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The Role of Personality, Working Tasks and Firm Effects

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Katja Görlitz and Marcus Tamm[1]

Revisiting the Complementarity between Education and Training – The Role of Personality, Working Tasks and Firm Effects

Abstract

This paper addresses the question to which extent the complementarity between education and training can be attributed to differences in observable characteristics, i.e. to individual, job and firm specific characteristics. The novelty of this paper is to analyze previously unconsidered characteristics, in particular, personality traits and tasks performed at work which are taken into account in addition to the standard individual specific determinants. Results show that tasks performed at work are strong predictors of training participation while personality traits are not. Once working tasks and other job related characteristics are controlled for, the skill gap in training participation drops considerably for off-the-job training and vanishes for on-the-job training.

JEL Classification: I21, J24

Keywords: Training; personality traits; working tasks; Oaxaca decomposition

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1. Introduction

Work related training is generally considered as important to increase labor productivity, to decrease turnover rates and to cope with technological and organizational innovations. A question of the previous training literature was to describe who participates in training and who does not. There is ample evidence from a variety of countries that high skilled workers participate more often in training then workers with lower skills even after controlling for individual specific characteristics.[1] Even though the positive relationship between education and training is well documented, the underlying reasons are not yet understood. Gaining insights into these reasons is crucial to infer about efficiency and equity of the training market. It also reveals scope for policy interventions in the case of underinvestment in training, e.g. if the low skilled face credit market constraints.

This paper addresses the question to which extent the complementarity between education and training can be attributed to differences in observable characteristics, i.e. to individual, job and firm specific characteristics. Because previous studies have found that the link between education and training can vary by type of training, the analysis distinguishes between on-the-job (ONJT) and off-the-job training (OFFJT), i.e. between training that is carried out by the firm or another institution, respectively.[2] The novelty of this paper is to analyze previously unconsidered characteristics, in particular, personality traits and tasks performed at work which are considered in addition to the standard individual specific determinants.

Personality traits seem to affect school attendance and performance as well as labor market success (e.g. Borghans et al. 2008, Heckman et al. 2006). Yet, little is known on whether this carries on to training participation. Traits like emotional stability might come along with test anxiety that prevents individuals from participating in training. Other aspects of personality, for example, the degree of openness to experience, might correlate with time or risk preferences which, in turn, might influence the training investment decision. Personality might as well influence aspects such as how individuals process information, envision counterfactual states or project into the future which might determine the training decision (Borghans et al. 2008, Coleman and DeLeire 2003). Some first evidence for the Netherlands shows that personality traits seem to affect the willingness to participate in training (Fouarge et al. 2010). Unfortunately, this study does not provide evidence on actual training participation.

[1] See e.g. Lynch (1992) and Lynch and Black (1998) for the US, Blundell et al. (1999) for the UK and Pischke (2001) for Germany. Using data for ten European countries, Brunello (2004) also confirms a strong complementarity in Europe. The complementarity is visible not only within countries but also across countries. Bassanini et al. (2007) show that at the country level higher average education is correlated with higher average training incidence.

[2] Lynch (1992) finds that the positive correlation between schooling and OFFJT is stronger than the correlation between schooling and ONJT. Using data from Thailand, Ariga and Brunello (2006) show that ONJT is a substitute for education while OFFJT is a complement.

There are also many reasons why working tasks might correlate with training participation. Acemoglu and Pischke (1999) argue that if output of some tasks is harder to measure than output of other tasks, the optimal degree of wage compression might differ between tasks. Higher levels of wage compression will lead to more firm sponsored training. Autor et al. (2003) and Spitz-Oener (2006, 2008) show that some tasks are more likely to be affected by processes of computerization and reorganization than other tasks. These processes often trigger training participation (Bresnahan et al. 2002).

Another novel element of this analysis is to keep firm attributes constant which was found to be important when estimating returns to training (Goux and Maurin 2000, Görlitz 2011). When analyzing the determinants of training this might be important if low and high skilled workers select into firms with different propensities to invest in training. Due to inadequate data, most of the previous studies included only few firm attributes when analyzing training processes. Since we have access to linked employer employee data for Germany, we can apply firm fixed effects.

The paper is organized as follows. Section 2 describes the data and section 3 presents the empirical strategy as well as results. Section 4 discusses the results and the final section concludes.

2. The Data

The analysis is based on the linked employer employee data "WeLL". WeLL is a panel data set that was particularly designed to analyze training activities of employees (see Bender et al. 2009). The employee sample was drawn from 149 firms. The firms were chosen according to pre-defined criteria (i.e. firm size between 100 and 2000 employees, manufacturing or service sector).[3] Within firms employees were sampled randomly. The first wave was conducted in 2007; follow up interviews took place in 2008, 2009 and 2010. The interviews were conducted by telephone.

In the WeLL data, individuals were asked whether they have participated in formal work-related training during the last 12 months, i.e. in any class-room training like courses, seminars or lectures. For each training, the data contains information on start and end date, whether the training was provided on-the-job or off-the-job and several aspects about training costs. The main analysis utilizes information on training that was attended between the first and the second interview.[4] The information on covariates is matched from the first

[3] Due to this particular sampling frame, the WeLL data is not necessarily representative for Germany as a whole. Therefore, we provide robustness checks where we re-estimate the results using a representative German data set (see Appendix B).

[4] Some individuals participated in the first wave 2007 and in the third wave 2009 but not in the second wave. To increase sample size and to reduce attrition, these individuals are also considered in

interview to avoid simultaneity issues. In the analysis, the focus lies on participation in ONJT and on participation in OFFJT. We only consider training of employed individuals and disregard training while being unemployed.

To classify employees by education, two skill groups are defined based on individuals' college qualification. High skilled workers have graduated from university or college. All other workers are defined as medium skilled. This latter group is composed of mostly apprenticeship graduates and to a smaller number of persons with no degree.[5]

Personality traits are measured with two common psychological concepts of personality: Locus of control and the Big Five. Locus of control indicates the extent to which individuals believe that they have control over their life as opposed to believing that luck or fate controls life (Rotter 1966). Eight items are included in the WeLL data that allow us to construct a measure of the work-related locus of control. Higher scales point at a higher external belief of control, i.e. that one's working life is controlled by luck or fate. The Big Five is a widely accepted concept to describe the psychological dimensions openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (McCrae and Costa 1999). For the analysis, we create binary variables that indicate workers with a high level of each trait. As questions on personality traits were included in the second interview for the first time (as opposed to all other covariates used in this paper), we consider them as exogenously predetermined factors in the analysis.[6] Appendix A provides further information on the definition of these variables. Given that the Big Five disregard differences in another potentially important aspect of personality, namely motivation, we additionally include a self-reported indicator of average monthly overtime as a proxy for motivation.

Following the concept of Autor et al. (2003) and Spitz-Oener (2006), we distinguish five categories of working tasks: Routine manual, nonroutine manual, routine cognitive, nonroutine analytical and nonroutine interactive tasks. Table 1 documents how work activities are assigned to task categories. The assignment is based on employees' response on whether they perform these activities frequently, occasionally or never. As suggested by Antonczyk et al. (2009), the following indices are constructed for each of the five task categories *j*:

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the analysis by using training information from the 2009 interview. This is possible because the date of the first interview was used as the reference period in the third interview providing a nearly complete training biography even for temporary panel drop-outs. None of our results hinges on the inclusion of these individuals.

[5] Even if it would be interesting to split the educational groups into three categories distinguishing high, medium and low skilled workers, this is impossible because the sample size for workers with no degree is too small. Note that none of our results hinges on the inclusion of workers with no degree into the group of medium skilled workers.

[6] Borghans et al. (2008) conclude that even if traits are not entirely stable over time, only radical changes in social roles with long-lasting consequences like labor market entry or becoming a parent may have an impact on traits.

$$\text{Task}_{ji} = \frac{\text{Number of activities in category j frequently performed by worker i}}{\text{Total number of activities frequently performed by worker i}}.$$

Since the sum over all five task indices equals one for each worker, one of the categories has to be omitted in the regressions. This tasks index has the advantage that the role of job complexity can be accounted for separately.[7] Job complexity is defined as:

$$\text{Job complexity}_i = \text{Total number of activities frequently performed by worker i.}$$

Table 2 summarizes the variables used in the analysis and presents descriptive statistics. In the sample, 23% of workers are high skilled and 77% are medium skilled. In line with previous results, it can be shown that high skilled workers participate more often in training than workers with a lower educational degree. Unconditional differences in participation rates are much larger for OFFJT (32% vs. 15%) than for ONJT (37% vs. 33%). Demographics (e.g. gender and age) and job-related characteristics (e.g. part-time contract and tenure) also differ by education. Interestingly, high skilled employees display a somewhat higher external locus of control, are more often highly open to experience and highly agreeable and less often highly conscientious. In addition, high skilled employees work more overtime. Tasks also differ between skill groups. While high educated workers are more engaged in nonroutine analytical and interactive tasks, workers with lower education are more often involved in manual and in routine cognitive activities. In addition, high skilled workers have on average more complex jobs, i.e. they perform a larger number of activities.

Table 1 – Assignment of work activities to task categories

Task category	Activities
Routine manual	Fabricating and producing goods; Supervising and controlling machines
Nonroutine manual	Repairing and patching; Nursing, serving and healing
Routine cognitive	Measuring, controlling and quality checks
Nonroutine analytic	Developing and researching; Gathering information and investigating
Nonroutine interactive	Informing and advising; Training, teaching and educating; Organizing and planning; Negotiating; Buying, providing and selling

[7] This is the reason why we prefer the task indices as suggested by Antonczyk et al. (2009) and do not use the index suggested by Spitz-Oener (2006). Note that the main results are robust to using either of the two indices.

Table 2 - Sample means WeLL data

	Mean			t-stat
	All	Medium skilled	High skilled	(high vs. medium)
On-the-job training (ONJT)	0.337	0.327	0.369	**2.42**
Off-the-job training (OFFJT)	0.191	0.153	0.316	**11.42**
Female	0.348	0.361	0.307	**-3.04**
Age <35	0.122	0.123	0.116	-0.61
Age 35-44	0.309	0.304	0.326	1.28
Age 45-54	0.403	0.416	0.358	**-3.18**
Age 55+	0.167	0.157	0.200	**3.12**
Migrant (1st or 2nd generation)	0.051	0.055	0.038	**-2.14**
Married	0.751	0.746	0.768	1.35
Living with kids	0.389	0.380	0.419	**2.15**
Living with kids below age 6	0.114	0.103	0.147	**3.77**
Temporary contract	0.049	0.047	0.056	1.18
Part-time	0.149	0.162	0.103	**-4.50**
Tenure <4 years	0.123	0.104	0.188	**7.00**
Tenure 4-6 years	0.095	0.084	0.130	**4.20**
Tenure 7-10 years	0.129	0.125	0.141	1.31
Tenure 11-20 years	0.289	0.294	0.275	-1.14
Tenure 21+ years	0.364	0.393	0.266	**-7.19**
Locus of control	14.2	14.2	14.5	**2.87**
High openness to experience	0.407	0.391	0.461	**3.86**
High concientiousness	0.962	0.966	0.948	**-2.58**
High extraversion	0.558	0.573	0.511	**-3.37**
High agreeableness	0.632	0.622	0.667	**2.54**
High neutroticism	0.120	0.125	0.102	*-1.90*
Overtime 0 hours per month	0.183	0.201	0.126	**-5.22**
Overtime 1 to 10 hours per month	0.380	0.402	0.309	**-5.17**
Overtime 10+ hours per month	0.436	0.398	0.564	**9.20**
Task index routine manual	0.158	0.189	0.055	**15.82**
Task index nonroutine manual	0.162	0.178	0.111	**-9.66**
Task index routine cognitive	0.110	0.121	0.077	**-7.97**
Task index nonroutine analytical	0.160	0.132	0.254	**20.94**
Task index nonroutine interactive	0.409	0.381	0.503	**12.88**
Job complexity	4.44	4.29	4.94	**8.86**
Observations	4104	3147	957	

Note: Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

3. Empirical Results

The aim of this paper is twofold: First, we are interested in whether personality traits and working tasks are determinants of training and whether it is important to control for firm fixed effects. The methods used are models for binary outcome variables, i.e. the Probit and the linear probability model. Second, we are interested in whether these additional covariates contribute to explaining the correlation between education and training. This is investigated using Blinder-Oaxaca techniques for non-linear models.

The results of the first step are presented separately for ONJT and OFFJT in Table 3. For both dependent variables, three different specifications are shown where the first one only considers standard personal and job characteristics, the second additionally incorporates personality and tasks and the third one, which is our main specification, also applies firm fixed effects. While specifications 1 and 2 are estimated using Probit models, specification 3 is estimated using a linear probability model.[8]

After controlling for standard covariates (specification 1), high skilled workers have a 5 percentage points higher probability to participate in ONJT and a 15 percentage points higher probability to participate in OFFJT compared to medium skilled workers. These estimates are almost identical to the unconditional differences that were presented in Table 2. This indicates that the standard covariates of training models hardly explain the skill gap in participation. When controlling for personality traits and working tasks, the average training difference between skill groups shrinks considerably (specification 2). For on-the-job training, the difference becomes virtually zero, while for off-the-job training, the gap reduces by one third to around 10 percentage points. Controlling for firm fixed effects hardly alters the results neither for ONJT nor for OFFJT (specification 3).

In the main specification, individual and job characteristics are insignificant determinants of ONJT. With regard to OFFJT, there is a significant negative correlation with age, part-time and tenure. Personality traits are generally insignificant and unrelated to participation except for openness that is a negative predictor of on-the-job training. A Wald test on the joint significance of all Big Five indicators is insignificant. For both ONJT and OFFJT alike, overtime is positively associated with training. The task indices and job complexity are strong predictors regardless of training type. Workers who perform a higher level of nonroutine tasks have higher participation rates than the reference category of workers who are involved in routine manual tasks. The more complex a job is, the higher is the average training probability.

[8] We use linear probability models for the firm fixed effects specifications to keep sample size constant and because nonlinear fixed effects models would only use observations when there is variation in the dependent variable within firms. Results using such non-linear models are very similar to those based on a linear probability model. Results are also very similar when using linear probability models instead of Probit for specifications 1 and 2.

Table 3 - Determinants of training participation

	On-the-job training						Off-the-job training					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Marg. eff.	t-stat	Marg. eff.	t-stat	Marg. eff.	t-stat	Marg. eff.	t-stat	Marg. eff.	t-stat	Marg. eff.	t-stat
Medium skilled	-0.053	**-2.95**	0.002	0.10	0.002	0.11	-0.154	**-10.10**	-0.097	**-6.20**	-0.112	**-6.90**
Female	0.077	**4.31**	0.060	**3.22**	0.032	1.55	0.014	0.99	-0.002	-0.13	-0.029	*-1.71*
Age <35	-0.011	-0.40	-0.003	-0.10	0.011	0.41	-0.029	-1.36	-0.028	-1.34	-0.026	-1.14
Age 45-54	-0.024	-0.83	-0.011	-0.38	0.009	0.30	-0.056	**-2.49**	-0.051	**-2.31**	-0.063	**-2.65**
Age 55+	-0.078	**-2.41**	-0.068	**-2.07**	-0.039	-1.17	-0.074	**-3.01**	-0.072	**-2.98**	-0.091	**-3.29**
Migrant	-0.036	-1.06	-0.013	-0.38	-0.007	-0.22	-0.035	-1.26	-0.015	-0.55	-0.012	-0.42
Married	0.013	0.67	0.002	0.12	0.009	0.47	0.016	1.03	0.009	0.58	0.011	0.66
Living with kids	-0.002	-0.08	-0.007	-0.36	-0.017	-0.87	-0.001	-0.03	-0.005	-0.29	-0.014	-0.85
Living with kids below age 6	-0.010	-0.36	-0.014	-0.52	-0.004	-0.16	0.002	0.07	0.001	0.05	0.002	0.09
Temporary contract	-0.001	-0.04	0.028	0.75	0.043	1.19	-0.012	-0.43	0.007	0.24	-0.006	-0.19
Part-time	0.028	1.17	0.023	0.93	0.007	0.30	-0.041	**-2.13**	-0.041	**-2.22**	-0.052	**-2.49**
Tenure <4 years	0.002	0.06	0.003	0.08	0.003	0.09	0.028	1.14	0.029	1.17	0.012	0.44
Tenure 4-6 years	0.013	0.40	0.022	0.68	0.017	0.52	-0.009	-0.34	0.000	0.02	-0.009	-0.33
Tenure 11-20 years	-0.005	-0.18	-0.008	-0.31	-0.017	-0.65	-0.013	-0.67	-0.013	-0.67	-0.034	-1.63
Tenure 21+ years	0.026	1.01	0.014	0.54	-0.001	-0.05	-0.031	-1.50	-0.037	*-1.84*	-0.044	**-1.99**
Locus of control			0.000	0.09	0.000	-0.08			-0.001	-0.49	-0.001	-0.59
High openness to experience			-0.037	**-2.33**	-0.039	**-2.49**			-0.006	-0.47	-0.005	-0.41
High concientiousness			0.034	0.87	0.031	0.82			-0.027	-0.86	-0.020	-0.63
High extraversion			0.007	0.46	0.012	0.80			-0.004	-0.33	0.004	0.28
High agreeableness			0.017	1.11	0.022	1.46			-0.019	-1.51	-0.023	*-1.84*
High neutroticism			-0.020	-0.84	-0.020	-0.89			-0.030	-1.59	-0.024	-1.28
Overtime 1 to 10 hours per month			0.068	**3.09**	0.066	**3.09**			0.027	1.47	0.023	1.31
Overtime 10+ hours per month			0.088	**3.99**	0.085	**3.90**			0.042	**2.37**	0.041	**2.30**
Task index nonroutine manual			0.254	**4.86**	0.094	*1.84*			0.278	**5.87**	0.100	**2.38**
Task index routine cognitive			-0.014	-0.19	-0.051	-0.79			0.176	**2.78**	0.089	*1.67*
Task index nonroutine analytical			0.194	**3.50**	0.082	1.53			0.255	**5.29**	0.160	**3.62**
Task index nonroutine interactive			0.216	**5.15**	0.109	**2.65**			0.274	**7.15**	0.190	**5.60**
Job complexity			0.026	**6.64**	0.019	**4.86**			0.016	**5.24**	0.011	**3.26**
Firm fixed effects	no		no		yes		no		no		yes	
Pseudo R^2	0.0097		0.0404		0.1167		0.0383		0.0739		0.1280	
Observations	4104		4104		4104		4104		4104		4104	

Note: Specifications 1 and 2 are estimated using Probit and specification 3 is estimated using a linear probability model. Dependent variables are binary, indicating participation in training carried out by the firm (on-the-job) or another institution (off-the-job) during the last 12 months. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

In the second step, we investigate to which extent the covariates account for the complementarity between education and training. In particular, we examine how the average training differential between high and medium skilled would look like, if the medium skilled had the same characteristics as the high skilled. Formally, the difference in average training participation $\overline{\mathrm{P(T)}}$ by skill group can be decomposed in the nonlinear framework proposed by Yun (2004):

$$\overline{P(T^{\text{high}})} - \overline{P(T^{\text{medium}})} = \left[\overline{\Phi(\mathrm{X}^{\text{high}}\beta^{\text{high}})} - \overline{\Phi(\mathrm{X}^{\text{medium}}\beta^{\text{high}})}\right] + \left[\overline{\Phi(\mathrm{X}^{\text{medium}}\beta^{\text{high}})} - \overline{\Phi(\mathrm{X}^{\text{medium}}\beta^{\text{medium}})}\right]$$

where X represents the covariates and β the regression coefficients of the training processes of the two skill groups. The first term in brackets shows the difference in training participation that can be explained by differences in the covariates.[9] The second term represents the unexplained part that can be attributed to differences in characteristics that are unobserved in the data such as preferences or innate ability. In addition to the overall decomposition we calculate the contribution of each covariate (or set of covariates) to the training gap to get information on the extent to which each of the covariates contributes to the education-training differential. Firm fixed effects cannot be incorporated easily in the decomposition analysis. Thus, they are restricted to be equal for both skill groups and only the coefficients of all other covariates are allowed to differ between groups. Therefore, we present results that first purge the raw difference in training participation from differences that are due to firm effects and then decompose the remaining gap into an explained and an unexplained part.

Table 4 represents the results of the decomposition analysis.[10] For both types of training, demographics and job characteristics perform poorly in explaining the skill gap. For ONJT, we even find that the gap would be larger, if medium skilled workers had similar characteristics to high skilled workers. Differences in working tasks and to a smaller extent also in overtime, explain almost the entire on-the-job training gap. Regarding OFFJT, the main contributor to the training gap are also overtime and working tasks, however, a much larger share of the raw differential remains unexplained compared to ONJT. Interestingly, results of specification 3 show that hardly any of the training difference is due to differences between firms for OFFJT (the skill gap changes from 16.3 to 16.5 percentage points after netting out the impact of firm effects) but for almost a quarter of the gap for ONJT. For ONJT we find that the skill gap decreases from 4.2 to 3.3 percentage points after netting out firm fixed effects, i.e. medium skilled workers are employed in firms that on average provide less on-the-job training.

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[9] The decomposition is not unique, i.e. one might use the coefficients of the medium skilled to calculate the explained part $\left[\overline{\Phi\left(\mathrm{X}^{\text{high}}\beta^{\text{medium}}\right)} - \overline{\Phi\left(\mathrm{X}^{\text{medium}}\beta^{\text{medium}}\right)}\right]$. However, results remain largely unchanged when using this alternative decomposition.

[10] The estimation was done using the December 2009 version of the Stata ado file `oaxaca` (Jann 2008).

Table 4 - Decomposition of the education-training gap

	On-the-job training						**Off-the-job training**					
	Specification 1		Specification 2		Specification 3		Specification 1		Specification 2		Specification 3	
	Effect	t-stat	Effect	t-stat	Effect	t-stat	Effect	t-stat	Effect	t-stat	Effect	t-stat
Raw difference	-0.042	**-2.39**	-0.042	**-2.39**	-0.042	**-2.39**	-0.163	**-9.99**	-0.163	**-9.99**	-0.163	**-9.99**
Raw difference net of firm fixed effects					-0.033	*-1.92*					-0.165	**-10.44**
Explained difference	0.024	**2.79**	-0.029	-1.36	-0.029	-1.26	-0.013	*-1.68*	-0.048	**-2.60**	-0.057	**-2.63**
Unexplained difference	-0.066	**-3.38**	-0.013	-0.50	-0.005	-0.16	-0.150	**-8.55**	-0.115	**-4.96**	-0.108	**-4.06**
Detailed decomposition of explained difference												
Female	0.004	1.57	0.004	*1.86*	0.004	1.56	0.001	0.48	0.000	0.23	-0.001	-0.41
Age	0.005	1.52	0.004	1.58	0.005	*1.80*	0.001	0.40	0.001	0.52	0.001	0.42
Migrant	0.003	1.42	0.002	1.54	0.003	1.53	0.001	0.97	0.001	1.13	0.001	1.01
Married	-0.002	-1.04	-0.001	-1.03	-0.001	-0.89	-0.001	-0.99	-0.001	-0.92	-0.001	-0.91
Kids	0.001	0.37	0.001	0.49	0.001	0.25	0.002	0.99	0.002	1.06	0.003	1.25
Temporary contract	-0.001	-0.86	-0.001	-0.94	-0.001	-0.97	-0.001	-1.01	-0.001	-1.01	-0.001	-0.99
Part-time	0.000	0.02	0.001	0.26	-0.001	-0.23	0.000	0.05	0.000	0.04	-0.001	-0.41
Tenure	0.015	**2.10**	0.011	**2.13**	0.012	*1.87*	-0.016	**-2.59**	-0.014	**-2.64**	-0.015	**-2.46**
Locus of control			0.002	1.32	0.003	1.22			0.001	0.82	0.001	0.57
Big five			0.002	0.48	0.002	0.60			0.002	0.78	0.004	1.06
Overtime			-0.012	**-2.41**	-0.015	**-2.75**			-0.004	-1.01	-0.005	-1.04
Tasks and job complexity			-0.041	**-2.15**	-0.039	*-1.87*			-0.036	**-2.08**	-0.043	**-2.10**
Firm fixed effects	no		no		yes		no		no		yes	
Observations	4104		4104		4104		4104		4104		4104	

Note: Decomposition follows Yun (2004). Specifications 1 and 2 are estimated using Probit. Specification 3 is estimated using a linear probability model and firm fixed effects are restricted to be equal for both skill groups. Dependent variables are binary, indicating participation in training carried out by the firm (on-the-job) or another institution (off-the-job) during the last 12 months. Significance levels are indicated in *italics* (10% level) and **boldface** (5%-level).

Robustness checks

In order to check the robustness of our results with regards to changes in the definition of covariates we ran several specifications changing the definition of personality traits and working tasks. Since the effect of personality traits might not be monotonically increasing or decreasing and the optimal level of traits may lie somewhere between the extremes (Borghans et al. 2008), we included additional indicators for low levels of traits instead of only indicators for high levels of traits. As an alternative we included continuous indices for traits and their squares. Doing so leaves results unchanged, i.e. personality traits are jointly insignificant in all specifications. As alternative to the task index suggested by Antonczyk et al. (2009) we included the index suggested by Spitz-Oener (2006). This also does not change any of our conclusions.

To check whether our results are valid for Germany as a whole and not only for the population of the WeLL data, we repeated the analysis using representative household panel data from the German Socio-Economic Panel (GSOEP). The GSOEP has the disadvantage of not containing direct information on tasks which is why we proxied tasks by occupation fixed effects. Furthermore, the GSOEP only identifies training participation but does not allow differentiating between ONJT and OFFJT. Finally, firm fixed effects cannot be incorporated. Results in Appendix B show that the main results remain unchanged.

4. Discussion

Our results raise two questions. First, why does a skill differential remain for OFFJT? Second, what drives the strong correlation between tasks and training? To shed more light on the first question, we present descriptive evidence on differences in characteristics of training courses undertaken by high and medium skilled employees. In the data, it can be distinguished whether training was of general or specific nature and whether it was fully or partly financed by employers where both monetary and opportunity costs (allowing participation during working hours) are considered. Furthermore we know who initiated training. Summary statistics are shown in Table 5 and refer to the characteristics of the last training course an individual attended. We find that more than 90% of OFFJT provides fully or mostly general skills and that there are hardly any differences between medium and high skilled workers. For ONJT the share of general skill training is almost 80% and there are no differences between skill groups either.

With respect to employers' financial involvement in training 45% of OFFJT courses are fully financed by employers, i.e. the entire course takes place during working hours and the employee does not have to bear any of the financial costs. Only for one out of seven courses employers do not take over at least part of the costs. Overall there are only few differences

Table 5 - Characteristics of training courses

	Mean			t-stat
	All	Medium skilled	High skilled	(high vs. medium)
On-the-job training				
Fully general skills	0.417	0.406	0.447	1.31
Mostly general skills	0.402	0.402	0.403	0.06
Mostly firm specific skills	0.120	0.127	0.098	-1.44
Fully firm specific skills	0.062	0.065	0.052	-0.87
Fully employer financed	0.630	0.630	0.629	-0.04
At least partly employer financed	0.979	0.983	0.966	**-2.00**
Employee's own initiative	0.293	0.270	0.363	**3.31**
Required/recommended by employer	0.488	0.492	0.478	-0.43
Required by law	0.212	0.232	0.153	**-3.12**
Recommended by other person	0.007	0.007	0.006	-0.21
Off-the-job training				
Fully general skills	0.551	0.537	0.574	0.99
Mostly general skills	0.370	0.377	0.359	-0.51
Mostly firm specific skills	0.044	0.047	0.040	-0.44
Fully firm specific skills	0.034	0.038	0.027	-0.86
Fully employer financed	0.446	0.446	0.446	0.01
At least partly employer financed	0.862	0.870	0.849	-0.84
Employee's own initiative	0.622	0.565	0.714	**4.19**
Required/recommended by employer	0.280	0.325	0.209	**-3.51**
Required by law	0.068	0.076	0.054	-1.21
Recommended by other person	0.030	0.034	0.024	-0.82

Note: Information on characteristics of courses refers to last ONJT and last OFFJT training activity for employees with at least one training. General vs. specific nature of training is rated by the employee. Financing of the training accounts for direct financial costs and opportunity costs (i.e. whether training was during working hours or during leisure time). Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

Table 6 - Determinants of training distinguishing financing and initiative

	Training fully financed by employer		Training initiated by employer		Training on employee's own initiative	
	Med./high skilled	t-stat	Med./high skilled	t-stat	Med./high skilled	t-stat
Mean	0.270 vs. 0.368	**5.86**	0.214 vs. 0.247	**2.14**	0.173 vs. 0.349	**11.83**
	Marg. eff.	t-stat	Marg. eff.	t-stat	Marg. eff.	t-stat
Medium skilled	-0.031	-1.63	-0.005	-0.30	-0.103	**-6.21**
Standard covariates, personality traits, overtime, working tasks	yes		yes		yes	
Firm fixed effects	yes		yes		yes	
R^2	0.1156		0.0814		0.1617	
Observations	4104		4104		4104	

Note: Specifications are estimated using a linear probability model. Dependent variables are binary, indicating participation in training that is fully employer financed, initiated by the employer or initiated by the employee himself, respectively. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

in employers' financial involvement between workers with different skill levels. For ONJT the picture is similar but employers' financial involvement is generally higher. For both OFFJT and ONJT alike, there are considerable differences by skill level with respect to who initiated training participation. High skilled workers are less likely to participate because of recommendations by employers or because training participation is required by law, e.g. as part of occupational regulations. Instead they decide to participate in training on their own initiative. When comparing OFFJT and ONJT, the former is more often initiated by employees. In sum, OFFJT is more often of general nature, to a fewer extent employer financed and more often initiated by employees themselves. And it is high skilled workers who are more likely to initiate training on their own.

To find out whether these characteristics of training courses explain our result of a remaining skill gap in OFFJT, we pool together all on-the-job and off-the-job training courses and define three new indicators for having participated in a least one training that was (i) fully employer financed, (ii) initiated by the employer, (iii) initiated by the employee on his own. These then serve as dependent variables in a model similar to specification 3 in Table 3. For "fully employer financed training" we find that the skill gap is insignificant (column 1 of Table 6). The same holds for "training initiated by the employer" (column 2 of Table 6). In contrast, a significant skill differential becomes evident for "training on employee's own initiative" (see column 3 of Table 6). From this we conclude that employers do not seem to treat medium and high skilled workers differently once tasks performed at work and firm effects are controlled for. Instead, we find that high skilled workers initiate training more often on their own than medium skilled workers which might explain why the skill gap remains significant for OFFJT, as OFFJT is generally more often initiated by employees than ONJT.

In a descriptive way, we also explore potential reasons for the correlation between working tasks and training participation. As pointed out in Bresnahan et al. (2002) processes of computerization and reorganization often trigger training participation. Using information from the WeLL data on whether an employee has experienced technological and organizational changes, it can be seen that the perception of being affected by changes at the workplace differs between high and medium skilled employees (Table 7). Medium skilled workers more often report having experienced the implementation of new information and communication technologies (ICT) or new software, of new production technologies or machinery and of teamwork. In addition, they say that their job was more often affected by new products or services that are offered by the firm.

Table 7 - Perceived changes at the workplace

	Mean			t-stat
	All	Medium skilled	High skilled	(high vs. medium)
Working with new information and communication technology or new software	0.471	0.452	0.534	**4.45**
Experienced implementation of new production technology or machinery	0.275	0.298	0.201	**-5.93**
Firm offers new products or services	0.360	0.381	0.293	**-5.00**
Work affected by reorganization	0.587	0.589	0.582	-0.39
Work affected by implementation of teamwork	0.146	0.168	0.071	**-7.52**

Note: Information on changes at the workplace are self reported by employees and refer to the two years preceeding the first interview. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

To find out whether the high explanatory power of tasks as predictor of training reflects other factors like technological or organizational changes, we extend the training determinants and the decomposition analysis presented in Tables 3 and 4 by these variables. The results suggest that there is a positive and in most cases significant correlation between all of the changes at the workplace and ONJT (Table 8). Concerning OFFJT, new ICT/software and new production technology/machinery are positive correlated with training as well, but the correlation is on average weaker than between changes and ONJT which might e.g. be the result of a higher engagement of firms in financing and providing (on-the-job) training when they introduce technological or organizational innovations. Surprisingly, the correlation between OFFJT and teamwork is negative. The decomposition results for ONJT and OFFJT controlling for perceived changes at the workplace are documented in Table 9. They show that the role of tasks to explain the skill gap remains completely unchanged for OFFJT and changes only slightly for ONJT. That is, there is no evidence that changes at the workplace are driving the correlation between tasks and training. In interpreting this result, however, one should keep in mind that the information on changes is self-reported and, thus, reflects a subjective view on changes which is not necessarily identical to actual changes. For instance, medium skilled workers might perceive an update of computer software as a change of their working environment while the high skilled might consider the same update as no change.

Table 8 - Determinants of training participation considering technological and organizational changes at the workplace

	On-the-job training		**Off-the-job training**	
	Specification 4		Specification 4	
	Marg. eff.	t-stat	Marg. eff.	t-stat
Medium skilled	-0.005	-0.23	-0.109	**-6.69**
Female	0.031	1.52	-0.029	*-1.71*
Age <35	0.018	0.67	-0.027	-1.19
Age 45-54	0.014	0.50	-0.062	**-2.63**
Age 55+	-0.030	-0.88	-0.090	**-3.24**
Migrant	-0.016	-0.48	-0.007	-0.23
Married	0.009	0.48	0.010	0.61
Living with kids	-0.020	-1.02	-0.013	-0.83
Living with kids below age 6	-0.003	-0.09	0.000	-0.02
Temporary contract	0.051	1.43	-0.003	-0.09
Part-time	0.007	0.29	-0.051	**-2.47**
Tenure <4 years	0.010	0.31	0.011	0.43
Tenure 4-6 years	0.016	0.50	-0.007	-0.28
Tenure 11-20 years	-0.017	-0.65	-0.033	-1.55
Tenure 21+ years	-0.005	-0.18	-0.042	*-1.89*
Locus of control	-0.001	-0.32	-0.002	-0.68
High openness to experience	-0.043	**-2.75**	-0.004	-0.35
High concientiousness	0.024	0.63	-0.017	-0.54
High extraversion	0.007	0.43	0.005	0.36
High agreeableness	0.023	1.53	-0.023	*-1.87*
High neutroticism	-0.023	-1.01	-0.023	-1.25
Overtime 1 to 10 hours per month	0.058	**2.76**	0.022	1.25
Overtime 10+ hours per month	0.071	**3.25**	0.040	**2.19**
Task index nonroutine manual	0.103	**2.02**	0.092	**2.18**
Task index routine cognitive	-0.049	-0.77	0.079	1.49
Task index nonroutine analytical	0.067	1.25	0.146	**3.28**
Task index nonroutine interactive	0.115	**2.77**	0.179	**5.17**
Job complexity	0.014	**3.40**	0.011	**3.19**
Working with new information and communication technology or new software	0.064	**4.12**	0.023	*1.74*
Experienced implementation of new production technology or machinery	0.007	0.35	0.031	*1.88*
Firm offers new products or services	0.036	**1.99**	-0.023	-1.53
Work affected by reorganization	0.033	**2.04**	0.003	0.25
Work affected by implementation of teamwork	0.055	**2.45**	-0.051	**-2.76**
Firm fixed effects	yes		yes	
Pseudo R^2	0.1270		0.1314	
Observations	4104		4104	

Note: All specifications are estimated using a linear probability model. Dependent variables are binary, indicating participation in training carried out by the firm (on-the-job) or another institution (off-the-job) during the last 12 months. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

Table 9 - Decomposition of the education-training gap considering technological and organizational changes at the workplace

	On-the-job training		**Off-the-job training**	
	Specification 4		Specification 4	
	Effect	t-stat	Effect	t-stat
Raw difference	-0.042	**-2.39**	-0.163	**-9.99**
Raw difference net of firm fixed effects	-0.030	*-1.76*	-0.165	**-10.40**
Explained difference	-0.029	-1.24	-0.058	**-2.56**
Unexplained difference	-0.001	-0.04	-0.107	**-3.94**
Detailed decomposition of explained difference				
Female	0.003	1.51	-0.001	-0.53
Age	0.005	*1.72*	0.001	0.46
Migrant	0.003	1.44	0.002	1.03
Married	-0.001	-0.89	-0.001	-0.96
Kids	0.001	0.40	0.003	1.34
Temporary contract	-0.001	-0.98	-0.001	-0.99
Part-time	-0.001	-0.19	-0.001	-0.35
Tenure	0.011	*1.66*	-0.016	**-2.49**
Locus of control	0.003	1.47	0.001	0.45
Big five	0.001	0.28	0.004	1.15
Overtime	-0.014	**-2.51**	-0.004	-0.81
Tasks and job complexity	-0.031	-1.47	-0.047	**-2.28**
Changes at the workplace	-0.008	-1.01	0.002	0.33
Firm fixed effects	yes		yes	
Observations	4104		4104	

Note: Decomposition follows Yun (2004). Specifications are estimated using a linear probability model and firm fixed effects are restricted to be equal for both skill groups. Dependent variables are binary, indicating participation in training carried out by the firm (on-the-job) or another institution (off-the-job) during the last 12 months. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).

5. Conclusions

This paper uses linked employer employee data to analyze the impact of previously unconsidered factors like working tasks, personality traits and firm fixed effects on participation in work related training. While tasks performed at work and job complexity (proxied by performing multiple tasks) are strong predictors of training, personality traits are not. We generally find that employees with routine manual tasks are considerably less likely to participate in training than workers with nonroutine tasks or with routine cognitive tasks. We also find that workers with complex jobs are more likely to participate in training. Tasks also play an important role in explaining the education-training gap which was found to be stronger for OFFJT than for ONJT when comparing high with medium skilled workers. Once controlling for tasks and other job-related characteristics, the skill gap in ONJT vanishes while it shrinks by one third for OFFJT. In addition to tasks, overtime is another important factor that contributes to the skill gap in training participation. Even though our results fail to have a causal interpretation, we conclude that the correlation between education and training is overestimated in studies that do not consider a large set of covariates.

Our results also suggest that firms' investments in training lead to more equity between skill groups. Employers seem to induce medium skilled workers to participate in training by initiating and financing training courses to a similar extend as high skilled workers performing the same working tasks, which reduces the training-education gap. In contrast, there are large differences between skill groups with respect to training on own initiative. High skilled workers initiate training more often on their own. Based on these results we would argue that future research should put more focus on the determinants of employer vs. employee initiated training.

Our results do not provide evidence on reasons why tasks and training are correlated. We do find that technological and organizational changes at the workplace are predictors of training (somewhat more for ONJT than for OFFJT). However, they do not contribute to explaining the skill gap and they are not associated with the correlation between tasks and training either. Assessing the impact of other potential reasons for the correlation between tasks and training remains an object for future research. It might be interesting to look at the impact of wage compression or market frictions as source of the correlation. Also, one might suspect that the depreciation rate of human capital differs by task. Another potential source might be that knowledge can also be acquired by learning by doing and that such learning by doing might more often occur in informal settings for workers with routine tasks, while workers with nonroutine tasks acquire knowledge in more formal settings like the class-room type training courses considered in this paper. Finally, it seems important that future research considers that the correlation between tasks and training found in this paper could also be driven by omitted variables like innate ability which has to be accounted for.

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Appendix

A. Data issues in WeLL

This section shortly documents several issues concerning the WeLL data, specifically our definition of measures for personality traits and for working tasks.

The work-related locus of control is constructed from answers to eight statements where respondents should indicate whether they fully agree, mostly agree, mostly disagree or fully disagree with each statement. These categories were coded from 1 to 4 and answers to all eight statements were summed up, i.e. the locus of control scale ranges from 8 to 32. Respondents with higher scores feel externally controlled, respondents with lower scores feel internally controlled. The eight statements are:

- When I am confronted with unexpected situations at work, I always know how to cope with them
- I have a solution for every problem that might arise at work
- I am easygoing about work-related problems, because I always can count on my skills

- When I am confronted with a problem at work, I generally have several ideas how to solve the problem
- Whatever happens to me at work, I will get through
- My previous work experience prepares me well for my future
- I achieve my own occupational objectives
- I feel well prepared for most job requirements

The WeLL data includes a short item scale for the Big Five based on 15 questions, i.e. three questions for each trait. The 15 questions are similar to those used in the BHPS or the GSOEP which have been shown to be coherent, reliable and valid (Gerlitz and Schupp 2005). One of the main differences to the items used in the GSOEP is that WeLL uses 4 point scales while GSOEP uses 7 point scales. The score for each of the five traits is constructed by adding up the answers to the three questions per trait, i.e. for each trait the score ranges from 3 to 12. In the main regressions, we use dummy variables indicating individuals with a high degree of each trait which are those where the underlying score exceeds 8.

B. Results using GSOEP data

Results based on the WeLL data are not necessarily representative for the German workforce because of the specific sampling design. Therefore we also present results based on data from the German Socio-Economic Panel (GSOEP). GSOEP is a representative survey but has several disadvantages: It does not allow controlling for firm fixed effects, it does not include information on working tasks and information on training does not allow differentiating between on-the-job and off-the-job training. Instead of working tasks we use dummies for occupational groups. (This is not perfect because occupational groups as defined in ISCO88 highly correlate with education; e.g. 57% of high skilled workers are professionals but only 5% of medium skilled, while 3% of high skilled are craft and trades workers, plant and machinery operators or in elementary occupations compared with 34% of medium skilled workers.)

Descriptive statistics of the GSOEP data are provided in Table B1 and regression results on the determinants of training in Table B2. Table B2 also presents results for WeLL using a similar definition of training participation as for GSOEP, i.e. an indicator pooling ONJT and OFFJT. We find that results are very similar when using GSOEP data. That is, there is a large unconditional difference between skill groups. Controlling for standard covariates does not explain the difference. Including information about the job (i.e. in the GSOEP these are the occupational dummies) reduces the difference between skill groups by half. Personality traits generally do not explain training participation, once job characteristics are controlled for.

Table B1 - Sample means GSOEP data

	Mean		
	All	Medium skilled	High skilled
Training participation	0.253	0.210	0.428
Female	0.473	0.472	0.477
Age <35	0.281	0.292	0.235
Age 35-44	0.304	0.297	0.333
Age 45-54	0.287	0.284	0.298
Age 55+	0.128	0.126	0.133
Migrant (1st or 2nd generation)	0.140	0.150	0.099
Married	0.568	0.568	0.568
Living with kids	0.358	0.360	0.350
Living with kids below age 6	0.114	0.106	0.147
Temporary contract	0.137	0.142	0.117
Part-time	0.247	0.258	0.203
Tenure <4 years	0.274	0.273	0.281
Tenure 4-6 years	0.159	0.157	0.166
Tenure 7-10 years	0.153	0.147	0.175
Tenure 11-20 years	0.237	0.241	0.221
Tenure 21+ years	0.177	0.182	0.156
High openness to experience	0.392	0.371	0.478
High concientiousness	0.810	0.815	0.790
High extraversion	0.404	0.409	0.385
High agreeableness	0.607	0.604	0.616
High neutroticism	0.146	0.147	0.144
Overtime 0 hours per month	0.468	0.490	0.376
Overtime 1 to 10 hours per month	0.232	0.230	0.241
Overtime 10+ hours per month	0.300	0.280	0.383
Armed forces	0.004	0.005	0.001
Legislators, senior officials, managers	0.056	0.042	0.101
Professionals	0.178	0.053	0.571
Technicians and associate professionals	0.244	0.257	0.205
Clerks	0.133	0.156	0.059
Service workers, sales workers	0.103	0.128	0.026
Skilled agricultural and fishery workers	0.007	0.009	0.001
Craft and trades workers	0.132	0.171	0.011
Plant and machine operators, assembler	0.071	0.090	0.012
Elementary occupations	0.064	0.082	0.008
Occupation missing	0.007	0.008	0.004
Observations	7049	5340	1709

Note: Data from GSOEP waves 2005, 2007 and 2008. Sample restricted to employed individuals. Training indicator considers participation in training during the last 12 months before the 2008 interview.

Table B2 - Determinants of participation in any training comparing GSOEP and WeLL

	Specification 1 (GSOEP)		Specification 2 (GSOEP)		Specification 1 (WeLL)		Specification 2 (WeLL)		Specification 3 (WeLL)	
	Marg. Eff.	t-stat	Marg. Eff.	t-stat	Marg. Eff.	t-stat	Marg. Eff.	t-stat	Marg. Eff.	t-stat
Medium skilled	-0.215	**-10.81**	-0.113	**-4.65**	-0.155	**-8.16**	-0.071	**-3.42**	-0.073	**-3.62**
Female	0.026	1.51	-0.008	-0.42	0.070	**3.70**	0.041	**2.03**	0.007	0.34
Age <35	0.030	1.25	0.025	1.08	-0.033	-1.11	-0.025	-0.84	-0.007	-0.23
Age 45-54	-0.013	-0.64	0.006	0.28	-0.062	**-2.04**	-0.049	-1.57	-0.037	-1.25
Age 55+	-0.094	**-3.83**	-0.073	**-2.90**	-0.136	**-3.90**	-0.130	**-3.63**	-0.109	**-3.16**
Migrant	-0.119	**-4.92**	-0.080	**-3.19**	-0.067	*-1.87*	-0.032	-0.86	-0.021	-0.59
Married	-0.040	**-2.16**	-0.033	*-1.80*	0.030	1.43	0.015	0.71	0.021	1.05
Living with kids	0.021	1.10	0.026	1.36	0.002	0.08	-0.005	-0.26	-0.023	-1.13
Living with kids below age 6	0.012	0.46	-0.007	-0.28	-0.012	-0.41	-0.017	-0.59	-0.006	-0.23
Temporary contract	-0.034	-1.27	-0.032	-1.20	-0.061	-1.60	-0.021	-0.53	-0.015	-0.42
Part-time	-0.054	**-2.90**	-0.029	-1.50	-0.012	-0.46	-0.025	-0.96	-0.047	*-1.80*
Tenure <4 years	-0.009	-0.34	0.009	0.33	0.042	1.27	0.041	1.23	0.030	0.93
Tenure 4-6 years	0.026	0.92	0.009	0.34	0.005	0.14	0.018	0.52	0.005	0.15
Tenure 11-20 years	0.038	1.54	0.023	0.96	-0.012	-0.43	-0.016	-0.60	-0.032	-1.22
Tenure 21+ years	0.080	**2.75**	0.057	**1.99**	0.017	0.64	-0.002	-0.06	-0.019	-0.71
Locus of control							-0.001	-0.16	-0.001	-0.30
High openness to experience			0.018	1.11			-0.033	*-1.91*	-0.034	**-2.10**
High concientiousness			0.004	0.22			0.036	0.87	0.035	0.88
High extraversion			0.017	1.03			0.000	-0.02	0.006	0.36
High agreeableness			0.004	0.29			0.006	0.38	0.008	0.49
High neutroticism			-0.009	-0.42			-0.029	-1.17	-0.024	-1.02
Overtime 1 to 10 hours per month			0.089	**4.56**			0.071	**3.07**	0.069	**3.14**
Overtime 10+ hours per month			0.084	**4.49**			0.096	**4.15**	0.095	**4.24**
Armed forces			0.216	*1.72*						
Legislators, senior officials, managers			-0.035	-1.07						
Professionals			0.024	0.89						
Clerks			-0.057	**-2.43**						
Service workers, sales workers			-0.075	**-3.09**						
Skilled agricultural and fishery workers			-0.138	**-2.35**						
Craft and trades workers			-0.128	**-5.55**						
Plant and machine operators, assemblers			-0.153	**-5.20**						
Elementary occupations			-0.203	**-7.44**						
Occupation missing			-0.194	**-4.52**						
Task index nonroutine manual							0.402	**7.25**	0.188	**3.59**
Task index routine cognitive							0.098	1.29	0.053	0.80
Task index nonroutine analytical							0.361	**6.13**	0.237	**4.30**
Task index nonroutine interactive							0.385	**8.59**	0.265	**6.26**
Job complexity							0.031	**7.29**	0.021	**5.07**
Firm fixed effects	no		no		no		no		yes	
Pseudo R^2	0.0551		0.0973		0.0202		0.0673		0.1578	
Observations	7049		7049		4104		4104		4104	

Note: Specifications 1 and 2 are estimated using Probit and specification 3 is estimated using OLS. Dependent variable is binary, indicating training participation (on- and off-the-job) during the last 12 months. Significance levels are indicated in *italics* (10%-level) and **boldface** (5%-level).