Continuous training and wages. An empirical analysis using a comparison-group approach.

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Abstract: Using German linked employer-employee data, this paper investigates the impact of further training on wages. The estimation technique applied was primarily introduced by Leuven and Oosterbeek (2008). The idea is to compare wages of employees who intended to participate in training but did not do so because of a random event with wages of employees who actually participated. The results suggest that the size of the point estimates of the wage returns is large, even though they are statistically insignificant. In addition, the decision to participate in training is associated with sizeable selection effects. On average, participants have an initial wage advantage of more than 3% compared to non-participants.

Keywords: Continuous training, wage returns, selection effects

JEL classification: J24, J31

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1. Introduction

The fact that the literature concerned with estimating individuals' training returns is large points, on the one hand, to the importance of this issue. It is important to discover the potential of further training to boost labor productivity and to secure job stability. Since many firms bear a substantial share of training costs, it also sheds some light on how training returns are shared between employers and employees. On the other hand, it also points to a literature that is characterized by ambiguous empirical findings. One reason for this ambiguity can be attributed to using different estimation techniques. Most papers investigate the effect of training incidence, i.e. whether training was attended or not. It was found that average wage differentials between training participants and non-participants (estimated by standard Mincer-type wage equations extended by formal training variables) are quite high (Parent 1999, Loewenstein and Spletzer 1999, Goux and Maurin 2000, Muehler et al. 2007). In some applications they were even higher than the wage differentials by years of education (Schøne 2004). As training courses are often of short duration, these estimates appear to be too high to represent the causal effect of training. Rather it seems to be likely that these wage differentials also encompass differences in unobserved characteristics (e.g. motivation or ability) between participants and non-participants.

One way to reduce selection bias is to apply individual fixed effects models that control for *time-invariant* omitted variables. Because the application of individual fixed effects produces much lower (and more credible) estimates (Lynch 1992, Pischke 2001, Schøne 2004, Frazis and Loewenstein 2005), selection bias is considered a serious problem when estimating training returns.[1] An alternative approach is to use IV or selection models that both require a source of exogenous variation for training participation (Lynch 1992, Parent 1999, Arulampalam and Booth 2001, Kuckulenz and Maier 2006). As such exclusion restrictions are difficult to find and estimates have a difficult interpretation in some applications, e.g. when estimating the local average treatment effects, LATE (Imbens and Angrist 1994), this group of models is difficult to implement as well.[2] An alternative approach was suggested by Leuven and Oosterbeek (2008), henceforth LO. This approach accounts for selection bias by defining a group of non-participants that is assumed to be similar to the group of participants in terms of observable and unobservable characteristics. Individuals who intended to participate in one training course but did not do so because of a random event are considered an appropriate comparison group. Cancelling a course because of family circumstances or transient illness are examples of random events. Even though one might argue that these reasons might not be exclusively at random, the authors can show that persons with training intentions are fairly similar to training participants.

In this paper, I contribute to the literature by applying the same comparison-group-approach as in LO to identify the causal effect of continuous training on wages in Germany. This approach has not yet been applied to German data. Furthermore, I extend the model of LO in two respects. First, besides providing estimates of the impact of participating in one course, I will also analyze the impact of participating in a second and a third course. By doing so, the selection effect of training incidence and training intensity which is measured by the number of attended courses can be analyzed as well. Second, I will account for employer

[1] Even though the application of individual fixed effects is standard in the training literature, it should be noted that it only accounts for initial differences in wage levels between training participants and non-participants, but not for differences in wage growth (Pischke 2001, Frazis and Loewenstein 2005).

[2] It is out of the scope of this paper to provide a complete literature review. For a recent and more comprehensive review see Hansson (2009).

characteristics to avoid serious biases of the results. Although the majority of studies account for at least some firm attributes such as size or industry, only few have access to more detailed information to account additionally for a larger set of firm attributes. Controlling for a broader set of firm attributes can change the results substantially (Goux and Maurin 2000). Since I am using the first wave of a new German linked employer-employee data set (the *WeLL data*), I can apply establishment fixed effects to remove all time-invariant firm-specific effects on wages.

The point estimate of participating in one training course is 1.1%, attending a second course is associated with a wage increase of 2.6% and participating in a third course has a positive impact in the amount of 0.9%. Even though the size of the estimates is large, each of the coefficient is insignificant. The results provided in LO using Dutch data are also insignificant, although the point estimator is much closer to zero compared to my findings. Furthermore, my results show that the decision to participate in training is associated with a sizeable selection effects. This paper is organized as follows. The next section presents the data, the empirical specification and descriptive statistics, e.g., on differences between treatment and comparison group. Section 3 provides the regression results and section 4 contains the conclusion.

2. Data and Method

The analysis is based on the WeLL data that is a new German linked employer-employee data that was particularly designed to analyze further training activities of individuals.[3] The first wave of the data is used covering 6,404 employees who were employed in December 31, 2006 in one of 149 establishments[4] that were selected for the survey. Only establishments with more than 100 employees operating in the manufacturing or sevice sector were considered for selection. Due to this sampling frame, the data is only representative of a small number of firms which should be kept in mind when interpreting the results. The employees were interviewed via telephone from October 2007 to January 2008. Training questions are asked with a reference period of approximately two years, i.e. from January 2006 to the time of the interview.

The final data sample is selected as follows. First, employees who left their firm between December 31th 2005 and the time of the interview are excluded. The results are, hence, only representative for job stayers and cannot be generalized to job movers. Second, employees with gross monthly wages of less than 500 euros and with more than 20,000 euros are excluded.[5] This is done to exclude workers with extremely low wages (e.g. marginally employed persons), since they might exhibit different training patterns and processes. The restriction on high wages was applied to eliminate outliers. Third, some data cleaning processes were conducted and only observations with full information are considered for the analysis. These restrictions reduced the data from 6,404 to 5,407 employees. A definition of variables and sample means is presented in Table A-1.

According to the approach of LO, wages of training participants are compared with wages of employees who wanted to participate, but did not do so because of a random event. In my data, the phrasing of the question to identify the second group is: *Did you intend to participate*

[3] See Bender et al. (2009) for further information on the data set.
[4] In the following, no distinction between firms and establishments will be made; both are referred to as firms.
[5] Further details on the wage variable is provided in the Data Appendix.

in training courses, seminars or lectures in the last two years without realizing this plan? It is crucial that the reason for non-participation is random because otherwise selection bias could enter the results. In particular, employees cancelling a course because of exorbitant costs might **not** be comparable to actual training participants. Therefore, respondents were asked for the reasons of cancelling training plans. When reporting that the course was cancelled by the organizer or when reporting family or health reasons or reasons related to the job (high work load), this is classified as a random event in the following. A further discussion of the validity of this assumption is provided below.

In their application, LO focus on the impact of participating in ***one*** training course. Since in my data the reference period of the training question covers the last two years and sample sizes are large, I am able to extent their model. In particular, I will not only compare employees who participated in one course with those who intended to take part in one course, but I will also compare employees who participated in two (three) courses with those who participated in one course (two courses) and intended to take part in an additional course. This helps to understand whether training returns are a linear function of the number of courses or whether they marginally decrease or increase.[6] According to human capital theory, worker productivity and therefore wages should increase as a function of skills. Skills in turn should grow with an increase in the knowledge acquired during training.[7] If the returns decrease marginally with the number of courses, this would be consistent with the finding that learning is more effective in the beginning and decreases at a later date when the most necessary was already learned. For example, participating in an introductory course to a word processing software might shift performance to a large extent, however, learning details about particular tools of this software (e.g. creating tables or graphs) might have a lower impact on performance. If the returns increase marginally with the number of courses, course contents are complements, i.e. labor productivity increases even further with every additional course. This could be the case for instance if a word processing and a typing course is attended.

Nine groups of training participants are classified according to employees' training attendance (see Table 1). In this study, training always refers to "class-room" training such as courses, seminars or lectures. There are 5,407 employees in the sample, of whom 1,686 are non-participants with no training intentions (~31%). The number of employees intending to participate in training is quite high. Among this group of employees who cancelled training plans around 30% did not participate in training at all (148), 37% attended at least one course (179) and the remaining 32% attended two courses (157). The majority of employees participated in training and had no further intention of participating in additional courses. There are 1,476 persons who participated in exactly one course, 801 attended two courses and 355 took part in three training courses. Related to the overall sample, this corresponds to 28%, 15% and 7%, respectively. 431 employees participated either in more than three courses or stated that they planned to attend a fourth course. Only 3% of employees reported that they had training intentions but cancelled them due to non-random reasons in the sample. This group does not reflect a proper comparison group, as was shown in LO.

[6] The literature investigating explicitly the effect of the number of courses is sparse. While Arulampalam and Booth (2001) find that only training incidence but not the number of courses matter for wage growth in Britain, Gerfin (2004) and Büchel and Pannenberg (2004) show that multiple training events lead to higher wage returns using Swiss and German data, respectively. In these papers, the number of courses is introduced as a linear function of wages.

[7] Even though it would be preferable to use the duration of training rather than the number of courses (as this might better approximate the accumulation of human capital), I cannot observe the desired duration of employees with training intentions.

Table 1: Training attendance of employees within the last 2 years

No training participation (tr_1)	1,686	31.182
No training participation, but intended to participate in one course (tr_2)	148	2.7372
Training participation in only one course (tr_3)	1,476	27.298
Training participation in only one course and intended to participate in a second course (tr_4)	179	3.3105
Training participation in exactly two courses (tr_5)	801	14.814
Training participation in two courses and intended to participate in a third course (tr_6)	157	2.9036
Training participation in exactly three courses (tr_7)	355	6.5656
Training participation in more than three courses or intended to do fourth course (tr_8)	431	7.9711
Employees cancelling training plans due to non-random reasons (regardless of actual participation) (tr_9)	174	3.2181
Total	5,407	100

The empirical strategy to identify the causal effect of training is calculated as follows:

$$\ln(wage)_{ij} = \alpha_0 + \sum_{k}^{K} tr_{ijk}\beta_k + X_{ij}'\gamma + \alpha_j + \varepsilon_{ij} \;\; with \; k = 2...9$$

where *ln(wage)* represents log gross monthly wage of individual *i* who is employed in establishment *j*. The dummy variables tr_k represent the nine training groups that were already described in Table 1 (tr_1 representing non-participants serves as the base group). The reason for considering all training groups in a joint regression rather than running separate regressions is to increase sample sizes. For estimating the training returns, only tr_2-tr_7 are analyzed. The causal effect for participating in one course corresponds to tr_3-tr_2, for participating in a second course it is tr_5-tr_4 and for the third course it equals tr_7-tr_6. Whether these differences are statistically significant is tested by applying an F-test with the null hypothesis that the differences are zero. X is a vector of individual characteristics that cover sociodemographic, occupational and job-specific characteristics (see Table A-1 for a full list of considered characteristics). The establishment-specific time-invariant effect is captured by α_j which is necessary to avoid biased results, for instance, if firms that sponsor training also pay higher wages. This could be the case, for example, for firms with a higher degree of technology use or better technological equipment of more complex working tasks. The estimation is conducted by Ordinary Least Squares regressions (OLS).

When comparing the effects of the first, second and third course with each other in order to draw conclusions on the functional form of the relationship between the number of courses and wages, I have to assume that the returns for the first, second and third course can be added up. This means that the return of attending the first course for those who participate in two courses must be equal to the return of those participating in one course only. Unfortunately, it is not possible to test this assumption empirically within the framework of my regression model.[8] Instead I compare the aggregate number of the hours of all courses to gain at least some descriptive information on differences between the courses. The average duration of taking part in one course (39 hours) equals half of the average value of participating in two courses (75 hours) and one-third of participating in three courses (108

[8] The model only allows estimating the return of the first course for employees participating in one course, the return to the second course for employees participating in two courses and the return to the third course for employees participating in three courses.

hours). A similar results emerges when looking at the median (18, 40 and 58, respectively). This provides indicative evidence that the estimated returns can be aggregated which is assumed for the rest of the paper.

A crucial identification assumption is that the comparison group consisting of those intending to participate is similar to the group of actual participants, not only in terms of observable but also in terms of unobservable characteristics. While differences in observable characteristics can be tested empirically, there is no way to test differences in unobservables. However, if there are no or only minor differences between average observable characteristics, this might also hold for unobserved characteristics. The results of balancing treatment and comparison group are presented in Table 2. The first column contains results for participants in one course only and their comparison group. With the exception of age and tenure, there are no statistically significant differences. On average, employees cancelling a course due to a random event are around two years younger than those realizing their plans. Column 2 documents results for treatment and comparison group for attending a second courses. Again, age differs significantly. Furthermore, employees intending to participate are more likely to have children which could represent an exogenous family-related reason for cancelation.

In column 3, the percentage of white collar workers is significantly larger in the comparison group. None of the other individual characteristics differ on a statistically significant level. Even though some differences exist, fortunately there are no differences in education which is one of the most important variables because it is closely linked to unobservable characteristics such as ability. Together, this suggest that treatment and comparison group do not differ substantially in terms of unobservable characteristics. For reasons of comparison, differences in average characteristics between the comparison groups and pure non-participants (tr_1) are contained in Table A-2 in the Appendix. It can be seen that differences are much more pronounced and now exist for a variety of individual characteristics. Most importantly, there are sizable differences in years of education that are always statistically significant.

Table 2: Balancing of treatment and comparison groups

	Employees with one course (tr_3) versus those willing to attend one course (tr_2) (1)				Employees with two courses (tr_5) versus those with one course willing to attend another (tr_4) (2)				Employees with three courses (tr_7) versus those with two courses willing to attend another (tr_6) (3)			
	tr_3	tr_2	$\Delta_{tr3\text{-}tr2}$	|t|-value	tr_5	tr_4	$\Delta_{tr5\text{-}tr4}$	|t|-value	tr_7	tr_6	$\Delta_{tr7\text{-}tr6}$	|t|-value
Male	0.66	0.68	-0.02	0.37	0.64	0.65	-0.01	0.24	0.59	0.61	-0.03	0.54
German	0.95	0.96	-0.01	0.32	0.96	0.93	0.03	1.65	0.97	0.96	0.01	0.72
Age	46.99	44.59	2.39	3.18 ***	46.43	44.60	1.83	2.63 ***	45.20	44.34	0.86	1.02
Married	0.76	0.74	0.02	0.64	0.77	0.77	0.00	0.07	0.66	0.68	-0.03	0.56
Child	0.38	0.42	-0.03	0.82	0.37	0.49	-0.11	2.74 ***	0.36	0.38	-0.02	0.53
Years of schooling	12.81	12.58	0.22	1.12	13.16	13.36	-0.20	0.93	13.58	13.93	-0.35	1.37
Tenure	233.65	205.50	28.15	2.61 ***	221.52	204.71	16.81	1.64	204.25	193.91	10.34	0.85
White collar employee	0.65	0.61	0.03	0.81	0.76	0.81	-0.05	1.47	0.84	0.89	-0.06	1.74 *
Full time job	0.87	0.84	0.03	0.81	0.85	0.87	-0.02	0.80	0.86	0.85	0.02	0.52
Temporary contract	0.04	0.03	0.00	0.09	0.02	0.04	-0.02	1.08	0.04	0.06	-0.02	0.98

Notes: The t-test for independent samples is used. Significance level: *** 1%, ** 5%, * 10%.

3. Results

The regression results of the coefficients of interest on wages are displayed in Table 3, full estimation results including other covariates can be found in Table A-3 in the Appendix.[9]

[9] The results are robust to using a non-linear functional form for age and tenure.

Without controlling for establishment fixed effects (Table 3, column 1), there is no statistically significant difference between those with training intention and those with actual participation according to a F-test. However, when comparing the point estimates of *tr3* with *tr2* and the point estimates of *tr5* with *tr4*, a surprising result emerges. The coefficients of intending to participate in a course are ***larger*** than the coefficients of actual participation. This result indicates an omitted variable bias due to missing firm characteristics. Thus, results without the establishment fixed effect rather represent an association than a causal effect.

When accounting for firm fixed effects (Table 3, column 2), training participants have higher average wages compared to the group of employees who did not realize their training plans. In particular, the effect of one course is 1.1% (tr_3-tr_2), the effect of the second course is 2.6% (tr_5-tr_4) and the effect of the third course is 0.9% (tr_7-tr_6). None of these differences are statistically significant which is consistent with the findings of LO who do not find an effect of training on wages. However, my point estimates are much larger in size than the results obtained by LO. Comparing the size of the three estimates, it can be seen that the return of the second course exceeds the return of the first and third course more than twice. This provides weak evidence of a non-linear relationship between wages and the number of courses. Given the limited significance of the estimation results, this evidence is only indicative. Further evidence is necessary to come to a final conclusion.

Table 3: Regression results for wage returns of training

Regressors	Log monthly wage (1)		Log monthly wage (2)	
	Coeff.	Stand. Err.	Coeff.	Stand. Err.
No training participation, tr_1	Base category		Base category	
No training participation, but intended, tr_2	0.069 ***	0.023	0.034 *	0.020
Training participation in only one course, tr_3	0.050 ***	0.014	0.044 ***	0.009
Training participation in one course, but intended to do another, tr_4	0.103 ***	0.026	0.044 **	0.018
Training participation in exactly two courses, tr_5	0.086 ***	0.017	0.070 ***	0.012
Training participation in two courses, but intended to do another, tr_6	0.123 ***	0.023	0.082 ***	0.015
Training participation in exactly three courses, tr_7	0.120 ***	0.019	0.091 ***	0.012
Training participation in more than three (intended) courses, tr_8	0.149 ***	0.024	0.138 ***	0.018
Training intention cancelled due to non-random reason, tr_9	0.078 ***	0.025	0.062 ***	0.017
Individual charact.	Yes		Yes	
Firm fixed effects	No		Yes	
F-test for tr_2=tr_3, (p-value)	0.57, (0.45)		0.29, (0.59)	
F-test for tr_4=tr_5, (p-value)	0.46, (0.50)		1.67, (0.20)	
F-test for tr_6=tr_7, (p-value)	0.02, (0.89)		0.25, (0.61)	
Observations	5,407		5,407	
R-squared	0.54		0.52	
F-statistic	85.96 ***		86.73 ***	

Notes: OLS regression results are shown. Standard errors are clustered at the establishment level. The control variables include male, German, age and age squared, married, child, an interaction term of male and child, years of schooling, tenure and tenure squared, white collar employee, full time job and temporary contract. Full estimation results are documented in Table A-3 in the Appendix. Significance level: *** 1%, ** 5%, * 10%.

Comparing the coefficients of column 1 with the coefficients of column 2 reveals some insights into the importance to control for firm effects. First, as the coefficients of interest differ to a large extent between column 1 and 2, controlling for firm fixed effects seems to be important in order to obtain unbiased results. Second, controlling for firm effects is of

particular importance for employees intending to participate in training because the coefficients tr_2, tr_4 and tr_6 drop sharply after applying firm fixed effects. There seem to be a strong correlation between cancelling training plans and firm characteristics. This indicates that employees cancelling training plans are more often employed in firms that pay higher wages. This is not surprising because some of the random events were actually firm related such as high work load. For applying the identification strategy based on the comparison-group approach, however, it can be concluded that proper control for individual and work-related characteristics is necessary for obtaining unbiased results.

The chosen estimation framework also allows me to disentangle the selection effect of training participation, i.e. the initial difference in wages between training participants and non-participants. This can be done by comparing the difference in average wages between non-participants without (tr_1) and with training intentions (tr_2). I find that non-participants with training intentions have a significantly higher average wage of approximately 3.4% compared to non-participants without intentions. This wage differential could represent, for example, the return to innate ability or motivation. It might also represent the medium or long run wage returns to training (i.e. to training that was attended before the reference period of two years), if employees with recent training intentions participated more often in training in the past. As a benchmark model, I have also estimated the average wage difference between training participants and non-participants without accounting for selection bias.[10] The average difference is 7.4% which suggests that the selection bias of the training decision accounts for almost half of the estimates of training incidence when running Mincer-type regressions only controlling for observable characteristics.

Due to the chosen estimation framework, I can also find out whether selection processes differ by the number of courses. In particular, it is investigated whether those participating in two courses (three) have an even higher initial wage than employees participating in one course (two courses). This can be done by comparing tr_4 with tr_3 and tr_6 with tr_5, respectively. The results indicate that employees participating in one course but willing to participate in a second courses have only a small and statistically insignificant wage difference of only -0.1% compared to employees participating in one course. The difference between employees who participated in two courses but who wanted to attend a third course and employees who participated in exactly two courses having no further training intentions is larger in size (1.2%), but nevertheless statistically insignificant. Therefore, I conclude that while the initial training decision is accompanied by serious selection effects, deciding on training intensity (conditional on participation) is not affected to such a large extent. Since this analysis only investigates selection effects for a maximum of three courses, this conclusion can only be approved for persons who attend a small number of courses. A further investigation might be important because the differences in the size of the point estimates -0.1 and 1.2 (even though they do not differ on a statistically significant level), might indicate that some further selection processes occur for persons participating in a larger number of courses.

[10] The following OLS regression was estimated: $\ln(wage)_{ij} = \alpha_{20} + \beta_2 T_{ij} + X_{ij}'\gamma_2 + \alpha_{2j} + \varepsilon_{2ij}$ where the variable T is a binary variable indicating whether person i participated in training in the last two years, or not. No further distinction by the number of courses or by training plans are made. The other variables were already explained in the second chapter. Results and notes for further details on how the estimation was accomplished are contained in Table A-4 in the Appendix.

4. Conclusion

This paper investigates wage returns to training in Germany by using a comparison-group-approach that was suggested by LO. The results suggest that the impact of participating in a first course is 1.1%, it is 2.6% for participation in a second course and it is 0.9% for participation in a third course. However, these results do not differ from zero on a statistically significant level. Before concluding that employees do not benefit from training in terms of wage increases, it should be noted that the sample size of the comparison groups is small. Furthermore, the size of the coefficients is quiet high especially when looking at the median participant (attending two courses) who has a returns of (1.1%+2.6%=) 3.7%. To reach a final conclusion, however, further research with larger sample sizes would be needed.

Additionally, this paper provides evidence that the selection effect of the training decision amounts to 3.4%. This corresponds to half of the wage differences estimated by comparing outcomes of participants and non-participants without correcting for selection bias. When the training decision was made, deciding on the number of courses does not seem to be accompanied by selection processes to a large extent, in particular, when the overall number of courses is small (e.g. one/two courses). When analyzing wage returns of some proxy for training intensity instead of training incidence, restricting the data to training participants already reduces selection bias to a large extent.

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Data Appendix: The wage variable

The information on wages is available for almost every person in the sample. It could be merged for 93% from administrative data taken from the social security records if employees gave their permission. The remaining 7% of employees not willing to merge the survey data with administrative sources were asked to report their gross monthly wage. Few individuals not willing to report this information either were requested to indicate their wages in categories. The group-specific mean of this information is used to impute few missing values. Wages contained in the administrative data represent gross wages obtained during a notification period divided by the duration of the period. Therefore, they represent daily gross wages. Since most of the individuals considered in this analysis did not change employers for the last two years, the notification period refers in many cases to the year 2007. This is also the case for interviews conducted in January 2008. To make this daily wage information comparable to employees reporting their monthly wage, the daily gross wage was multiplied by 30. Since the administrative data is right censored (because data from the social security system are reported up to a maximum limit), as a sensitivity check all the regressions were run with imputed values for right censored wages as suggested in Gartner (2005). The main conclusions remain unaffected.

Appendix

Table A-1: Variable description and mean values

Variable	Description	N	Mean	Std. Dev.
ln(wage)	Logarithm of gross monthly wages	5,407	7.96	0.417
Male	Dummy variable: 1 for males, 0 otherwise	5,407	0.64	0.481
German	Dummy variable: 1 for Germans, 0 otherwise	5,407	0.94	0.234
Age	Age in years	5,407	46.68	9.059
Married	Dummy variable: 1 for maried employees, 0 otherwise	5,407	0.74	0.437
Child	Dummy variable: 1 for employees with underaged children, 0 otherwise	5,407	0.37	0.483
Male*Child	Interaction term between male and child	5,407	0.25	0.433
Years of schooling	Years of schooling	5,407	12.78	2.421
Tenure	Tenure in current job (in months)	5,407	224.75	131.099
White collar employee	Dummy variable: 1 for white collar workers, 0 otherwise	5,407	0.64	0.480
Full time job	Dummy variable: 1 for employees working full-time, 0 otherwise	5,407	0.86	0.349
Temporary contract	Dummy variable: 1 for employees with temporary contract, 0 otherwise	5,407	0.04	0.187

Table A-2: Comparison of average characteristics between non-participants and comparison group

	Non-participants (tr_1) versus those willing to attend one course (tr_2)				Non-participants (tr_1) versus those with one course willing to attend another course (tr_4)				Non-participants (tr_1) versus those with two courses willing to attend another course (tr_6)			
	tr_2	tr_1	$\Delta_{tr2\text{-}tr1}$	|t|-value	tr_4	tr_1	$\Delta_{tr4\text{-}tr1}$	|t|-value	tr_6	tr_1	$\Delta_{tr6\text{-}tr1}$	|t|-value
Male	0.68	0.65	0.03	0.62	0.65	0.65	0.00	0.08	0.61	0.65	-0.04	0.96
German	0.96	0.91	0.05	2.71 ***	0.93	0.91	0.02	0.76	0.96	0.91	0.04	2.44 **
Age	44.59	48.07	-3.48	4.65 ***	44.60	48.07	-3.47	5.26 ***	44.34	48.07	-3.73	5.34 ***
Married	0.74	0.74	-0.01	0.16	0.77	0.74	0.02	0.68	0.68	0.74	-0.06	1.57
Child	0.42	0.32	0.10	2.42 **	0.49	0.32	0.17	4.33 ***	0.38	0.32	0.07	1.61
Years of schooling	12.58	11.95	0.63	3.27 ***	13.36	11.95	1.41	6.91 ***	13.93	11.95	1.98	8.77 ***
Tenure	205.50	239.07	-33.57	3.13 ***	204.71	239.07	-34.36	3.50 ***	193.91	239.07	-45.16	4.34 ***
White collar employee	0.61	0.42	0.20	4.75 ***	0.81	0.42	0.39	12.42 ***	0.89	0.42	0.48	17.23 ***
Full time job	0.84	0.86	-0.02	0.50	0.87	0.86	0.01	0.43	0.85	0.86	-0.01	0.43
Temporary contract	0.03	0.04	-0.01	0.57	0.04	0.04	0.00	0.23	0.06	0.04	0.01	0.76

Notes: The t-test for independent samples is used. Significance level: *** 1%, ** 5%, * 10%.

Table A-3: Full regression results for wage returns of training

Regressors	Log monthly wage (1)		Log monthly wage (2)	
	Coeff.	Stand. Err.	Coeff.	Stand. Err.
No training participation, tr_1	Base category		Base category	
No training participation, but intended, tr_2	0.069 ***	0.023	0.034 *	0.020
Training participation in only one course, tr_3	0.050 ***	0.014	0.044 ***	0.009
Training participation in one course, but intended to do another, tr_4	0.103 ***	0.026	0.044 **	0.018
Training participation in exactly two courses, tr_5	0.086 ***	0.017	0.070 ***	0.012
Training participation in two courses, but intended to do another, tr_6	0.123 ***	0.023	0.082 ***	0.015
Training participation in exactly three courses, tr_7	0.120 ***	0.019	0.091 ***	0.012
Training participation in more than three (intended) courses, tr_8	0.149 ***	0.024	0.138 ***	0.018
Training intention cancelled due to non-random reason, tr_9	0.078 ***	0.025	0.062 ***	0.017
Male	0.232 ***	0.022	0.148 ***	0.013
German	-0.017	0.019	0.050 ***	0.018
Age	0.014 ***	0.005	0.021 ***	0.004
Age squared	-0.0001 ***	0.000	-0.0002 ***	0.000
Married	-0.010	0.011	-0.003	0.008
Child	-0.065 ***	0.023	-0.084 ***	0.020
Male*Child	0.139 ***	0.025	0.118 ***	0.022
Years of schooling	0.039 ***	0.003	0.037 ***	0.003
Tenure	0.001 **	0.000	0.0002	0.000
Tenure square	0.0000	0.000	0.0000	0.000
White collar employee	0.215 ***	0.021	0.202 ***	0.013
Full time job	0.461 ***	0.029	0.463 ***	0.030
Temporary contract	-0.059 **	0.030	-0.055 **	0.023
Firm fixed effects	No		Yes	
Observations	5,407		5,407	
R-squared	0.54		0.52	
F-statistic	85.96 ***		86.73 ***	

Notes: OLS regression results are shown. Standard errors are clustered at the establishment level.
Significance level: *** 1%, ** 5%, * 10%.

Table A-4: Regression results comparing wages of training participants with non-participants

Regressors	Log monthly wage	
	Coeff.	Stand. Err.
Training incidence (yes/no)	0.074 ***	0.014
Male	0.230 ***	0.022
German	-0.017	0.019
Age	0.015 ***	0.005
Age squared	-0.0002 ***	0.000
Married	-0.012	0.011
Child	-0.065 ***	0.023
Male*Child	0.140 ***	0.026
Years of schooling	0.040 ***	0.003
Tenure	0.001 **	0.000
Tenure square	0.0000	0.000
White collar employee	0.225 ***	0.021
Full time job	0.462 ***	0.030
Temporary contract	-0.060 **	0.030
Firm fixed effects	No	
Observations	5,407	
R-squared	0.53	
F-statistic	118.99 ***	

Notes: OLS regression results are shown. Standard errors are clustered at the establishment level. Significance level: *** 1%, ** 5%, * 10%.