	0.56	16459	0.52	8450	0.63	7045	0.55
Formal education (during tenure)	37177	0.14	18924	0.13	8886	0.17	9367	0.11
Currently well-matched	37095	0.56	18878	0.70	8862	0.65	9355	0.19
Currently under-skilled	37095	0.06	18878	0.04	8862	0.15	9355	0.02
Currently over-skilled	37095	0.38	18878	0.26	8862	0.21	9355	0.79
Individual characteristics								
Age (24-65) s.d. = 9.8	37177	42.10	18924	42.39	8886	41.33	9367	42.25
Female	37177	0.39	18924	0.39	8886	0.42	9367	0.37
Low level of education	37177	0.12	18924	0.13	8886	0.12	9367	0.10
Intermediate level of education	37177	0.41	18924	0.43	8886	0.42	9367	0.38
High level of education	37177	0.47	18924	0.44	8886	0.47	9367	0.52
Years of tenure (0-50) s.d.= 9.1	37177	10.47	18924	10.82	8886	11.31	9367	8.96
Permanent contract	37177	0.87	18924	0.87	8886	0.88	9367	0.85
Fixed temporary contract	37177	0.10	18924	0.10	8886	0.09	9367	0.12
Temporary agency contract	37177	0.01	18924	0.01	8886	0.01	9367	0.01
No formal contract	37177	0.02	18924	0.02	8886	0.02	9367	0.02
Telephone (interviewed)	37177	0.21	18924	0.23	8886	0.24	9367	0.13
Industry								
Agriculture	37177	0.02	18924	0.02	8886	0.02	9367	0.02
Manufacturing	37177	0.19	18924	0.19	8886	0.21	9367	0.18
Construction	37177	0.06	18924	0.07	8886	0.06	9367	0.05
Sales and transportation	37177	0.20	18924	0.19	8886	0.17	9367	0.23
Information and communication	37177	0.07	18924	0.07	8886	0.08	9367	0.07
Financial and real state	37177	0.06	18924	0.06	8886	0.06	9367	0.06
Professional and Tech	37177	0.07	18924	0.07	8886	0.08	9367	0.06
Public administration	37177	0.25	18924	0.26	8886	0.25	9367	0.25
Other services	37177	0.08	18924	0.08	8886	0.07	9367	0.08
Occupation								
Managers	37177	0.09	18924	0.08	8886	0.09	9367	0.10
Professionals	37177	0.22	18924	0.22	8886	0.24	9367	0.18
Technicians	37177	0.17	18924	0.17	8886	0.19	9367	0.15
Service and sales workers	37177	0.12	18924	0.12	8886	0.11	9367	0.14
Clerical support	37177	0.21	18924	0.20	8886	0.18	9367	0.24
Skilled agricultural	37177	0.01	18924	0.01	8886	0.01	9367	0.01

Building, crafts or related trades	37177	0.08	18924	0.09	8886	0.09	9367	0.06
Plant and machine operators	37177	0.07	18924	0.07	8886	0.07	9367	0.08
Elementary	37177	0.04	18924	0.04	8886	0.03	9367	0.05
Firm size								
1-9	37177	0.20	18924	0.20	8886	0.20	9367	0.20
10-49	37177	0.28	18924	0.28	8886	0.29	9367	0.27
50-99	37177	0.13	18924	0.14	8886	0.12	9367	0.13
100-249	37177	0.13	18924	0.13	8886	0.13	9367	0.14
250-499	37177	0.08	18924	0.08	8886	0.08	9367	0.09
>500	37177	0.17	18924	0.17	8886	0.18	9367	0.17

Table A3. Estimations of training and informal learning participation

	(1) Probit AME Training	(2) Probit AME IL	(4) OLS IL intensity
Initially under-skilled	0.0682***	0.0476***	0.0553***
	(0.0067)	(0.0036)	(0.0113)
Initially over-skilled	-0.0045	-0.0165***	-0.0709***
	(0.0047)	(0.0032)	(0.0156)
Age	0.0053**	-0.0008***	-0.0099**
	(0.0022)	(0.0002)	(0.0044)
Age^2	-0.0001***	-0.0000	0.0001
	(0.0000)	(0.0001)	(0.0001)
Female	-0.0043	0.0005	-0.0047
	(0.0074)	(0.0038)	(0.0153)
Intermediate level of education	0.0540***	0.0087	0.0827**
	(0.0118)	(0.0059)	(0.0353)
High level of education	0.0935***	0.0187***	0.1319***
	(0.0125)	(0.0062)	(0.0328)
Years of tenure	0.0093***	-0.0008***	-0.0017**
	(0.0004)	(0.0002)	(0.0007)
Temporary contract	-0.0750***	0.0134*	0.0931***
	(0.0093)	(0.0069)	(0.0171)
Agency contract	-0.1365***	0.0290***	0.1237**
	(0.0362)	(0.0109)	(0.0515)
No formal contract	-0.1432***	-0.0011	0.0681
	(0.0231)	(0.0081)	(0.0504)
Learning attitude (std)	0.0156***	-0.0020	0.1269***
	(0.0029)	(0.0020)	(0.0142)
Other controls	*Yes*	*yes*	*yes*
N	37177	37177	37177

Columns (1) and (2) in this table show average marginal effects computed based on probit regressions. Column (3) reports OLS coefficients. Other controls include occupation, industry, firm size and country dummies. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.