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

Maria Ferreira[*ψ] Annemarie Künn-Nelen[*¥] Andries de Grip[*¥]

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Abstract**

Although human capital theory considers training and on-the-job learning investments that further improve workers' skills, this has not been directly tested in the empirical literature. In this paper, we analyse the extent to which training and informal learning are related to employees' skills development. We consider the heterogeneity of this relation with regard to employees' initial skills mismatch. Using unique data from the European Skills Survey (2014) conducted by the European Centre for the Development of Vocational Training, we find that employees who participated in training or informal learning show greater improvement of their skills than those who did not. Informal learning appears to be more effective in increasing workers' skills than training participation is; however, both forms of learning are shown to be complementary, which has an additional positive influence on the improvement of workers' skills. Both informal learning and training appear to be most beneficial for skills improvement for those who were initially under-skilled for their job and least beneficial for those who were initially over-skilled. For over-skilled workers, work-related learning seems to be more functional in offsetting skills depreciation rather than fostering skills accumulation.

JEL-Codes: J24, M53

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

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*Research Centre for Education and the Labour Market, Maastricht University.
Corresponding author: m.ferreirasequeda@maastrichtuniversity.nl

ψ and Industrial University of Santander (Colombia)
¥ and IZA, Bonn (Germany)

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1. INTRODUCTION

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 human capital theory (Mincer 1962, 1968; Becker 1964; Heckman 1976). However, due to a lack of data on skills improvement, the assumption that human capital investments indeed foster workers' skills has not yet been tested in the empirical literature. Instead, most studies focus on the role of job-related training in 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 the extent to which 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 and analyse whether the complementarity between these types of work-related training favours skills development. Moreover, we allow for heterogeneity in the relation between work-related learning and skills development by workers' initial skills mismatch[1].

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 in their job 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. Workers who are under-skilled probably need training or informal learning on the job to perform at an adequate level. Workers who are over-skilled 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 these different underlying reasons, it is expected that the skills development of initially mismatched workers who participate in job-related learning differs from the skills development of workers whose skills fully matched the skill 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 in which different types of job-related learning as well as employee skills development and mismatch are measured. We contribute to the literature in three ways. First, we provide empirical evidence of 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 provide empirical evidence showing that the complementarity between training and informal learning on the job has a significant additional positive impact on the skills development of workers that can be related to the dynamic complementarity of human capital (Cunha and Heckman, 2007). Third, we are the first who examine the heterogeneous effects of training and on-the-job learning on skills development in relation to workers' initial skills mismatch. Thereby,

[1] Since workers' skills mismatch could improve when they participate in learning, we use information on individuals' skills mismatch at the start of the job with their current employer rather than their current skills mismatch status. Hereafter, we use the terms *under-skilled*, *well matched*, and *over-skilled* to refer to the initial skills mismatch status of employees.

we find differences between under and over-skilled workers in the impact of investments in training and informal learning and their complementarity on skills development.

We find that employees who are involved in training and informal learning show a greater skill improvement. The contribution of informal learning to workers' skills appears to be larger than that of training participation, although both forms of learning are shown to be complementary. This holds for matched as well as mismatched workers. Moreover, this complementarity has an additional significant positive influence on workers' skills development. However, training and informal learning seem to be most efficient for skills improvement among under-skilled employees and least efficient among over-skilled employees. Human capital investments in the latter group seem to be more functional in offsetting skills depreciation and maintaining their skill level than in fostering skills accumulation. We also find that the additional contribution of the complementarity between training and informal learning to skills improvement holds only for initially matched and over-skilled workers.

We also analyse the contribution of different types of training and informal learning to workers' skills development. We find that among well-matched and under-skilled employees, training during working hours and training paid by the employer is far more beneficial than training outside working hours and training paid by the employee, respectively. Among over-skilled workers, however, these differences are rather small and statistically insignificant. With respect to informal learning, we find that, for workers in well-matching jobs, informal learning from others and informal learning from by self-study contribute equally to their skills improvement, whereas the contribution of learning by trial and error is slightly lower. For under-skilled workers, learning by self-study seems to be more beneficial than learning from others. In contrast, for over-skilled workers, informal learning from colleagues and supervisors appears to be more important than learning by trial and error.

The remainder of the paper is structured as follows. Section 2 discusses the relevant literature. Section 3 describes the dataset and 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 to interpret the results. The results are presented in Section 5. Section 6 concludes the paper.

2. LITERATURE

2.1 Human capital investments and skills development

Human capital theory considers on-the-job learning an investment that increases workers' productivity and wages via the accumulation of skills (Mincer 1962, 1968; Becker 1964; Heckman 1976). However, due to a lack of data, this skills accumulation has hardly been tested in empirical studies. First, at the individual level, most of the literature deals with the relation between training and wages, since 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 assess 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 (Bartel, 1994, 2000; Lowenstein and Spletzer, 1998; Barrett and O'Connell, 2001;Dearden *et al.*, 2006; Boothby *et al.,* 2010; Sepulveda, 2010). Third, although Mincer (1974) claimed that learning on the job could constitute the essential part and the major productivity investment 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 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 in explaining workers' earnings and 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) analyse training on and off the job as a determinant of skills supply. Using the British Skills Survey, the authors find 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 the dependent variable. Furthermore, their skills measure refers only to one point in time, which does not allow for analysing workers' skills development over time. Moreover, due to lack of data, the authors cannot explore the contribution of informal learning to skills formation.

On-the-job learning consists of both formal training and informal learning. Mincer (1974) claimed that learning on the job could constitute the essential part and the major human capital investment in the workplace; however, due to a lack of direct and readily available measures, it has often been omitted from empirical economic analyses. Furthermore, there could be 'dynamic complementarities' (Cunha and Heckman, 2007) between training and informal learning in the workplace. If training participation encourages informal learning and vice versa, investments in one type of learning could raise the marginal productivity of investments in the other type, in terms of skills accumulation. That is, skills acquired by training and informal learning could boost each other and then be mutually-reinforcing. Hence, the availability of 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 workplace skills in the economic literature (De Corte, 2003; De Grip and Sauermann, 2013).

2.2 Skills mismatch and human capital investment

Research on job mismatch concentrates mostly on the wage outcomes of over-education (see Groot, 1996; Kiker et al., 1997; Dolton and Vignoles, 2000; Hartog, 2000; Chevalier, 2003; Di Pietro and Urwin, 2006; McGuinness, 2006; Dolton and Silles, 2008). More recently, the literature has exhibited a shift in emphasis from over-education to skills mismatches (McGuinness and Bennett, 2007; Chevalier and Lindley, 2009; Mavromaras et al., 2009, 2010, 2012; McGuinness and Wooden, 2009; O'Leary *et al.,* 2009; Green and Zhu, 2010; McGuinness and Sloane, 2011; Mavromaras and

McGuinness, 2012; McGuinness and Byrne, 2014). These studies have shown that over-education and over-skilling refer to different phenomena and that over-education 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[2] or skills acquired through employment, while job entry requirements are imprecise at measuring the job's skill content. Measuring workers' skills mismatch could solve these difficulties by requesting individuals to compare the actual skills requirement of their job with their own skills either acquired by initial education, training, or informal learning or related to their general ability. Although susceptible to measurement error due to subjective bias, skills mismatch is still considered a more adequate and potentially more robust measure of skills under- and over-utilisation than educational mismatch is (Mavromaras and McGuinness, 2012).

Studies on workers' human capital accumulation only emphasise the role of training in reducing educational mismatch. Search and matching theory considers training a supplement to education in the way that it bridges the gap between generic skills acquired through schooling and specific skills required in the workplace (Baldwin and Johnson, 1995; Acemoglu and Pischke, 1999; Arulampalam *et al.,* 2004). Consequently, training contributes to the adjustment between workers' potential productivity and the productivity ceiling of the job in which they are employed (Blazquez and Jansen, 2008). In this regard, empirical studies find that over-educated workers participate less often in training than those who are well matched, whereas under-educated workers participate more often. Moreover, Van Smoorenburg and Van der Velden (2000) and Messinis and Olekalns (2007) find that training contributes to closing the gap between the actual and required education of under-educated workers through the acquisition of new skills and offsets the depreciation of human capital. The latter particularly holds for over-educated and older workers and employees who experience technological innovations or career interruptions. Messinis and Olekalns (2008) find that training participation relates to substantial wage benefits for under-educated workers in relation to their co-workers with higher education and enables over-educated 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. The survey was based on a representative sample of the working population age 24–65 years in each of the participant countries and administered either online or by telephone to 48,676 individuals.[3] The survey yields a unique dataset that measures employees' changes in skills

[2] It has been argued that over-educated workers are likely of lower ability and, therefore, the wage penalty could be largely explained by this unobserved heterogeneity (Groot, 1996; Green et al., 1999; Sloane et al., 1999). This supports the idea that employers learn about the productive abilities of over-educated employees and pay them lower wages.

[3] See Ipsos MORI (2014) for further details about data validation.

accumulation as well as changes in skills mismatch over years of tenure with the same employer. Comparable measures are not available from 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 restrict our analyses to full-time employees,[4] obtaining a sample of 37,177 individuals. Table A1 in the Appendix shows the sample distribution by country.

3.2 Variables and descriptive analyses

Table A2 in the Appendix shows the main descriptive statistics of the variables included in our analyses.

3.2.1 Dependent variable

Our outcome variable, workers' skills development is based on self-assessed changes in skills[5] 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 they had current skills not comparable to those they had before or did not to know the answer to the question. The mean reported skills development is 7.77, with a standard deviation of 1.77. Table 1 shows the distribution of this variable. As shown in the table, approximately 86 percent of the individuals in the sample reported that their skills had improved (scores of six to 10), whereas 14 percent indicated that their skills had stayed the same (score of five) or worsened (scores of one to four).

Table 1. Distribution of skills development

Skills change		%
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

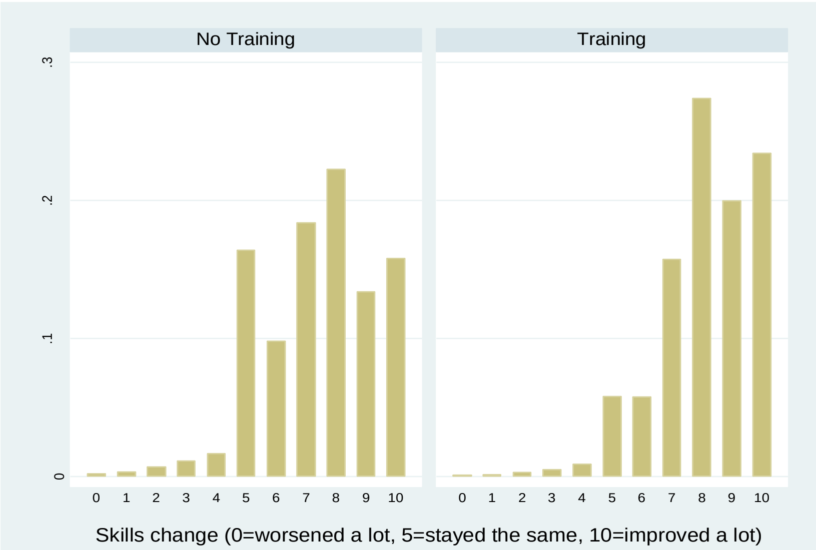
First, we distinguish between two types of work-related learning: training and informal learning.

4 We consider those who reported a minimum of 35 working hours a week full-time employees.

5 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'.

- *Training* is a dummy variable that takes the value one if the employee has participated in training courses since the start of the current job and zero 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)?' Since this question was only asked to those who reported having experienced positive skills development, we impute the information on training participation in the last 12 months for those whose skills declined.[6] Table A2 of the Appendix shows that 62 percent of all employees in our sample 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 62 percent underwent their training during working hours, while 22 percent did so outside working hours. For 66 percent of the workers, training was fully financed by the employer, whereas 7 percent financed it themselves. As shown in Graph 1, the density distribution of employees' development of skills shifts to the right when workers participate in training. It already indicates a positive relation between training participation and skills development.

Graph 1. Skills development distribution by training participation

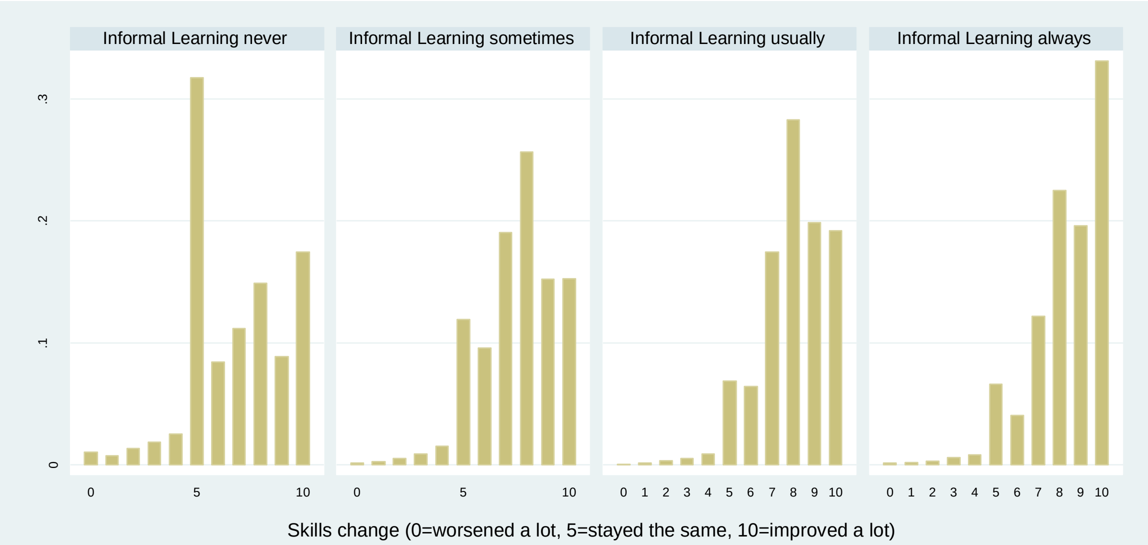


- Informal learning is measured by a categorical variable *IL* derived from the question, 'How often, if at all, does your job involve learning new things?' The respondent's options were 'never', 'sometimes', 'usually', or 'always'. Table A2 of the Appendix shows that 55 percent of all the employees in our sample stated learning 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 graph provides some first evidence that informal learning is also positively related to workers' skills development. In additional analyses, we differentiate between three types of informal

[6] A total of 81 percent of workers who answered both questions on training participation since the start of the job and during the last 12 months gave the same answer to both questions. Workers' answers to these two questions are highly positively correlated (0.67).

learning by including dummy variables for 1) learning from colleagues and supervisors, 2) learning by trial and error, and 3) learning from self-study.[7]

Graph 2. Skills development distribution by frequency of informal learning



Second, we distinguish between workers who experienced a mismatch at the start of their current job and those who did not.

- Initial job-skills mismatch 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 the employees stated having a good skills match at the start of their jobs, while 24 percent considered themselves initially under-skilled and 25 percent considered themselves initially over-skilled. As shown in Graph 3, the distribution of skills development differs between the three different groups in favour of 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 7.15 for the over-skilled. This graph suggests that workers who start a job with fewer skills than required make the largest skills progress when gaining years of tenure.

[7] 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?' Respondents could indicate as many of the following answers as applicable: '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)'.

Graph 3. Skills development distribution by initial job-skills mismatch

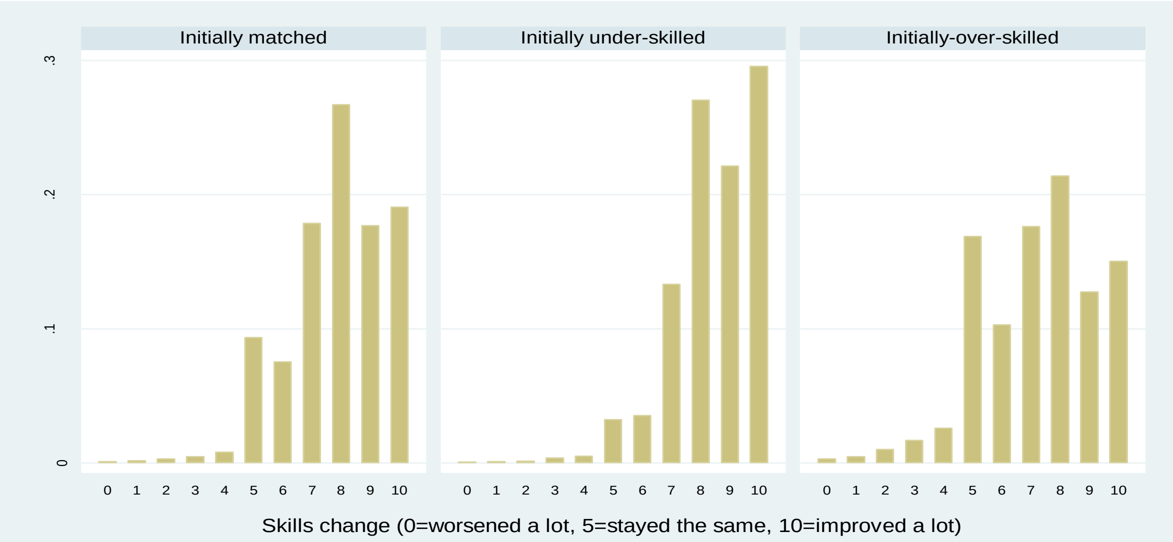


Table A2 shows other differences between initially under and over-skilled workers. For those who were initially over-skilled, a slightly higher proportion is male and higher educated. Moreover, these workers more often have temporary contracts and fewer years of tenure. Furthermore, the table shows a higher percentage of under-skilled workers in manufacturing and among professionals; technicians; and craft and related trades workers. Over-skilled workers are over-represented in the sales and transportation industries as well as in the service and sales, and clerical support occupations. It is worth mentioning that there is no difference in workers' ages between the three skills mismatch groups (mean= 42, standard deviation = 9.8) or in the sizes of the firms that employ them.

It is important to note that under-skilled workers participated more often in training and formal education. They also stated learning more often on an informal basis than well-matched and over-skilled workers did. The latter invested the least in their human capital.[8] This may not be surprising, since these workers already had more skills than required in their job. This suggests that having a job that initially mismatches the skills of workers is related to participation in training as well as informal learning, which may influence workers' skills development.

3.2.3 Control variables

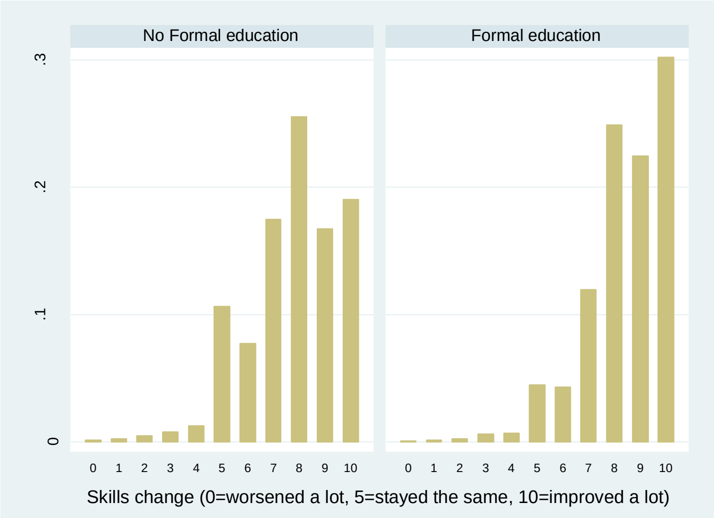
We explicitly include participation in formal education – which has led to a higher degree while working for the current employer – as a control variable in our model. This variable measures human capital investments in the form of schooling rather than job-related learning. Formal education is a dummy variable of participation in formal educational programmes resulting in a higher or different educational degree while working for the current employer. We construct this variable by assigning the value one to those who achieved their highest level of education after they started to work with their current employer and zero otherwise. As shown in Table A2, 14 percent of all employees in our

[8] Multivariate analyses do not fully support these correlations. We find that initially under-skilled workers are, on average, 6.8 percent more likely to participate in training courses, 4.8 percent more likely to engage in informal learning, and more intensively involved in informal learning by approximately 0.6 of a standard deviation than well-matched workers. However, the initially over-skilled do not significantly differ from the well matched in terms of training participation but do have a lower probability of taking part in informal learning (-1.7 percent). In addition, informal learning intensity is lower among over-skilled than well-matched workers by approximately 0.07 of a standard deviation (see Table A3 in the Appendix).

sample participated in formal education while working for their current employer. Graph 4 shows that skills development is greater for this group.

As suggested by human capital theory, we additionally 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 one-digit ISCO categories), industry (10 one-digit ISIC categories), firm size (five categories), and country dummies. Moreover, we include a dummy variable that indicates whether the survey was conducted by telephone.

Graph 4. Skills development distribution by participation in further formal education



4. ESTIMATION METHOD

To estimate the relation between employees' job-related learning and skills development, we use ordered probit models. The fact that responses to our dependent variable are concentrated in 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 changes 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 zero 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:

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

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 $u_i \sim N(0, 1)$. 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 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 $\gamma, \delta, \zeta,$ and ψ 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, our analyses consider interactions between the learning variables L (training, informal learning and formal education) and the employee's initial skills match *ISM*. As Norton *et al.*(2004), Greene (2010), and Karaca-Mandic *et al.*(2011) 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 of the interaction term (Ai and Norton, 2003). For nonlinear models that include interactions between categorical variables as in this paper, the interaction effect becomes the following discrete double difference:

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

Some implications need to be taken into account. First, the interaction effects in nonlinear models are conditional on the independent variables. Second, since two additive terms can be either positive or negative, the interaction effects could have opposite signs for different values of covariates and, therefore, the sign of ψ does not necessarily 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 (Ai and Norton, 2003; 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 their statistical significance to correctly interpret our results.

5. ESTIMATION RESULTS

5.1 Work-related learning and skills development

In Table 2, we estimate two ordered probit regressions for skills development.[9] 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). Generally, we also observe that the estimated threshold parameters are not equally spread out, implying that the meaning of certain categories is more expansive than others (specifically those corresponding to categories 5-6, and 9-10) and, therefore, that nonlinear estimations are more accurate.

[9] *t-Tests* of differences between the 10 cut points obtained from the ordered models were all significant at the 95 percent confidence level. Therefore, we keep the original zero to 10 scale structure of the dependent variable to estimate our models.

Table 2. Ordered probit coefficients for skills development

Skills change	(1)	(2)
Training	0.315***	0.313***
	(0.022)	(0.022)
IL sometimes	0.328***	0.303***
	(0.058)	(0.062)
IL usually	0.552***	0.497***
	(0.064)	(0.069)
IL always	0.799***	0.748***
	(0.070)	(0.074)
Formal education	0.155***	0.141***
	(0.020)	(0.028)
Initially under-skilled	0.324***	0.528***
	(0.015)	(0.077)
Initially over-skilled	-0.250***	-0.456***
	(0.024)	(0.084)
Training # Initially under-skilled		-0.036
		(0.023)
Training # Initially over-skilled		0.056***
		(0.020)
IL sometimes # Initially under-skilled		-0.160**
		(0.077)
IL sometimes # Initially over-skilled		0.114
		(0.080)
IL usually # Initially under-skilled		-0.151**
		(0.075)
IL usually # Initially over-skilled		0.217***
		(0.080)
IL always # Initially under-skilled		-0.170**
		(0.081)
IL always # Initially over-skilled		0.218**
		(0.091)
Formal education # Initially under-skilled		-0.027
		(0.033)
Formal education # Initially over-skilled		0.103**
		(0.043)
Age	-0.008***	-0.008***
	(0.002)	(0.002)
Female	0.209***	0.210***
	(0.018)	(0.018)
Intermediate level education	-0.067***	-0.063**
	(0.025)	(0.025)
High level education	-0.204***	-0.198***
	(0.029)	(0.030)
Years of tenure	0.022***	0.022***
	(0.002)	(0.002)
Temporary contract	-0.124***	-0.123***
	(0.016)	(0.016)
Agency contract	-0.263***	-0.263***
	(0.074)	(0.074)
No formal contract	-0.023	-0.027
	(0.051)	(0.049)
Other controls	*yes*	*yes*
cut1	-2.658*** (0.118)	-2.703*** (0.115)
cut2	-2.340*** (0.116)	-2.384*** (0.114)
cut3	-2.041*** (0.117)	-2.084*** (0.115)
cut4	-1.779*** (0.115)	-1.821*** (0.115)
cut5	-1.527*** (0.113)	-1.569*** (0.113)
cut6	-0.678*** (0.100)	-0.717*** (0.102)
cut7	-0.339*** (0.108)	-0.376*** (0.109)
cut8	0.235** (0.115)	0.209** (0.101)
cut9	0.966*** (0.118)	0.930*** (0.119)
cut10	1.542*** (0.131)	1.505*** (0.132)
Pseudo R2	0.562	0.579
BIC-stat	7531.7	7595.3

The dependent variable *skills change* is measured categories from categories zero to 10 (0= skills have worsened a lot, 5= skills have stayed the same, 10= skills have improved a lot). Other controls include dummies for occupation, industry, firm size, country and survey answered by phone. Standard errors clustered at country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

The estimation results presented in Table 2 suggest that both participation in training and informal learning positively contribute to employees' skills development. This is in line with expectations from human capital theory and our descriptive evidence. However, we can only infer from the signs of the coefficients how an explanatory variable is related to the probability of the end categories (Wooldridge, 2010; Greene, 2012). Since the coefficients from ordered models are not directly interpretable (Long, 1997; Long and Freese, 2014), we therefore provide in Table 3 the marginal effects of the estimates in column (2) of Table 2.[10] To facilitate the interpretation of results, we compute the resulting marginal effects in four categories: worsened skills (scores zero to four), no or hardly any change in skills (scores five and six), intermediate improvement of skills (scores seven and eight), and high improvement of skills (scores nine and 10).[11]

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

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Training	-0.019***	-0.063***	-0.023***	0.105***
	(0.001)	(0.004)	(0.003)	(0.007)
IL sometimes	-0.031***	-0.063***	0.011***	0.083***
	(0.007)	(0.011)	(0.004)	(0.016)
IL usually	-0.045***	-0.108***	-0.005	0.158***
	(0.007)	(0.012)	(0.003)	(0.018)
IL always	-0.054***	-0.152***	-0.042***	0.247***
	(0.007)	(0.013)	(0.005)	(0.020)
Formal education	-0.009***	-0.031***	-0.015***	0.055***
	(0.001)	(0.004)	(0.003)	(0.007)
Initially under-skilled	-0.014***	-0.061***	-0.045***	0.120***
	(0.001)	(0.003)	(0.003)	(0.006)
Initially over-skilled	0.019***	0.052***	0.005***	-0.076***
	(0.002)	(0.005)	(0.002)	(0.007)
Age	0.001***	0.002***	0.001***	-0.003***
	(0.000)	(0.000)	(0.000	(0.001)
Female	-0.011***	-0.039***	-0.021***	0.072***
	(0.001)	(0.004)	(0.002)	(0.006)
Intermediate level education	0.003***	0.011**	0.007**	-0.022**
	(0.001)	(0.004)	(0.003)	(0.009)
High level education	0.011***	0.037***	0.020***	-0.068***
	(0.002)	(0.006)	(0.003)	(0.010)
Years of tenure	-0.001***	-0.004***	-0.002***	0.007***
	(0.000)	(0.000)	(0.000)	(0.001)
Temp contract	0.007***	0.024***	0.010***	-0.041***
	(0.001)	(0.003)	(0.001)	(0.005)
Agency contract	0.018***	0.052***	0.016***	-0.086***
	(0.006)	(0.016)	(0.002)	(0.023)
No formal contract	0.002	0.005	0.003	-0.010
	(0.003)	(0.009)	(0.005)	(0.017)

*This table shows the average marginal effects computed on the ordered probit specification (2) in Table 2. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

[10] Specification (2) is our preferred regression 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 Bayesian information criterion between the two models provides strong support for the second model.

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

As we observe in Table 3, 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, zero to eight. The marginal effects confirm our descriptive results that the probability of a high improvement of skills is greater for employees who participate in training and informal learning. Workers who participated in training are, on average, 10.5 percentage points more likely to have highly improved their skills than those who did not participate in any training course. Similarly, participation in training reduces the odds of experiencing skills worsening and stagnation by 1.9 and 6.3 percentage points, respectively. In addition, employees' involvement in informal learning raises the probability of their skills improving. For instance, the likelihood of a high improvement of skills is 25, 16, and 8 percentage points greater for workers who, respectively, always, usually, and sometimes learn informally on the job, in comparison with those who are never involved in informal learning in their job. The marginal effects show that informal learning seems to be more effective in increasing the probability of improving employees' skills than training participation is.

Moreover, we find that the initial skills mismatch significantly explains workers' skills development over time while in the same job. We find that initially under-skilled workers develop their skills more than those who started in a job that matched their skills well. 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, confirming the evidence on skills depreciation shown by De Grip *et al.* (2008).

Regarding the covariates in our model, we find that the marginal probability of workers' skills development 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 and years of tenure (which compensates for the negative effect of age by approximately 2.5 times) and tends to be higher for female employees and for those who conducted the survey by phone. Other controls indicate that high skills development is less likely for individuals employed in low-skilled occupations.

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 the 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 skills mismatch. Two types of heterogeneity can be analysed. First, in Table 4, we show the difference in skills development within the same initial job-skills mismatch group between those who have been engaged in learning and those who have not. Second, in Table 5, we show the interaction effects or the difference in the benefit of training and informal learning for skills development between the three skills mismatch groups.

Table 4 shows that the findings of Table 3 that both participation in training and informal learning contribute to employees' skill development, hold for all workers, independent of their initial skills mismatch. Compared to workers with the same initial skills mismatch status, those who participated in training or informal learning are more likely to improve their skills than those who have not been involved in any learning activity. The only exemption is that initially under-skilled workers who engage only sometimes in informal learning do not differ from those who never engage in informal learning. This suggests that informal learning needs to take place more often in this group to increase their probability of skills development. Remarkably, also among initially over-skilled employees, training courses and informal learning are shown to contribute to their skills development. For instance, over-skilled workers who participate in training or always engage 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 who never engage in informal learning on the job. This could be because over-skilled employees who invest in the development of their human capital acquire new skills that are different from those they have previously accumulated (e.g. non-technical or non-cognitive skills) or are more functional to offset skills depreciation. The latter explanation could be inferred from the significantly larger marginal effects for over-skilled workers in the skills change categories scored zero to four, and five and six (i.e. skills decline and more or less stable skills) in all types of learning.

Table 4. Marginal effects of work-related learning by initial job-skills mismatch

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Initially well matched				
Training	-0.017***	-0.065***	-0.027***	0.109***
	(0.002)	(0.005)	(0.003)	(0.008)
IL sometimes	-0.026***	-0.069***	0.001	0.093***
	(0.007)	(0.014)	(0.004)	(0.017)
IL usually	-0.036***	-0.110***	-0.015***	0.161***
	(0.007)	(0.015)	(0.003)	(0.020)
IL always	-0.045***	-0.156***	-0.053***	0.254***
	(0.007)	(0.016)	(0.004)	(0.022)
Initially under-skilled				
Training	-0.007***	-0.041***	-0.047***	0.094***
	(0.001)	(0.007)	(0.007)	(0.015)
IL sometimes	-0.006	-0.027	-0.019*	0.052*
	(0.004)	(0.017)	(0.011)	(0.031)
IL usually	-0.011***	-0.061***	-0.056***	0.129***
	(0.004)	(0.016)	(0.010)	(0.029)
IL always	-0.015***	-0.092***	-0.109***	0.216***
	(0.004)	(0.018)	(0.014)	(0.035)
Initially over-skilled				
Training	-0.032***	-0.082***	0.000	0.113***
	(0.003)	(0.006)	(0.003)	(0.007)
IL sometimes	-0.060***	-0.089***	0.050***	0.099***
	(0.014)	(0.014)	(0.014)	(0.015)
IL usually	-0.085***	-0.156***	0.051***	0.190***
	(0.015)	(0.016)	(0.014)	(0.017)
IL always	-0.099***	-0.208***	0.028**	0.279***
	(0.015)	(0.017)	(0.010)	(0.021)

This table shows the average marginal effects computed on the ordered probit specification (2) in Table 2. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

Table 5 shows the differences in the skills development of workers who have been involved in training and/or informal learning between the three skills mismatch groups. These are the interaction terms, which need to be interpreted together with the marginal effects for well-matched workers, the reference category, shown in the first panel of Table 4. Table 5 shows a clear difference between under 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, 11.5 and 12.4 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 could be related to a greater interest in maintaining their jobs and richer learning opportunities at work (De Grip *et al*., 2008).

Table 5. Marginal effects (interaction effects) between the initial job-skills mismatch groups

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Initially under-skilled *(well matched ref)*				
Training	-0.009***	-0.052***	-0.054***	0.116***
	(0.001)	(0.004)	(0.004)	(0.008)
IL sometimes	-0.013***	-0.059***	-0.030***	0.102***
	(0.002)	(0.003)	(0.002)	(0.006)
IL usually	-0.006***	-0.055***	-0.057***	0.119***
	(0.001)	(0.004)	(0.007)	(0.011)
IL always	-0.011***	-0.060***	-0.053***	0.124***
	(0.001)	(0.005)	(0.004)	(0.009)
Initially over-skilled *(well matched ref)*				
Training	0.013***	0.046***	0.017***	-0.075***
	(0.001)	(0.005)	(0.002)	(0.007)
IL sometimes	0.026***	0.067***	-0.005**	-0.089***
	(0.003)	(0.008)	(0.002)	(0.009)
IL usually	0.012***	0.041***	0.014***	-0.067***
	(0.002)	(0.005)	(0.002)	(0.008)
IL always	0.005***	0.031***	0.027***	-0.063***
	(0.002)	(0.007)	(0.005)	(0.012)

This table shows the average marginal effects computed on the ordered probit specification (2) in Table 2. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

Conversely, over-skilled employees who participated in training are, on average, 7.5 percentage points less likely to develop their skills than similar workers in a well-matching job are. This means that trained over-skilled employees are, respectively, approximately 1.3 and 4.6 percentage points more likely to experience skills depreciation and stagnation than trained matched workers are. 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 approximately 0.5 and 3.1 percentage points, respectively, more likely to experience skills worsening and stagnation.

This does not mean that learning has a negative impact on the skills accumulation of over-skilled workers but that the positive impact is much lower than it is for workers in a well-matching job. For example, whereas well-matched employees who participate in training and who are always learning informally have average probabilities of high skills development of 10.9 percent and 25.4 percent, respectively, the same probabilities for over-skilled employees are, on average, 3.3 percent and 19 percent. For over-skilled workers, the fact of having a job below their skills not only affects negatively 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. Nonetheless, the more often over-skilled workers engage in informal learning and if they participate in training, the lower their probability of skills decline and stagnation is. This result again suggests that the learning investments of over-skilled workers prevent skills depreciation rather than foster skills accumulation.[12]

5.3 Types of job-related learning that matter most for workers' 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 2 but, instead of the single training participation variable, we include a categorical variable to distinguish between training during and outside regular working hours.

The results in Panel 1 of Table 6 show that training undertaken during working hours is generally more beneficial for workers' skills development than training outside working hours is. However, workers who participate in training during both working and non-working hours improve their skills the most. Panel 2 shows that this holds within each skill mismatch group. Despite this, among over-skilled workers, the difference between the marginal effects of training during and outside working hours is much lower (and statistically insignificant) than in the other two groups. This result suggests that training outside working hours is more important for over-skilled workers, probably to retain or improve their skills for possible future jobs. Panel 3 shows that, in comparison with well-matched workers, training during and outside regular working hours are both equally more beneficial for under-skilled workers. For over-skilled employees, however, only training during working hours is less beneficial, since training outside working hours seems to be as beneficial for their skills as it is for workers in a well-matching job. Although over-skilled workers who participate in training both during

[12] Our results in Sections 5.1 and 5.2 could be affected by workers' attitudes such as learning motivation or the importance of career development opportunities. We perform several robustness checks, including in our estimations information on the learning attitude of employees and the importance of career development opportunities to accept their job. The most relevant results are shown in Tables A4 and A5 in the Appendix. These tables show that our main findings remain the same when we account for workers' attitudes. Moreover, we observe that workers with a strong learning attitude achieve the greatest skills increase from both training and informal learning. Similarly, workers who considered the career development opportunities very important to accept the job show higher skills benefits from both training and informal learning. We also assess the robustness of our main results when controlling for major changes in the job position over tenure, that is, if the worker has experienced a promotion, a demotion, a change of unit/department, or a substantial change in the nature of the job tasks. The results in Table A6 in the Appendix show that our main findings remain the same. These results all hold for over-skilled, under-skilled, and well-matched employees (detailed tables are available upon request).

and outside working hours gain less in skills development than similarly matched workers, they still have a positive average probability of highly improving their skills of 5.5 percent.

Table 6. Marginal effects of training during and outside working hours

Skills change	0-4	5-6	7-8	9-10
1. AME				
Training only during working hours	-0.013***	-0.041***	-0.016***	0.069***
	(0.001)	(0.003)	(0.002)	(0.005)
Training only outside working hours	-0.008***	-0.024***	-0.005***	0.038***
	(0.001)	(0.003)	(0.001)	(0.005)
Training during and outside working hours	-0.018***	-0.062***	-0.029***	0.109***
	(0.001)	(0.004)	(0.003)	(0.008)
2.AME within the same initial job-skills mismatch group				
Initially well-matched				
Training only during working hours	-0.011***	-0.042***	-0.019***	0.071***
	(0.001)	(0.004)	(0.002)	(0.006)
Training only outside working hours	-0.006***	-0.021***	-0.008***	0.035***
	(0.001)	(0.005)	(0.002)	(0.009)
Training during and outside working hours	-0.014***	-0.059***	-0.032***	0.105***
	(0.001)	(0.005)	(0.004)	(0.009)
Initially under-skilled				
Training only during working hours	-0.004***	-0.0253***	-0.0304***	0.0599***
	(0.001)	(0.0036)	(0.0040)	(0.0080)
Training only outside working hours	-0.002**	-0.0114**	-0.0124**	0.0257**
	(0.001)	(0.0050)	(0.0055)	(0.0114)
Training during and outside working hours	-0.006***	-0.0370***	-0.0483***	0.0911***
	(0.001)	(0.0047)	(0.0071)	(0.0122)
Initially over-skilled				
Training only during working hours	-0.021***	-0.055***	-0.001	0.077***
	(0.002)	(0.005)	(0.002)	(0.007)
Training only outside working hours	-0.022***	-0.044***	0.001	0.065***
	(0.003)	(0.008)	(0.002)	(0.011)
Training during and outside working hours	-0.032***	-0.093***	-0.016**	0.141***
	(0.003)	(0.011)	(0.006)	(0.018)
3.AME between the initial job-skills mismatch groups(well matched ref)				
Initially under-skilled				
Training only during working hours	-0.010***	-0.056***	-0.054***	0.119***
	(0.001)	(0.003)	(0.003)	(0.006)
Training only outside working hours	-0.013***	-0.062***	-0.047***	0.122***
	(0.002)	(0.009)	(0.007)	(0.017)
Training during and outside working hours	-0.008***	-0.050***	-0.059***	0.117***
	(0.001)	(0.006)	(0.008)	(0.014)
Initially over-skilled				
Training only during working hours	0.012***	0.024***	0.013***	-0.049***
	(0.002)	(0.004)	(0.002)	(0.006)
Training only outside working hours	0.011	0.016	0.007*	-0.034
	(0.010)	(0.013)	(0.005)	(0.029)
Training during and outside working hours	0.007**	0.029**	0.014**	-0.050**
	(0.003)	(0.013)	(0.007)	(0.023)

This table shows the average marginal effects computed on an ordered probit regression similar to specification (2) in Table 2 that includes a categorical variable that distinguishes between training during and outside regular working hours. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

5.3.2 Different training funding sources

In this section, we analyse whether the contribution of training to skills development differs by funding source, that is, i) training paid by the employer, ii) training paid by the employee or a third party, and iii) training paid by both the employer and employee. We run the same regression as specification (2) in Table 2 but include a categorical training variable that distinguishes between the three funding sources mentioned above.

The results in Panel 1 of Table 7 show that training paid by the employer is generally the most beneficial for workers' skills development. Panel 2 shows that this holds for well-matched and under-skilled employees, whereas training paid by both the employer and employee is the most beneficial for over-skilled workers. We again observe that, among over-skilled workers, the difference between the marginal effects of training paid by the employer and training paid by the employee is lower than in the other two groups. Assuming that training paid by the employee is rather general and training paid by the employer is more specific, these results suggest that investing in general training is more important for over-skilled workers, since it can be more useful to improve their skills or update the skills they do not use in their job, which could provide them with more opportunities to find a better job match, in the current firm or other firms. That could be why, in Panel 3, there does not seem to be any significant difference between over-skilled and matched workers concerning the skills gain from training paid by themselves, whereas training paid by the employer is significantly less beneficial for the over-skilled. Lastly, as shown in Panel 3, in comparison with workers in a well-matching job, under-skilled workers benefit more from training regardless of the funding source.

Table 7. Marginal effects of training financed by different source

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
1. AME				
Training paid by employer	-0.0129***	-0.0419***	-0.0165***	0.0714***
	(0.0007)	(0.0025)	(0.0016)	(0.0042)
Training paid by employee/third party	-0.0090***	-0.0282***	-0.0104***	0.0477***
	(0.0020)	(0.0070)	(0.0037)	(0.0119)
Training paid by employer-employee	-0.0126***	-0.0396***	-0.0139***	0.0661***
	(0.0011)	(0.0040)	(0.0032)	(0.0079)
2.AME within the same initial job-skills mismatch group				
Initially well matched				
Training paid by employer	-0.0108***	-0.0448***	-0.0192***	0.0748***
	(0.0009)	(0.0032)	(0.0020)	(0.0056)
Training paid by employee/third party	-0.0075***	-0.0279***	-0.0111**	0.0465***
	(0.0024)	(0.0099)	(0.0053)	(0.0175)
Training paid by employer-employee	-0.0117***	-0.0374***	-0.0128***	0.0619***
	(0.0012)	(0.0043)	(0.0026)	(0.0077)
Initially under-skilled				
Training paid by employer	-0.0043***	-0.0264***	-0.0318***	0.0624***
	(0.0006)	(0.0036)	(0.0043)	(0.0083)
Training paid by employee/third party	-0.0035***	-0.0213***	-0.0248**	0.0496**
	(0.0012)	(0.0082)	(0.0103)	(0.0196)
Training paid by employer-employee	-0.0038***	-0.0233***	-0.0275***	0.0546***
	(0.0011)	(0.0071)	(0.0091)	(0.0172)
Initially over-skilled				
Training paid by employer	-0.0225***	-0.0537***	-0.0024	0.0786***
	(0.0016)	(0.0044)	(0.0017)	(0.0059)
Training paid by employee/third party	-0.0155***	-0.0476***	0.0018	0.0649***
	(0.0043)	(0.0122)	(0.0017)	(0.0177)
Training paid by employer-employee	-0.0234***	-0.0612***	-0.0028	0.0874***
	(0.0020)	(0.0063)	(0.0024)	(0.0094)
3.AME between the initial job-skills mismatch groups(well matched ref)				
Initially under-skilled				
Training paid by employer	-0.0105***	-0.0560***	-0.0542***	0.1207***
	(0.0011)	(0.0036)	(0.0040)	(0.0078)
Training paid by employee/third party	-0.0130***	-0.0648***	-0.0524***	0.1302***

	(0.0028)	(0.0133)	(0.0113)	(0.0264)
Training paid by employer-employee	-0.0111***	-0.0576***	-0.0529***	0.1215***
	(0.0013)	(0.0064)	(0.0080)	(0.0150)
Initially over-skilled				
Training paid by employer	0.0136***	0.0164***	0.0145***	-0.0445***
	(0.0018)	(0.0020)	(0.0021)	(0.0080)
Training paid by employee/third party	0.0086	0.0139	0.0000	-0.0225
	(0.0072)	(0.0187)	(0.0029)	(0.0209)
Training paid by employer-employee	0.0087***	0.0131***	0.0099***	-0.0317***
	(0.0020)	(0.0037)	(0.0031)	(0.0097)

This table shows the average marginal effects computed on an ordered probit regression similar to specification (2) in Table 2 that includes a categorical variable that distinguishes between the three training funding sources. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

5.3.3 Three types of informal learning

In this section, we analyse whether there are any differences in the relevance of different types of informal learning for workers' skills development. We run the same regression as in Table 2, 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 scoring six to 10), here we use only 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 possibly higher cost of mistakes when workers learn by trial and error in comparison with the other two types of informal learning. This would increase skills benefits of learning by self-study or from colleagues and supervisors. 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.[13] Panel 3 again shows that, in comparison with well-matched workers with similar informal learning participation, under-skilled workers benefit more from all three types of informal learning, while the over-skilled benefit less.

[13] Note, however, that we cannot make any inference regarding skills maintenance or decline in this section due to 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	-0.012***	-0.014***	-0.004***	0.007***	0.023***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.005)
IL by trial and error	-0.007***	-0.008***	-0.002*	0.004***	0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)
IL by self-study	-0.009***	-0.013***	-0.006***	0.005***	0.023***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.004)
2.AME within the same initial job-skills mismatch group					
Initially well matched					
IL from others	-0.011***	-0.013***	-0.003***	0.007***	0.020***
	(0.004)	(0.004)	(0.001)	(0.002)	(0.007)
IL by trial and error	-0.008***	-0.010***	-0.003***	0.005**	0.016***
	(0.003)	(0.004)	(0.001)	(0.002)	(0.006)
IL by self-study	-0.012***	-0.014***	-0.004***	0.007***	0.022***
	(0.004)	(0.004)	(0.001)	(0.002)	(0.007)
Initially under-skilled					
IL from others	-0.010***	-0.016***	-0.009***	0.005***	0.030***
	(0.004)	(0.005)	(0.003)	(0.002)	(0.010)
IL by trial and error	-0.002	-0.003	-0.002	0.001	0.007
	(0.003)	(0.004)	(0.003)	(0.001)	(0.009)
IL by self-study	-0.013***	-0.022***	-0.014***	0.007***	0.042***
	(0.003)	(0.005)	(0.003)	(0.002)	(0.009)
Initially over-skilled					
IL from others	-0.016***	-0.016***	-0.002***	0.010***	0.024***
	(0.005)	(0.005)	(0.001)	(0.003)	(0.007)
IL by trial and error	-0.010**	-0.011**	-0.002**	0.006**	0.016**
	(0.005)	(0.005)	(0.001)	(0.003)	(0.007)
IL by self-study	-0.001	-0.001	-0.000	0.001	0.002
	(0.005)	(0.005)	(0.001)	(0.003)	(0.007)
2.AME between the initial job-skills mismatch groups(well matched ref)					
Initially under-skilled					
IL from others	-0.033***	-0.046***	-0.021***	0.019***	0.081***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.006)
IL by trial and error	-0.032***	-0.041***	-0.014***	0.020***	0.067***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.008)
IL by self-study	-0.034***	-0.049***	-0.024***	0.019***	0.088***
	(0.003)	(0.005)	(0.003)	(0.002)	(0.008)
Initially over-skilled					
IL from others	0.007***	0.011***	0.003***	-0.009***	-0.013***
	(0.003)	(0.004)	(0.001)	(0.002)	(0.005)
IL by trial and error	0.013**	0.015**	0.003***	-0.009**	-0.022**
	(0.006)	(0.006)	(0.001)	(0.004)	(0.010)
IL by self-study	0.016***	0.020***	0.005***	-0.011***	-0.030***
	(0.005)	(0.005)	(0.001)	(0.003)	(0.008)

This table shows the average marginal effects computed on an ordered probit regression similar to specification (2) in Table 2 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 six to10. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 31,954.

5.4 Complementarity between training and informal learning and its effect on skills development

The previous findings raise the question of the substitutability or complementarity between informal learning and training and how it affects the skills accumulation of the working population.

5.4.1 Complementarity effect on workers' skills development

Consistent with human capital theory, there is a positive and significant correlation of 0.14 between work-related training and informal learning in our data. This initially suggests that these two forms of learning complement each other. Further multiple regression analyses confirm that there is indeed complementarity between training and informal learning on the job. This result also holds within the three skills mismatch groups (see Tables A7 and A8 in the Appendix).[14]

Table 9. Conditional and interaction effects between training and informal learning

Skills change	0-4	5-6	7-8	9-10
1. Conditional marginal effects				
AME of Training				
at IL never	-0.040***	-0.065***	0.024***	0.081***
	(0.005)	(0.005)	(0.006)	(0.006)
at IL sometimes	-0.024***	-0.068***	-0.007***	0.099***
	(0.002)	(0.005)	(0.002)	(0.007)
at IL usually	-0.016***	-0.063***	-0.031***	0.110***
	(0.001)	(0.004)	(0.004)	(0.008)
at IL always	-0.010***	-0.053***	-0.054***	0.117***
	(0.001)	(0.004)	(0.005)	(0.008)
AME of IL sometimes				
at Training=0	-0.040***	-0.062***	0.029***	0.072***
	(0.009)	(0.011)	(0.007)	(0.011)
at Training=1	-0.025***	-0.065***	-0.001	0.091***
	(0.005)	(0.012)	(0.003)	(0.013)
AME of IL usually				
at Training=0	-0.059***	-0.111***	0.028***	0.141***
	(0.009)	(0.012)	(0.007)	(0.013)
at Training=1	-0.035***	-0.108***	-0.026***	0.170***
	(0.006)	(0.013)	(0.003)	(0.015)
AME of IL always				
at Training=0	-0.072***	-0.159***	0.005*	0.226***
	(0.010)	(0.013)	(0.004)	(0.016)
at Training=1	-0.042***	-0.148***	-0.072***	0.262***
	(0.006)	(0.013)	(0.006)	(0.019)
2. Interaction effect *(Training = 0 and IL never ref.)*				
Training = 1 and IL always	-0.081***	-0.214***	-0.048***	**0.343*** **
	(0.009)	(0.013)	(0.006)	(0.021)

This table shows the conditional marginal effects computed on an ordered probit regression similar to specification (2) in Table 2 that includes an interaction term between the training and informal learning variables. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

Panel 1 in Table 9 shows the marginal effects of training and informal learning conditional on each other. This allows us to assess if investment in one type of learning increases the marginal effect on workers' skills development of the other type of learning when both training and informal learning take place. As we observe, this is indeed the case. On average, training participation raises the probability of a high improvement of skills by 8 percentage points if the worker never learns informally, whereas the contribution of training increases to 11.6 percentage points if the worker is always involved in informal learning.[15] The same holds for the contribution of informal learning to workers' skills development; it is significantly higher when workers also participate in training. This

[14] Nonetheless, the strength of the complementarity differs between the three skill-mismatch groups. In comparison with initially well-matched workers, the complementarity is generally stronger among those initially under-skilled and slightly weaker among the over-skilled. The complementarity means that, on the one hand, the frequency of informal learning increases when a worker participates in training and, on the other hand, the average individual probability of training participation is higher the more often the worker engages in informal learning.

[15] This difference (0.036) is significant with 99 percent confidence (Chi 2 (1) = 47.5, p = 0.000).

result suggests that training and informal learning provide workers with complementary skills rather than substitutable skills. Moreover, this complementarity appears to favour their skills accumulation. This is confirmed by the interaction effect shown in Panel 2 of Table 9. The probability of a high improvement of skills when employees engage in both types of work-related learning (0.343) is significantly higher than the sum (0.308) of the partial marginal effects of training (0.081) and informal learning (0.227) if workers participate in only one of them.[16] This means that the complementarity between training and informal learning on the job additionally contributes to the improvement of workers' skills.

5.4.2 Difference in the complementarity effect across job-skills mismatch groups

To assess if the additional complementarity effect, previously shown, holds for initially under and over-skilled employees, we estimated three-way interaction effects between the learning variables and the indicator for the initial skills mismatch. We present the most relevant results in Table 11.[17] These results show that the complementarity of human capital in the workplace has a significant additional impact only on the high skills development of initially well-matched[18] and over-skilled[19] workers. Although the complementarity itself is stronger for initially under-skilled workers, it does not seem to add any further to their skills improvement.[20] If we can extend the analysis of Cunha and Heckman (2007) to the workplace, this finding is consistent with the idea that the lower the stock of skills, the lower the complementarity effect. That is, higher initial stocks of job skills raise the productivity of new learning investments and facilitate the accumulation of human capital. All this suggests that eliminating the skills gap of under-skilled workers can be slightly more costly due to the greater need for investments in both training and informal learning and because their lower initial stock of job skills seems to moderate the dynamic complementarity effect of these investments on their skills development. Nevertheless, initially under-skilled workers still benefit the most among all workers when these investments are made.

[16] This difference (0.036) is significant with 99 percent confidence (Chi 2 (1) = 72.7, p = 0.000).

[17] Complete tables are available upon request.

[18] For workers in an initially well-matching job, the probability of a high improvement of skills when they engage in both types of work-related learning (0.352) is higher than the sum (0.319) of the partial effects of training (0.085) and informal learning (0.234). The difference (0.033) is significant with 99 percent confidence (Chi 2 (1) = 37.4, p = 0.000).

[19] For initially over-skilled workers, the probability of a high improvement of skills when they engage in both types of work-related learning (0.372) is higher than the sum (0.305) of the partial effects of training (0.067) and informal learning (0.238). The difference (0.067) is significant with 99 percent confidence (Chi 2 (1) = 107.2, p = 0.000).

[20] For initially under-skilled workers, the probability of a high improvement of skills when they engage in both types of work-related learning (0.308) is not significantly different from the sum (0.304) of the partial effects of training (0.090) and informal learning (0.214). (Chi 2 (1) = 0.5, p = 0.478).

Table 10. Conditional and interaction effects between training and informal learning by initial skill-job mismatch

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Initially well-matched				
AME of Training at IL never	-0.035***	-0.074***	0.024***	0.085***
	(0.005)	(0.005)	(0.007)	(0.007)
at IL always	-0.009***	-0.053***	-0.056***	0.118***
	(0.001)	(0.004)	(0.005)	(0.008)
AME of IL always at Training = 0	-0.061***	-0.169***	-0.003	0.234***
	(0.010)	(0.016)	(0.008)	(0.016)
at Training = 1	-0.035***	-0.149***	-0.083***	0.267***
	(0.006)	(0.016)	(0.006)	(0.019)
Interaction effect (Training = 0 and IL never ref.)				
Training = 1 and IL always	-0.070***	-0.222***	-0.060***	**0.352*****
	(0.010)	(0.016)	(0.007)	(0.021)
Initially under-skilled				
AME of Training at IL never	-0.012***	-0.052***	-0.026***	0.090***
	(0.003)	(0.009)	(0.008)	(0.014)
at IL always	-0.006***	-0.039***	-0.051***	0.096***
	(0.001)	(0.007)	(0.008)	(0.015)
AME of IL always at Training = 0	-0.0204***	-0.1059***	-0.0880***	0.214***
	(0.0053)	(0.0201)	(0.0106)	(0.034)
at Training = 1	-0.0118***	-0.0838***	-0.1223***	0.218***
	(0.0033)	(0.0169)	(0.0165)	(0.036)
Interaction effect (Training = 0 and IL never ref.)				
Training = 1 and IL always	-0.024***	-0.136***	-0.149***	**0.308*****
	(0.005)	(0.020)	(0.012)	(0.036)
Initially over-skilled				
AME of Training at IL never	-0.071***	-0.069***	0.072***	0.067***
	(0.010)	(0.006)	(0.011)	(0.005)
at IL always	-0.016***	-0.073***	-0.045***	0.134***
	(0.002)	(0.005)	(0.006)	(0.009)
AME of IL always at Training = 0	-0.132***	-0.207***	0.101***	0.238***
	(0.021)	(0.015)	(0.021)	(0.017)
at Training = 1	-0.077***	-0.211***	-0.016	0.304***
	(0.012)	(0.018)	(0.012)	(0.024)
Interaction effect (Training = 0 and IL never ref.)				
Training = 1 and IL always	-0.148***	-0.280***	0.057***	**0.372*****
	(0.021)	(0.016)	(0.019)	(0.022)

This table shows the conditional marginal effects computed on an ordered probit regression similar to specification (2) in Table 2 that includes a third-way interaction term between the learning variables and the initial skill mismatch indicator. The dependent variable *skills change* is measured by 11 ordinal categories from zero 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 into 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 37,177.

6. CONCLUSIONS

In this paper, we have analysed the extent to which training and informal learning on the job are related to the skills development of workers in 28 European countries. Consistent with expectations from human capital theory, we find that employees who have been involved in training and informal learning show greater improvement of their skills. In line with Mincer's (1974) claim, we also find that informal learning seems to be more effective in improving workers' skills than training participation is. However, this does not mean that participation in training is not important. Training and informal learning are shown to be complementary, which has an additional positive influence on workers' skills development. This is probably due to the dynamic complementarities (Cunha and Heckman, 2007) of human capital that can also occur in the workplace, making the skills acquired by training and informal learning to be mutually-reinforcing.

We have also analysed the heterogeneity in the relation between job-related learning and skills development in terms of workers' initial skills mismatch. First, our results show that workers who participate in training or informal learning are more likely to considerably improve their skills than those with the same initial skills mismatch 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 more from both training and informal learning, whereas the over-skilled benefit less. 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 could be related to richer learning opportunities at work and a greater interest in maintaining their jobs (De Grip *et al.*, 2008). This suggests that the learning investments of under-skilled workers contribute to closing the gap between their actual skills and the skills required in 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 less beneficial to their skills development compared to workers with a well-matching job. However, the learning investments of over-skilled employees are more functional in offsetting skills depreciation and maintaining their skills level than in fostering skills accumulation. This result confirms De Grip and van Loo's (2002) suggestion that adults' human capital accumulation may be a key mitigating factor counteracting skill obsolescence.

Third, we also find further heterogeneity across workers with a different initial job-skills mismatch. Our results show that the complementarity of human capital in the workplace has a significant additional impact on the skills development of initially well-matched and over-skilled workers, but not on the skills development of the initially under-skilled. This finding is consistent with the idea that higher initial stocks of job skills promote the productivity of new investments and facilitate the accumulation of human capital (Cunha and Heckman, 2007). Therefore, workers with lower skill stocks have a lower complementarity effect. This result suggests that substituting the deficits of initially under-skilled workers with learning investments is costly. Nevertheless, under-skilled employees benefit the most from such investments.

We have also 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. Our results show that, among well-matched and under-skilled employees, training during working hours is far more beneficial for their skills development than training outside regular working hours is. Among over-skilled workers, however, the difference between the influence of training during and outside working hours on a worker's skills improvement is smaller and statistically insignificant. In addition, training during working hours seems to contribute slightly more to the skills maintenance of over-skilled workers than training outside working hours does. Furthermore, we find that training paid by the employer is the most beneficial for well-matched and under-skilled workers, whereas training paid by both the employer and the employee is the most beneficial for the over-skilled. Among the latter group, the difference between the contribution of training paid by the employer and training paid by the employee is also lower than in the other two groups. Assuming that training paid by the employee (or outside working hours) is more general while training paid by the employer (or during working hours) is more firm specific, these results suggest that investing in general training is more important for over-skilled workers than for those who are well-matched or under-skilled in their job. This because general training can be more useful in improving their skills or in updating the skills they do not use in their job, which could provide them more opportunities to find a better-matching job.

Since the lifelong learning and skills development of workers are essential for economic progress and productivity (World Economic Forum, 2014), knowledge about these heterogeneities in the role of training and informal learning in workers' skills development with respect to their initial skills mismatch is crucial to make efficient decisions on human capital investments. Optimal learning decisions could also contribute to reduce the misalignment between workers' potential productivity and the optimal productivity of their jobs, due to skills mismatch in the labour market.

REFERENCES

Ai, C., and E. Norton (2003) Interaction Terms in Logit and Probit Models. *Economics Letters* 80(1): 123–9.

Acemoglu, D. and J. Pischke (1999) The Structure of Wages and Investment in General Training. *Journal of Political Economy* 107(3): 539-572.

Arulampalam, W., A. Booth, and M. Bryan (2004) Training in Europe. *Journal of the European Economic Association* 2(2-3): 346-60.

Baldwin, J. and J. Johnson (1995), Human Capital Development and Innovation: The Case of Training in Small and Medium Sized-Firms, Micro-Economic Analysis Division, Statistics Canada: Ottawa.

Bartel, A. (1994) Productivity Gains from the Implementation of Employee Training Programs. *Industrial Relations: A Journal of Economy and Society* 33 (4): 411–425.

Bartel, A. (2000) Measuring the Employer Return on Investment in Training: Evidence from the Literature. *Industrial Relations* 39 (3): 502-524.

Barrett, A. and P. O'Connell (2001) Does Training Generally Work – The Returns to In-Company Training. *Industrial and Labour Relations Review* 54(3): 647-662.

Becker, G. (1964) Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education. New York: Columbia University Press.

Blazquez, M. and M. Jansen (2008) Search, Mismatch and Unemployment. *European Economic Review* 52(3): 498-526.

Blundell, R., L. Dearden, C. Meghir and B. Sianesi (1999) Human Capital Investment: The Returns from Education and Training to the Individual, the Firm and the Economy. *Fiscal Studies* 20(1): 1–23.

Boothby, D., A. Dufour, and J. Tang (2010) Technology adoption, training and productivity performance. *Research Policy* 39(5): 650–661.

Chevalier, A. (2003) Measuring Overeducation. *Economica* 70 (279): 509–531.

Chevalier, A. and J. Lindley (2009) Overeducation and the skills of UK graduates. *Journal of the Royal Statistics Society* 172(2): 307-337.

Cunha, F. and J. Heckman (2007) The technology of skills formation. *American Economic Review* 97(2): 31-47.

De Corte, E. (2003). Transfer as the productive use of acquired knowledge, skills and motivations. *Current Directions in Psychological Science* 12(4): 142–146.

De Grip, A. and J. Sauermann (2012) The Effects of Training on Own and Co-Worker Productivity: Evidence from a Field Experiment. *The Economic Journal* 122: 376–399.

De Grip, A. and J. Sauermann (2013) The effect of training on productivity: The transfer of on-the-job training from the perspective of economics. *Educational Research Review* 8: 28–36.

De Grip, A., H. Bosma, D. Willems and M. Van Boxtel (2008) Job-worker mismatch and cognitive decline. *Oxford Economic Papers* 60 (2): 237–253.

De Grip, A. and J. van Loo, (2002) The Economics of Skills Obsolescence: A Review, in: A. de Grip, J. van Loo and K. Mayhew (Eds.), *The economics of Skills Obsolescence: Theoretical innovations and empirical applications*. Research in Labor Economics 21, Amsterdam: Elsevier Science, 1-26.

Dearden, L., H. Reed and J. van Reenen (2006) The impact of training on productivity and wages: Evidence from British panel data. *Oxford Bulletin of Economics and Statistics* 68(4): 397-421.

Destré, G., L. Lévy-Garboua and M. Sollogoub (2008) Learning from experience or learning from others? Inferring informal training from a human capital earnings function with matched employer–employee data. *The Journal of Socio-Economics* 37(3): 919–938.

Di Pietro, G. and P. Urwin (2006) Education and skills mismatch in the Italian graduate labour market. *Applied Economics* 38: 79–93.

Dolton, P. and M. Silles (2008) The effects of over-education on earnings in the graduate labour market. *Economics of Education Review* 27(2): 125-139.

Dolton, P. and Vignoles, A. (2000) The incidence and the effects of overeducation in the UK graduate labour market. *Economics of Education Review* 19(2): 179–98.

European Commission (2010) Europe 2020: A strategy for smart, sustainable and inclusive growth. Brussels: European Commission.

Green, F., D. Ashton and A. Felstead (2001). Estimating the determinants of supply of computing problem-solving, communication, social, and teamworking skills. *Oxford Economic Papers* 53(3): 406–433.

Green, F. and Y. Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers* 62(4): 740–763.

Green, F., S. McIntosh and A. Vignoles (1999) Overeducation and Skills: Clarifying the Concepts. Working paper No. 435. London, Centre for Economic Performance, London School of Economics and Political Science.

Greene, W. (2010) Testing Hypotheses about Interaction Terms in non-Linear Models. *Economic Letters* 107 (2): 291– 296.

Greene, W. (2012) *Econometric Analysis*, seventh edition. New York, Pearson Education.

Görlitz, K. (2011) Continuous training and wages: An empirical analysis using a comparison-group approach. *Economics of Education Review* 30(4): 691–701

Groot, W. (1996) The incidence of, and returns to overeducation in the UK. *Applied Economics* 28: 1345-1350.

Hartog, J. (2000) Overeducation and earnings: Where are we, where should we go? *Economics of Education Review* 19(2): 131–147.

Heckman, J. (1976) A Life-Cycle Model of Earnings, Learning, and Consumption. *Journal of Political Economy* 84 (4): 11-44.

Heckman, J. (2007) The economics, technology and neuroscience of human capability formation. IZA discussion papers 2875. Bonn: Institute for the Study of Labour.

Ipsos MORI (2014) Cedefop European Skills Survey: Data collection and quality report. London, Ipsos MORI publications.

Karaca-Mandic, P., E. Norton and B. Dowd (2012) Interaction Terms in Nonlinear Models. *Health Services Research* 47(1): 255–274.

Kiker, B., M. Santos and M. Mendes de Oliveiria (1997) Overeducation and undereducation: evidence for Portugal. *Economics of Education Review* 16(2): 111-125.

Leuven, E. (2005) The Economics of Private Sector Training: A Survey of the Literature. *Journal of Economic Surveys* 19(1): 91-111.

Leuven, E. and H. Oosterbeek (2008) An alternative approach to estimate the wage returns to private-sector training. *Journal of Applied Econometrics* 23(4): 423-434.

Levitt, S., J. List and C. Syverson (2012) Toward an understanding of learning by doing: evidence from an automobile assembly plant. NBER Working paper series No. 18017. Massachusetts, National Bureau of Economic Research.

Long, J. (1997) Regression Models for Categorical and Limited Dependent Variables. London: Sage Publications.

Long, J. and J. Freese (2014) *Regression Models for Categorical Dependent Variables in Stata*. 3rd ed. College Station, TX: Stata Press.

Lowenstein, M. and J. Spletzer (1998) Dividing the Costs and Returns to General Training. *Journal of Labor Economics* 16(1): 142-171.

Mavromarasa, K. and S. McGuinness (2012) Overskilling dynamics and education pathways. *Economics of Education Review* 31(5): 619–628.

Mavromaras, K., S. McGuinness and F. King (2009). Assessing the incidence and wage effects of overskilling in the Australian labour market. *The Economic Record* 85(268): 60–72.

Mavromaras, K., S. McGuinness, N. O'Leary, P. Sloane and Y. Fok (2010). The problem of overskilling in Australia and Britain. *Manchester School* 78(3): 219-241.

McGuinness, S. (2006). Overeducation in the labour market. Journal of Economic Surveys, 20, 387–418.

McGuinness, S., and J. Bennett (2007). Overeducation and the graduate labour market: A quantile regression approach. *Economics of Education Review* 6(5): 521–531.

McGuinness, S. and D. Byrne (2014) Examining the Relationships between Labour Market Mismatches, Earnings and Job Satisfaction among Immigrant Graduates in Europe. IZA DP No. 8440. Bonn: The Institute for the Study of Labor.

McGuinness, S. and P. Sloane (2011) Labour market mismatch among UK graduates: An analysis using REFLEX data. *Economics of Education Review* 30(1): 130–145.

McGuinness, S., and M. Wooden (2009). Overskilling, job insecurity and career mobility. *Industrial Relations* 48(2): 265–286.

Messinis, G. and Olekalns, N. (2007) Skill Mismatch and Training in Australia: Some Implications for Policy. *Australian Economic Review* 40(3): 300–306.

Messinis, G. and Olekalns, N. (2008) Returns to Training and Skill Mismatch: Evidence from Australia. CSES Working Paper No. 40. Victoria: Victoria University.

Mincer, J. (1962) On-the-Job Training: Costs, Returns, and Some Implications. Journal of Political Economy 70(5): 50-79.

Mincer, J. (1968) Job Training, Wage Growth and Labour Turnover. NBER Working paper series No. 2690. Massachusetts: National Bureau of Economic Research.

Mincer, J. (1974). *Schooling, Experience and Earnings*. New York: Columbia University Press.

Norton, E., H. Wang, and C. Ai (2004) Computing Interaction Effects and Standard Errors in Logit and Probit Models. *Stata Journal* 4(2): 154–67.

O'Connell, P. and D. Byrne (2012) The determinants and effects of training at work: bringing the workplace back in. *European Sociological Review* 28(3): 283-300.

O'Leary, N., P. Sloane, S. McGuinness, P. O'Connor and K. Mavromaras (2009). A taxonomy of skill mismatch. Report to CEDEFOP. Thessaloniki: CEDEFOP.

Sepulveda, F. (2010) Training and productivity: evidence for US manufacturing industries. *Oxford Economic Papers* 62 (3): 504–528

Sloane, P., H. Battu, H. and P. Seaman (1999). Overeducation, undereducation and the British Labour Market. *Applied Economics* 31(11): 1437–1453.

Van Smoorenburg, M. and R. van der Velden (2000) The Training of School-Leavers: Complementarity of Substitution? *Economics of Education Review* 19(2): 207-217.

Winship, C. and R. Mare (1984) Regression Models with Ordinal Variables. *American Sociological Review* 49(4): 512-525.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*, second edition. Cambridge, MA: MIT Press.

World Economic Forum (2014) Global Agenda Council on Employment: Matching Skills and Labour Market Needs; Building Social Partnerships for Better Skills and Better Job. Geneva, World Economic Forum.

APPENDIX

Table A1. Distribution of the sample

Country	*Obs.*	*% Sample*	*Initially well matched*	*Initially under-skilled*	*Initially over-skilled*
Germany	2,920	7.9	51.8	19.0	29.2
France	3,088	8.3	50.7	23.8	25.5
United Kingdom	2,822	7.6	41.7	24.0	34.3
Sweden	738	2.0	57.5	18.8	23.7
Italy	2,271	6.1	53.5	20.7	25.9
Greece	1,449	3.9	41.8	19.9	38.4
Czech Republic	1,272	3.4	48.7	32.9	18.4
Poland	3,157	8.5	51.0	21.5	27.5
Netherlands	818	2.2	57.2	20.2	22.6
Denmark	690	1.9	52.2	24.0	23.8
Hungary	1,276	3.4	54.5	21.9	23.7
Spain	2,893	7.8	51.1	17.7	31.3
Austria	723	1.9	43.4	23.0	33.6
Belgium	1,001	2.7	52.6	20.2	27.3
Ireland	747	2.0	42.8	26.8	30.4
Slovakia	834	2.2	41.9	36.0	22.2
Finland	1,575	4.2	43.8	29.0	27.2
Portugal	1,280	3.4	57.7	24.0	18.3
Estonia	848	2.3	48.4	41.0	10.6
Romania	1,299	3.5	59.5	25.6	14.9
Lithuania	824	2.2	49.9	39.0	11.2
Cyprus	396	1.1	46.0	29.0	25.0
Slovenia	852	2.3	60.5	18.5	21.0
Bulgaria	881	2.4	55.7	27.0	17.3
Latvia	808	2.2	52.6	36.8	10.6
Luxembourg	420	1.1	73.6	11.4	15.0
Malta	408	1.1	57.6	28.9	13.5
Croatia	887	2.4	57.1	22.3	20.6
TOTAL	37,177	100	50.9	23.9	25.2

Table A2. Descriptive statistics

	All	*Initially well matched (51%)*	*Initially under-skilled (24%)*	*Initially over-skilled (25%)*
Training (during tenure)	0.62	0.61	0.70	0.58
Training 12 months	0.57	0.56	0.60	0.55
Training in working hours	0.62	0.61	0.66	0.61
Training outside working hours	0.22	0.24	0.18	0.23
Training paid by the employer	0.66	0.67	0.69	0.62
Training paid by the employee	0.07	0.07	0.05	0.10
IL never	0.04	0.04	0.02	0.05
IL sometimes	0.41	0.40	0.38	0.45
IL usually	0.33	0.34	0.36	0.30
IL always	0.22	0.22	0.23	0.20
IL from others*	0.77	0.76	0.86	0.72

IL by trial and error*	0.61	0.58	0.70	0.58
IL by self-study*	0.56	0.52	0.63	0.55
Formal education (during tenure)	0.14	0.13	0.17	0.11
Individual characteristics				
Age (24-65) s.d. = 9.8	42.10	42.39	41.33	42.25
Female	0.39	0.39	0.42	0.37
Low level of education	0.12	0.13	0.12	0.10
Intermediate level of education	0.41	0.43	0.42	0.38
High level of education	0.47	0.44	0.47	0.52
Years of tenure (0-50) s.d.= 9.1	10.47	10.82	11.31	8.96
Permanent contract	0.87	0.87	0.88	0.85
Fixed temporary contract	0.10	0.10	0.09	0.12
Temporary agency contract	0.01	0.01	0.01	0.01
No formal contract	0.02	0.02	0.02	0.02
Telephone (interviewed)	0.21	0.23	0.24	0.13
Industry				
Agriculture	0.02	0.02	0.02	0.02
Manufacturing	0.19	0.19	0.21	0.18
Construction	0.06	0.07	0.06	0.05
Sales and transportation	0.20	0.19	0.17	0.23
Information and communication	0.07	0.07	0.08	0.07
Financial and real state	0.06	0.06	0.06	0.06
Professional and Tech	0.07	0.07	0.08	0.06
Public administration	0.25	0.26	0.25	0.25
Other services	0.08	0.08	0.07	0.08
Occupation				
Managers	0.09	0.08	0.09	0.10
Professionals	0.22	0.22	0.24	0.18
Technicians	0.17	0.17	0.19	0.15
Service and sales workers	0.12	0.12	0.11	0.14
Clerical support	0.21	0.20	0.18	0.24
Skilled agricultural	0.01	0.01	0.01	0.01
Building, crafts or related trades	0.08	0.09	0.09	0.06
Plant and machine operators	0.07	0.07	0.07	0.08
Elementary	0.04	0.04	0.03	0.05
Firm size				
1-9	0.20	0.20	0.20	0.20
10-49	0.28	0.28	0.29	0.27
50-99	0.13	0.14	0.12	0.13
100-249	0.13	0.13	0.13	0.14
250-499	0.08	0.08	0.08	0.09
>500	0.17	0.17	0.18	0.17
Observations	37177	18924	8886	9367

* For these variables we have fewer observations (31954). It is because the respective questions were only asked to respondents who reported a positive skills change in our dependent variable (i.e. above category 5 in the 0-10 scale).

Table A3. Estimations of training and informal learning participation

	(1) Probit AME Training	(2) Probit AME IL	(4) OLS IL intensity
Initially under-skilled	0.068***	0.048***	0.055***
	(0.007)	(0.004)	(0.011)
Initially over-skilled	-0.005	-0.017***	-0.071***
	(0.005)	(0.003)	(0.016)
Age	0.005**	-0.001***	-0.010**
	(0.002)	(0.000)	(0.004)
Age^2	-0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Female	-0.004	0.001	-0.005
	(0.007)	(0.004)	(0.015)
Intermediate level of education	0.054***	0.009	0.083**
	(0.012)	(0.006)	(0.035)
High level of education	0.094***	0.019***	0.132***
	(0.013)	(0.006)	(0.033)
Years of tenure	0.009***	-0.001***	-0.002**
	(0.000)	(0.000)	(0.001)
Temporary contract	-0.075***	0.013*	0.093***
	(0.009)	(0.007)	(0.017)
Agency contract	-0.136***	0.029***	0.124**
	(0.036)	(0.011)	(0.052)
No formal contract	-0.143***	-0.001	0.068
	(0.023)	(0.008)	(0.050)
Learning attitude (std)	0.016***	-0.002	0.127***
	(0.003)	(0.002)	(0.014)
Other controls	*yes*	*yes*	*yes*

Columns (1) and (2) in this table show the 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 parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N= 37,177.

Table A4. Skills development (AME) including learning attitude

Skills change	**0-4**	**5-6**	**7-8**	**9-10**
Training	-0.020***	-0.058***	-0.019***	0.097***
	(0.002)	(0.005)	(0.002)	(0.008)
IL sometimes	-0.048***	-0.082***	0.018***	0.111***
	(0.008)	(0.010)	(0.006)	(0.013)
IL usually	-0.063***	-0.126***	0.006	0.183***
	(0.008)	(0.010)	(0.005)	(0.013)
IL always	-0.072***	-0.163***	-0.023***	0.258***
	(0.008)	(0.011)	(0.005)	(0.015)
Under-skilled	-0.015***	-0.061***	-0.048***	0.123***
	(0.001)	(0.003)	(0.003)	(0.006)
Over-skilled	0.025***	0.060***	0.004	-0.089***
	(0.002)	(0.005)	(0.002)	(0.007)
Learning attitude (std)	-0.014***	-0.042***	-0.019***	0.076***
	(0.001)	(0.002)	(0.001)	(0.003)
Interactions between learning participation and learning attitude				
Training				
Low learning attitude	-0.026***	-0.066***	-0.002	0.094***
	(0.002)	(0.005)	(0.002)	(0.007)
High learning attitude	-0.012***	-0.058***	-0.042***	0.112***
	(0.001)	(0.004)	(0.004)	(0.008)
IL sometimes				
Low learning attitude	-0.040***	-0.060***	0.028***	0.071***
	(0.008)	(0.011)	(0.006)	(0.014)
High learning attitude	-0.017***	-0.063***	-0.018***	0.099***
	(0.005)	(0.014)	(0.002)	(0.020)
IL usually				
Low learning attitude	-0.041***	-0.102***	0.017***	0.126***
	(0.006)	(0.015)	(0.007)	(0.018)
High learning attitude	-0.024***	-0.093***	-0.040***	0.157***
	(0.005)	(0.015)	(0.004)	(0.022)
IL always				
Low learning attitude	-0.052***	-0.150***	-0.001	0.202***
	(0.009)	(0.015)	(0.006)	(0.019)
High learning attitude	-0.029***	-0.129***	-0.082***	0.241***
	(0.005)	(0.015)	(0.006)	(0.023)

All other controls are included. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N= 29,018.

Table A5. Skills development (AME) importance of career development opportunities

Skills change	0-4	5-6	7-8	9-10
Training	-0.017***	-0.058***	-0.021***	0.097***
	(0.001)	(0.004)	(0.003)	(0.007)
IL sometimes	-0.025***	-0.054***	0.007*	0.072***
	(0.006)	(0.011)	(0.004)	(0.016)
IL usually	-0.037***	-0.093***	-0.007**	0.138***
	(0.007)	(0.012)	(0.003)	(0.018)
IL always	-0.046***	-0.134***	-0.040***	0.220***
	(0.007)	(0.012)	(0.005)	(0.020)
Under-skilled	-0.014***	-0.064***	-0.046***	0.124***
	(0.001)	(0.003)	(0.003)	(0.006)
Over-skilled	0.017***	0.046***	0.005***	-0.067***
	(0.002)	(0.005)	(0.002)	(0.007)
Importance of career (std)	-0.009***	-0.030***	-0.015***	0.054***
	(0.001)	(0.002)	(0.001)	(0.004)
Interactions between learning variables and importance of career development				
Training				
Low importance career	-0.022***	-0.063***	-0.008***	0.092***
	(0.002)	(0.005)	(0.002)	(0.007)
High importance career	-0.011***	-0.055***	-0.044***	0.109***
	(0.001)	(0.004)	(0.004)	(0.008)
IL sometimes				
Low importance career	-0.034***	-0.061***	0.022***	0.073***
	(0.008)	(0.011)	(0.006)	(0.012)
High importance career	-0.016***	-0.062***	-0.021***	0.098***
	(0.005)	(0.014)	(0.002)	(0.015)
IL usually				
Low importance career	-0.036***	-0.104***	0.010	0.131***
	(0.008)	(0.015)	(0.006)	(0.014)
High importance career	-0.022***	-0.092***	-0.044***	0.159***
	(0.005)	(0.015)	(0.004)	(0.017)
IL always				
Low importance career	-0.060***	-0.147***	-0.007	0.214***
	(0.008)	(0.013)	(0.006)	(0.016)
High importance career	-0.028***	-0.129***	-0.090***	0.246***
	(0.005)	(0.015)	(0.006)	(0.019)

All other controls are included. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N= 37,177.

Table A6. Skills development (AME) including changes in the job position

Skills change	0-4	5-6	7-8	9-10
Training	-0.018***	-0.060***	-0.022***	0.100***
	(0.001)	(0.004)	(0.003)	(0.007)
IL sometimes	-0.029***	-0.060***	0.009**	0.080***
	(0.006)	(0.011)	(0.004)	(0.016)
IL usually	-0.043***	-0.104***	-0.006*	0.152***
	(0.007)	(0.012)	(0.003)	(0.017)
IL always	-0.052***	-0.147***	-0.042***	0.241***
	(0.007)	(0.012)	(0.005)	(0.020)
Under-skilled	-0.013***	-0.060***	-0.044***	0.117***
	(0.001)	(0.003)	(0.003)	(0.006)
Over-skilled	0.019***	0.053***	0.006***	-0.078***
	(0.002)	(0.005)	(0.002)	(0.007)
Changed position	-0.010***	-0.034***	-0.017***	0.060***
	(0.001)	(0.003)	(0.002)	(0.005)

All other controls are included. The marginal effect for categorical variables is the discrete change from the base level. Standard errors clustered at country level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N= 37,019.

Table A7. Training (probit) estimations including informal learning as explanatory variable

Training	Probit AME
1. All sample	
IL sometimes	0.176***
	(0.019)
IL usually	0.238***
	(0.019)
IL always	0.255***
	(0.023)
2. AME between the initial job-skill mismatch groups (well matched ref)	
Initially under-skilled	
IL sometimes	0.072***
	(0.011)
IL usually	0.064***
	(0.009)
IL always	0.045***
	(0.010)
Initially over-skilled	
IL sometimes	-0.009
	(0.007)
IL usually	0.007
	(0.011)
IL always	0.015
	(0.012)

All other controls are included. AME is the average marginal effect (discrete change from the base level). Standard errors clustered at country level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. N= 37,076.

Table A8. Informal learning (oprobit) estimations including training as explanatory variable

Informal learning	Never	Sometimes	Usually	Always
1. All sample				
Training	-0.019***	-0.072***	0.026***	0.065***
	(0.003)	(0.006)	(0.003)	(0.006)
2. AME between the initial job-skill mismatch groups (well matched ref)				
Initially under-skilled				
Training	-0.008***	-0.026***	0.011***	0.023***
	(0.002)	(0.008)	(0.003)	(0.007)
Initially over-skilled				
Training	0.005***	0.027***	-0.007***	-0.026***
	(0.001)	(0.007)	(0.002)	(0.007)

All other controls are included. AME is the average marginal effect (discrete change from the base level). Standard errors clustered at country level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. N= 37,076.