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ABSTRACT

Technological Change and Returns to Training

Do returns to training differ if training is accompanied by technological innovations at the workplace? We analyze this potential heterogeneity of returns based on panel data from Germany that provide a unique measure for individuals' adoption of new technology at the workplace. In the preferred analysis we run fixed effects estimations. As a robustness test we also allow for individual time trends. The findings indicate positive wage effects and more job stability for training participants in general but no effects on wages and job mobility for new technology adoption. Furthermore, the combined occurrence of new technology adoption and of training participation does not make individuals better off in terms of wages or job stability compared with individuals experiencing neither training nor new technology adoption.

JEL Classification: I26, J24, J62, M53, O33

Keywords: returns to education, training, technology

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1. Introduction

The labor market and employees are confronted with technological change that has far-reaching effects on tasks, job requirements and occupations (e.g. Spitz-Oener 2006, Dustmann et al. 2009, Autor 2015). Training is often seen as a measure to adapt to new technologies and as a safeguard against possible negative consequences of technological change (e.g. Schmidpeter and Winter-Ebmer 2021). Against this background we investigate returns to training and whether returns differ when training and technological change interact. We examine this interaction by analyzing the effects of training on wages and job mobility for individuals who adopt a new technology at the workplace within the same year and for those without technology adoption.

Analyzing whether returns to training are different for training that is accompanied by new technology from returns to other types of training is important, given that individuals' willingness to bear the costs of training (either the monetary costs or the cost of time and effort) crucially depends on the size of the return. An increase in training participation to adapt to technological change can only be realized if training returns to individuals are positive and not lower than to other types of training. Otherwise, firms or governments would have to step in and take over even larger parts of the monetary costs, assuming that training has a benefit for firms or societies overall.

There is a large literature documenting the labor market returns to training in terms of wages (see, e.g. Lynch 1992, Frazis and Loewenstein 2005, Leuven and Oosterbeek 2008) or aspects of job mobility (e.g. Parent 1999, Görlitz and Tamm 2016), as well as literature documenting the heterogeneity of returns to training based on sociodemographic characteristics (e.g. Ruhose et al. 2019) or type of training[1]. We contribute to this strand of literature by analyzing heterogeneity with respect to the parallel adoption of new technology.

In addition, we contribute to the literature on the interplay of technology and training. Most of the literature that has examined the link between technology and training has concentrated on the provision of training or on employee's participation. Lukowski et al. (2021) found that firms with a higher proportion of digital technology users provide more training and once individuals are familiar with digital technologies they participate less frequently in training. Furthermore, Kleinert and Wölfel (2018) as well as Heß et al. (2019, 2023) show that

[1] Pischke (2001) analyzed differences in returns to training during work hours vs. training during leisure hours. Booth and Bryan (2005) looked at heterogenous returns between self-financed and firm-financed training. Tamm (2018) examined differential effects of training on job tasks based on the content of training.

individuals that are most threatened by technological progress (by having a large share of routine tasks at work or by being highly exposed to robot technology) are less likely to participate in training. Studies that look at returns to training that is accompanied by technology have mostly looked at productivity outcomes instead of individual wage or mobility so far. Boothby et al. (2010) estimate the relationship between technology-training combinations and productivity performance. They find that firms that adopt new technologies and at the same time invest in skills (via training) report higher productivity. Similar results are presented in Bresnahan and Brynjolfsson (2002). They find a positive association between information technology (IT), complementary workplace reorganization (training is part of this), and product and service innovation. Finally, Bartel et al. (2007) find that investments in new computer-based IT improve the efficiency of the production process at all stages and promotes the adoption of new human resource practices that include training. Instead of productivity outcomes we are the first who provide insights on individual wage and job mobility effects of training which is conducted alongside the adoption of new technologies at the workplace.

Another contribution of the paper to the literature is to analyze the effects of technological change on worker mobility. Bauer and Bender (2004) find that firms that introduce new organizational and technological change experience lower employment growth rates. These can be explained by lower net employment growth rates for unskilled workers, while highly educated workers are not significantly affected. Technological change is assessed via the firms' investment in information and communication technology. Dauth et al. (2021) look at robot adoption at the workplace and find more stable employment within firms for incumbents. Robot adoption is measured at the occupation level. Contrary to the previous papers our measure of technology has the advantage of being at the individual level and thereby providing more accurate effects for the individual worker.

Our analysis is based on data from the German Socioeconomic Panel (SOEP) which includes many questions on labor market aspects as well as personal characteristics. In comparison to previous studies using the SOEP (e.g. Pischke 2001 and Ruhose et al. 2019) which had to rely on retrospective information on training participation for 3-year periods, which is plagued by considerable recall bias, we exploit recent waves with new questions regarding training participation within the last calendar year. We also use a survey module regarding new technological innovations at the workplace. As outcomes we analyze wages and two dimensions of job mobility in the form of job changes and promotions.

The analysis is structured in two main analytical sections: First we descriptively investigate the determinants of training participation and its association with the adoption of new technologies in Section 2.2. Secondly, in Section 4 we examine returns to training, to new technology adoption, and the combination of training and technology. We looks at returns in terms of wages and two indicators for job mobility. For the main analysis, we estimate fixed effects models that take the longitudinal nature of our data into account. Given that individuals might also differ in time-variant unobserved characteristics, we additionally estimate fixed effects models that control for individual-specific time trends. Thus, under the assumption that there are no time-varying changes in unobservable factors or circumstances that simultaneously affect outcomes, training participation and technology adoption, we can consider our estimated wage and mobility effects as causal.

Our results indicate that adopting a new technology at the workplace is on average associated with a higher likelihood of participating in training. This association holds even when controlling for an extensive set of observables as well as time-invariant unobservable characteristics. Furthermore, we find that training participation in general increases wages by 0.9%. In contrast new technologies have no impact on wages, once individual fixed effects are taken into account. The interaction of training and new technology has a negative sign and is not significant but findings indicate that new technology adopters do not benefit in terms of wage increases when participating in training. Robustness tests that additionally include individual time trends find similar results though with larger standard errors. With regard to the mobility outcomes, we can see a reduction in the probability of job changes for training participants. This effect is only present for training that is not accompanied by technology adoption. In contrast, if training is accompanied by technology adoption there is no effect of job change. We also analyze several dimensions of heterogeneity. Our results show that low-educated individuals experience no wage effects from training or new technologies while highly educated individuals do in fact have significant positive wage effects from technology adoption.

The remainder of the paper is organized as follows: Section 2 describes the data, and presents descriptive statistics and analyzes the association between training participation and new technology adoption. Section 3 discusses the estimation strategy for estimating returns. Results on returns are presented in Section 4. The final section summarizes the findings and offers a conclusion.

2. Data and Descriptives

The following section describes the data that is used in the analysis and provides first descriptive evidence on the relation between training participation and new technologies at the workplace.

2.1 Data

The analysis is based on data from the Socio-economic Panel (SOEP) v37, a representative longitudinal survey of private households in Germany. It covers a wide range of topics, including household characteristics, income, employment, and education. From 2014 onwards questions regarding training activities performed during the last calendar year are included. Within the period 2015 – 2018 a question regarding technological innovations at the workplace was included in the annual interviews as well. With respect to outcome variables, we look at log hourly wages and two indicators for job mobility. Specifically, we define indicators for a job change (taking place either by a change of employer or within the firm) and for a promotion within the firm (we count any job change within the firm as a promotion[2]).

The analysis is restricted to the four panel waves (2015 – 2018) with information on both explanatory variables of interest. The estimation sample consists of working-age individuals from age 21 – 60 that have some kind of employment (full time, part time, marginal, self-employed or apprenticeship). Armed forces and sheltered workshops are excluded. Any observations with item non-response in our key variables are also dropped from the analysis. The resulting sample covers 44,791 person-year observations from 17,856 individuals of which 7,735 are observed in all four waves.

In SOEP the question on technology adoption is as follows: "Sometimes there are changes in the tools and technologies of the workplace—for example, when new technologies, devices, or working or production processes are introduced. What about you? Have there been any changes of this kind in your job in (the last calendar year)?" In the analysis sample, 22%[3] of employees report that they did adopt a new technology.

Our measure for training participation refers to any vocational training program that was completed in the last calendar year. It encompasses "all types of vocational measures that are

[2] While not every job change within the same company is necessarily a promotion, we observe that the average hourly wage increase for an individual who changes his/her job within the same firm is nearly twice as high as the average hourly wage increase of a worker who remains within the same job at the same employer. Therefore, we consider internal job transitions as promotions.

[3] In the subsample of training participants this share is at 31% whereas for the non-participants it is only 18%.

designed to build on previous professional training or to pave the way for a change of profession." The initiator of the training could be the individual, the employer or a government agency. In case that a measure was completed follow-up questions inquire the total number of completed training programs, the number of days spent in training as well as who paid for the training. The overall training participation rate is 30% and relatively stable across all four panel waves. Other studies looking at training within the SOEP find similar participation rates (e.g. Caliendo et al. 2022 or Caliendo et al. 2023). Among all participants, the average duration of training is 9.8 days with a median of 4 days. For training participants with a parallel technology adoption this duration is slightly higher at 10.3 days with a median of 5 days. In most cases, the training is paid by the employer (85%) which is typical for the German labor market and many other economies (e.g. Pischke 2001, Bassanini et al. 2007). Among the new technology adopters the share of (at least partly) employer-financed training is slightly higher at 87% than among non-adopters (84%) and the share of training participants who (at least partly) self-finance training is somewhat lower among new technology adopters than among non-adopters (14% vs 15%).

Descriptive statistics on the characteristics of training participants and non-participants are presented in Table 1. There are hardly any differences in the proportion of women between the groups. However, individuals with a migration background are less likely to participate in training, which was also found in previous studies (e.g. Beicht and Walden 2017). In line with the literature (e.g. Kramer and Tamm 2018), we find large educational differences, with the low educated being less likely to participate in training, while the high educated are over-represented in the population of training participants. In terms of job characteristics, it can be seen that training participants are more likely to be in full-time employment. They are also slightly more likely to be self-employed and less likely to be in an apprenticeship. Additionally, training participants are also more frequently employed in large firms (more than 200 workers) than non-participants. With regard to technological change, we can see that, on average, 31% of training participants indicate the adoption of a new technology at the workplace, while for non-participants this proportion is much lower at around 18%. Our outcome variables also show differences. Training participants earn on average around 4.3 euros more per hour than non-participants. They are less likely to change jobs but more likely to be promoted within the same company.

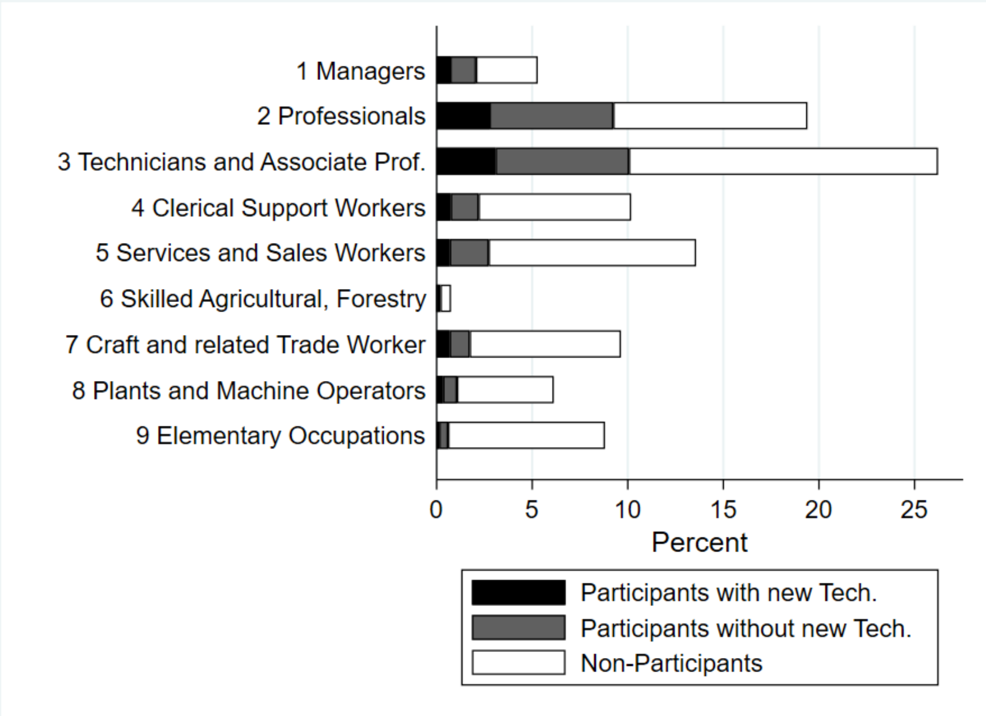
Table 1 – Summary statistics of training participants vs. non-participants

Variables	Non-Participants		Participants		H0: equal means
	Mean	Std. Dev.	Mean	Std. Dev.	p-Value
Individual characteristics					
Female	0.512	0.500	0.521	0.500	0.089
Age	42.830	10.467	43.381	9.794	0.000
East	0.186	0.389	0.212	0.409	0.000
Migrant	0.305	0.461	0.192	0.394	0.000
Married	0.638	0.481	0.652	0.476	0.005
Low Education	0.105	0.306	0.032	0.177	0.000
Medium Education	0.615	0.487	0.483	0.500	0.000
High Education	0.280	0.449	0.485	0.500	0.000
Job characteristics					
Full Time	0.636	0.481	0.715	0.451	0.000
Part Time	0.262	0.440	0.256	0.436	0.165
Marginal Employment	0.074	0.261	0.015	0.122	0.000
Tenure at Employer	9.626	9.633	10.927	9.722	0.000
Self Employed	0.029	0.168	0.035	0.183	0.002
Apprenticeship	0.554	0.878	0.199	0.585	0.000
Firm Size small	0.176	0.381	0.108	0.310	0.000
Firm Size medium	0.353	0.478	0.300	0.458	0.000
Firm Size large	0.471	0.499	0.592	0.492	0.000
New Technology	0.176	0.381	0.308	0.462	0.000
Outcome Variables					
Hourly Wage in Euro	16.054	12.789	20.333	12.764	0.000
Job Change	0.155	0.362	0.126	0.332	0.000
Promotion	0.006	0.077	0.008	0.090	0.010
N	31,423		13,368		

Notes: The last column refers to a t-test on the equality of means for the non-participants and participants.

Figure 1 further presents the distribution of training participants' occupations according to the International Standard Classification of Occupations (ISCO-08) aggregated on the 1-digit level. The figure distinguishes between training participants with or without new technologies. The share of training participants is largest within the group of Professionals and Technicians and Associate Professionals. Their respective participation shares are 47% (Professionals) and 38% (Technicians and Associate Professionals), well above the sample average at 30%. These occupations are generally associated with a high degree of education and encompass occupations like Engineers, Health Professionals and Information and Communication Professionals. Trade and manufacturing occupations on the other hand report lower training participation rates. The adoption of new technologies at the workplace follows a similar pattern. Around 30% of all training participants also report a new technology. Among training participants, the highest share of new technology adopters is observed among Plant and Machine Operators. Despite their low absolute number of training participants, nearly 40% of those that do participate also report a new technology at the workplace. For the Professionals and Associate Professionals this share is at around 30%. Overall, there is clear evidence that training participation rates and the parallel adoption of new technology differ between occupations.

Figure 1 – Distribution of ISCO-08 occupations (1-digit level)



2.2 Association between training participation and new technology adoption

In order to learn more about the correlation between training participation and the adoption of new technologies, Table 2 presents results that account for individual- and job-related characteristics that may affect selection into training. The specification in column (1) only includes the new technology dummy as well as a set of year dummies as controls. Column (2) adds individual controls and job-related characteristics. Column (3) additionally controls for individual fixed effects. The effect of the new technology dummy is positive and highly significant across all specifications. The preferred fixed-effects specification in column (3) indicates that having a new technology at the workplace is associated with a 3.5% points higher probability of participating in a training measure, even when controlling for the whole set of individual and job-related characteristics as well as unobservable time-invariant factors. Overall, individuals who have experienced some technological innovation at their workplace seem to be more likely to participate in training. One reason for this could be that the training is necessary to acquire new skills and knowledge that are required to operate the new technology.

Table 2 – Association between training participation and new technology adoption

	(1) OLS	(2) OLS	(3) FE
New Technology	0.165^{***}	0.130^{***}	0.035^{***}
	(0.006)	(0.006)	(0.006)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	No	Yes	Yes
Individual fixed effects	No	No	Yes
Observations	44.791	44.791	44.791
R^2	0.022	0.140	0.009

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

To learn more about the longitudinal pattern of training participation and of new technology adoption, Table A.1 shows the proportion of individuals with 0, 1, 2, 3 or 4 years of training (of new technology adoption) in the 4-year period of observation. These shares refer to individuals that are part of the analysis sample in all four waves. Almost half of respondents never experience any training or new technology within the four-year period. Among training participants, a participation in only one year is more common than frequent participations. Similarly, among new technology adopters a new technological change at the workplace during one year is the most common incidence. Only about a quarter of respondents report more than one technological innovation. In comparison, participating in more than one training measure from 2015 – 2018 is more common at around 37%. A joint occurrence of training and new technology in one year is reported by 15% and in more than one year by hardly 10% of the individuals.

3. Empirical strategy for the estimation of returns

The literature on returns to training has been using several strategies to estimate causal effects, among others fixed-effects methods (e.g. Pischke 2001), matching (e.g. Ruhose et al. 2019), instrumental variables strategies (e.g. Brunello et al. 2012) and settings where training participation is determined by plausibly exogenous factors (e.g. Leuven and Oosterbeek 2008, Görlitz 2011). Because plausibly exogenous factors and credible instruments are hard to come by and because our data provides us with longitudinal information on outcomes and training participation as well as new technology adoption, we use a fixed effects approach to estimate the wage and mobility effects of training.

This is implemented by regressing log hourly wages and the respective mobility indicators on the individual- and job-related characteristics listed in Table 1 as well as dummies for industries (2-digit level NACE code) and for occupations (1-digit level ISCO code) and an individual-specific fixed effect. In these specifications the control variables of main interest are indicators for training participation, for new technology adoption and the combined occurrence of the two. Specifically, the training and new technology indicators measure the stock of (years of) training and (years of) new technology adoption, rather than simple indicators for participation in the preceding year. Using dummies indicating participation in the preceding year would not make sense in a longitudinal framework, because this would imply that any returns to training (or new technology) are short-lived and vanish completely after one year. Rather, similar to what is typically assumed for schooling, we prefer a specification where each (year with) training adds to the stock of human capital and (potentially) has a long-term impact on outcomes.[4] The combined occurrence of training and new technology refers to the stock of years in which both training and new technology adoption took place.

This fixed-effects estimator identifies causal effects if after taking into account observed time-variant factors, on average, differences in the level of an outcome between participants and nonparticipants would have remained constant over time in the absence of training (of new technology adoption, respectively). This might not necessarily hold, given findings in Frazis and Loewenstein (2005) that training participants and nonparticipants might not only differ in wage levels but also in wage trends. We account for this by also estimating fixed effects models that additionally control for individual-specific time trends (in the robustness section). In such a specification only *time-variant* unobserved factors that simultaneously affect outcomes and training participation and/or the adoption of new technology might contaminate the results and lead to biased estimates of returns. Such limitations concern most non-experimental identification strategies.

[4] In a fixed effects setting it is irrelevant that the stock out training only refers to (years of) training since wave 2015 because any effects of training (or new technology) that were taken before that year are captured in the fixed effects.

4. Results on returns

The section on returns starts out with descriptive evidence on wage differences between training participants and nonparticipants. Then the preferred specification based on fixed effects is shown, both for wages and two indicators for job mobility. Afterwards, as a robustness tests, we present a specification controlling for individual time trends that takes into account that training participants might not only have different (e.g. wage) levels than nonparticipants due to unobserved characteristics but might also experience different (wage) trends, even in the absence of training. Next, we draw some conclusions on the selection into training in terms of unobservable characteristics that complements findings from Section 2.2. Finally, we probe whether the estimated wage and mobility effects are heterogeneous by gender, level of education and other characteristics.

4.1 Main results

Specifications (1) and (2) of Table 3 show the correlation between wages and training participation as well as new technology adoption. They are estimated using OLS and do not take the longitudinal nature of the data into account. Following most analyses focusing on training returns in a cross-sectional setting, training is measured by a dummy indicating training participation in the preceding year. Specification (1) shows that training participants have wages that are more than a quarter higher than the wages of nonparticipants. According to the interaction term the wage premium of training participants compared to nonparticipants is smaller when a new technology is adopted in the same year than without new technology. Yet, individuals having experienced technological change during the preceding year have wages that are 16% higher on average. Specification (2) indicates that most of the wage premia are due to selection into training and new technology because compared to specification (1), the point estimates drop considerably when controlling for observable individual- and job-related characteristics.

The training premium in specification (2) is at 5.5% and the new technology premium is at 2.2%. This training premium of 5.5% is in the range of training returns estimated in other studies, but it is unlikely that this represents the causal effect of training, due to potential differences in unobservable characteristics. Our preferred specification takes these into account by controlling for individual fixed effects. Results are shown in specification (3) and in this longitudinal setting training and new technology refer to the cumulated stock of years with training and years of new technology adoption.

Table 3 – Estimates for log hourly wages (OLS and fixed effects results)

	(1) OLS	(2) OLS	(3) FE
Training	0.268***	0.055***	0.009***
	(0.008)	(0.006)	(0.003)
New Technology	0.157***	0.022***	0.003
	(0.009)	(0.006)	(0.004)
Training x New Technology	-0.089***	-0.013	-0.008
	(0.013)	(0.009)	(0.007)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	No	Yes	Yes
Individual fixed effects	No	No	Yes
Observations	44791	447915	44791
R^2	0.060	0.548	0.129

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Dependent variable is the log hourly wage. In specifications (1) and (2) Training (New Technology) is a dummy indicating participation (adoption) in the preceding year. In specification (3) Training (New Technology) refers to the stock of years with training (new technology adoption) and the Training x New Technology variable refers to the stock of years when both training and new technology took place.

In the preferred specification the effect of training on wages equals 0.9% and is statistically significant. This estimate is close to the (insignificant) return estimated in Görlitz (2011) that relies on exogenous variation in training participation. Given that training participants have an average of 9.8 days of training and taking into account that most wage returns to a year of schooling are in the range of 7 to 10% (e.g. Card 1999) the training return of 0.9% in the preferred specification is much more plausible than that of the OLS specifications. With respect to new technology, the point estimate is small and insignificant in the main specification, i.e. individuals adopting a new technology do not experience wage increases. The training-new technology interaction is insignificant as well, indicating that the wage returns of training do not differ between individuals with and without new technology adoption. However, note that the sum of the training effect and of the interaction term is close to zero and statistically not significant (0.009 – 0.008 = 0.001 with an F-statistic of 0.10 and a p-value of 0.758) and the sum of the training effect, of the technology effect and of the interaction term is small as well and not significant (0.009 + 0.003 – 0.008 = 0.004 with an F-statistic of 1.07 and a p-value of 0.301) which would imply that individuals participating in training and adopting a new technology do not fare better than individuals with neither training nor new technology adoption.

Table 4 shows results of the preferred fixed effects specification on two mobility indicators. It shows that training has no significant effect on promotions (column 2) but training reduces the likelihood of a job change by 1 percentage point (column 1). Taken together this indicates that turnover is reduced and thus job stability in a given firm increases. In contrast, new technology adoption does not affect promotions nor job change. Note that while for job change the interaction term for training and new technology is not statistically significant, it is of the same size but of opposite sign to the training effect. This implies that training has no significant effect on job change if it is accompanied by new technology adoption in the same year (the F-test of significance of the sum of the training effect and the training x new technology interaction is 0.00 with a p-value of 0.987 and the F-test of significance of the sum of the training effect and the new technology effect and the training x new technology interaction is 0.01 with a p-value of 0.921).

Table 4 – Estimates for job mobility (fixed effects results)

	(1) Job change	(2) Promotion
Training	-0.010**	-0.001
	(0.005)	(0.001)
New Technology	0.001	0.002
	(0.006)	(0.002)
Training x New Technology	0.010	-0.000
	(0.010)	(0.003)
Year dummies	Yes	Yes
Individual and job characteristics	Yes	Yes
Individual fixed effects	Yes	Yes
Observations	38204	38204
R^2	0.044	0.008

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Job change is a dummy indicating a job change between the preceding and the current wave, either within the firm or to another firm (conditional on employment in both waves). Promotion indicates a job change within the same firm between the preceding and the current wave (conditional on employment in both waves).

4.2 Robustness checks

Do these fixed effects estimates represent causal effects of training (and new technology) on outcomes? Not necessarily, given that individuals with and without training participation (new technology adoption) might not only differ in (e.g. wage) levels but also in (wage) growth patterns, as has been suggested by Pischke (2001) and Frazis and Loewenstein (2005). To account for this possibility Table 5 presents estimates that in addition to individual fixed effects also control for individual time trends. Because in such a setting only individuals with at least three observations help to identify the training and new technology effects, individuals with less than three observations are dropped from the analysis.[5]

[5] Individuals with only one or two observations would only contribute to estimate their individual fixed effect and their individual time trend.

Overall, the point estimates in Table 5 are relatively similar to those in Tables 3 and 4. Yet, the inclusion of more than 8,000 individual time trends leads to an increase of standard errors, which approximately triple for most outcomes and coefficients of interest. Accordingly, some of the previously significant results turn statistically insignificant. Specifically, for wages the point estimate of training is 0.6% (slightly smaller than the 0.9% of the preferred specification) and insignificant (due to three-times larger standard errors than in the preferred specification). The point estimate of training for job change is at -1.4 percentage points, i.e. it is even larger than the -1.0 percentage point in the preferred specification, but now becomes insignificant because of less precise standard errors. Since point estimates change only slightly, we interpret the insignificance of findings for wages and job change as a lack of power rather than a truly zero effect and conclude that our main findings are generally not challenged. Thus, the estimated wage and mobility effects from Table 3 column 3 and from Table 4 can be interpreted as causal effects as long as there are no temporary changes in unobservable characteristics or in unobserved circumstances that influence labor market outcomes and the participation decision for training and for new technology adoption.

Table 5 – Robustness check controlling for individual time trends

	(1) Log Hourly Wage	(2) Job Change	(3) Promotion
Training	0.006	-0.014	-0.000
	(0.009)	(0.015)	(0.004)
New Technology	-0.008	-0.016	0.004
	(0.009)	(0.016)	(0.004)
Training x New Tech	0.008	0.018	0.003
	(0.014)	(0.024)	(0.007)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Individual time trends	Yes	Yes	Yes
Observations	30475	28673	28673
R^2	0.946	0.769	0.675

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Job change is a dummy indicating a job change between the preceding and the current wave, either within the firm or to another firm (conditional on employment in both waves). Promotion indicates a job change within the same firm between the preceding and the current wave (conditional on employment in the same firm in both waves).

4.3 Selection into training due to unobservable characteristics

Subsection 2.2 already presented information on the selection into training for observable characteristics and the drop of the wage premia of training and of new technology between Specifications (1) and (2) of Table 3 indicated that selection into training (and into new technology) in terms of observable time-variant characteristics is strong. This confirms previous findings on selectivity into training (e.g. Bassanini et al. 2007) and the adoption of new technology (e.g. Bartel and Sicherman 1999). This subsection looks at selection in terms of unobservable characteristics.

The decrease of the wage premium of training between the specifications with and without fixed effects, i.e. Specifications (2) and (3) of Table 3, indicates that sorting into training is not only based on observable but also on unobservable characteristics. To learn more about the sorting in terms of unobservables, column (1) of Table A.2 in the Appendix presents results from an analysis similar in spirit of Bartel and Sicherman (1999) where the prediction of the fixed effect from Specification (3) of Table 3 is used as outcome and regressed on information on the frequency of training participation and new technology adoption within the four-year period and observable characteristics that are constant over time (i.e. gender and migration status). The regression uses one observation per individual and focuses on those individuals that are observed in all four waves.

Results indicate that training participants are positively selected and that frequent training participants (i.e. those with 2 or more years with training in the 4 year period) are somewhat more positively selected than occasional training participants (i.e. those with 1 year with training in the 4 year period). Similarly, new technology adopters are positively selected as well and the size of selectivity is similar to training participants, at least for frequent new technology adopters. Occasional new technology adopters appear to be less selected than occasional training participants and less than frequent new technology adopters. The additional effects of parallel training participation and new technology adoption are not significant, i.e. for those individuals the amount of selectivity equals the sum of the selectivity observed for training and the selectivity observed for new technology adoption. Overall, the positive selection might indicate that training participants and new technology adopters have traits that lead to higher wages such as motivation and other relevant skills or it might represent the wage effects of training and of new technology adoption that took place before 2015.

Column (2) of Table A.2 shows results when using the individual time trend estimated from Specification (1) of Table 5 as dependent variable. According to these results there are hardly any differences in individual-specific wage trends by the frequency of training or the frequency of new technology adoption. Only one of the coefficients is statistically significant. This corroborates that the wage effects are similar in Specification (3) of Table 3 and Specification (1) of Table 5 as it indicates that wage *levels* differ between training participants and nonparticipants and between new technology adopters and nonadopters but not wage *trends*. This contrasts findings in Frazis and Loewenstein (2005).

4.4 Heterogeneity of returns between groups

In this subsection we investigate whether the estimated returns to training and to new technology differ by gender, level of education, between blue- and white-collar workers and by firm size. These characteristics have been found to influence the training participation rate (see i.e. Oosterbeeck 1996, Bassanini et al. 2007, Lynch and Black 1998) and could, therefore, also play a role in the returns that individuals experience from training. For gender we differentiate between women and men (our reference category), for level of education between those with low education (i.e. no vocational degree), those with medium education (i.e. vocational degree or degree from highest school track *Abitur*, which is our reference category) and those with high education (i.e. college degree) and for firm size between small (i.e. less than 10 employees), medium our reference category and large (i.e. more than 200 employees). Finally, given that it is not feasible to estimate heterogeneous effects for a multitude of different occupations we differentiate between blue- and white-collar workers. Disparities between these two categories could capture broad differences between occupations and/or heterogeneity of returns by job tasks. The estimated specifications are similar to our preferred specification, i.e. they include fixed effects but no individual time trends, and the explanatory variables of main interest are interacted with the group indicators. Results are shown in Tables A.3 to A.6 in the Appendix.

Table A.3 reveals that returns to training for wages and job change do not differ significantly by gender.

For level of education (see Table A.4), we find that the return to training on wages is absent for low educated individuals (while the interaction term is not significant, the point estimate of the interaction with low education is larger and of opposite sign to the training effect in the baseline group and an F-test of significance of the sum of the baseline training effect and low education interaction is 0.03 with a p-value of 0.868). Furthermore, while new technology has no effect on wages of employees on average, it does have a significant positive effect on wages of highly educated individuals (the F-test on the sum of the baseline new technology effect and the high education interaction is 11.71 with a p-value of 0.001) but apparently only if this is not accompanied by training. This is in line with evidence showing that technological change is skill biased and in favor of highly educated individuals (e.g. Bartel and Sicherman 1999). In contrast, for medium-educated individuals in the reference group the new technology variable now indicates even negative wage effects, which are significant at the 10% level. The heterogeneity of wage effects of technological change by level of education, favoring highly educated individual and harming medium-educated individuals conforms with results from Cortes (2016). Effects of training on job change are only present for medium-skilled individuals in the reference category but do not exist for low or highly educated employees (F-statistic for the sum of the baseline training effects and the interaction terms being equal to zero are 0.83 for low and 0.10 for high education with p-values of 0.361 and 0.746, respectively). Note, that for medium-skilled individuals in the reference category the interaction term of training and new technology is of opposite sign to the training effect similar to the preferred result in Table 4 and now also statistically significant. This implies that training increases job stability (of medium-skilled employees) only if it is not accompanied by new technology.

The blue- vs white-collar status is highly correlated with occupation (ISCO-08 1-digit-level) where white-collar workers are dominating the managerial, professional, technical, clerical and sales occupations, that are characterized by higher training participation rates (cf. Figure 1). This notwithstanding, Table A.5 does not show that returns to training and to new technology adoption differ between blue- and white-collar workers.

As well, for firm size Table A.6 does not indicate any major differences in returns to training or to new technology adoption, except for the effect of training on job change, that is significant only for medium and large firms but not for employees in small firms (the F-test on the sum of the baseline training effect and the small firm interaction is 0.37 with a p-value of 0.542).

5. Conclusion

Labor markets around the world are undergoing tremendous changes due to technological progress. New machines or processes at the workplace can alter the whole make-up of a job. Training is often regarded as the key instrument for individuals to keep up with the changing demands for skills and qualifications. For workers, additional human capital is often acquired through training. Using panel data from Germany, we investigate the interaction of training and new technologies in regard to wage effects and two indicators for job mobility. Our results show that new technologies go along increased training participation rates. We also show that there is a wage increase for training participants of around 0.9%, which is in line with other research that relies on exogenous variation in training participation. In contrast, we do not find significant effects for new technology adoption. With regard to the joint occurrence of training and new technology adaption, on the one hand we do not find that the interaction term is statistically significant when looking at the impact on wages – hinting at similar wage returns for training with and without parallel technology adaption. Yet, on the other hand when looking at the sum of the training and interaction coefficients and F-statistics for joint significance, the wage effect of training is close to zero and not statistically significant for training participants with technology adoption, while it is significant for training participants without technology adoption. With respect to the mobility indicators, we find that training reduces the probability of working in a new job. This result hints towards a binding effect of human capital as individuals that acquire knowledge are less likely to leave their employer, which theory predicts for firm-specific human capital. Like for wages, the interaction term for the parallel occurrence of training and new technologies adoption is not significant, but there is evidence that the binding effect of training is not significant for training participants with parallel technology adoption.

Our results in terms of returns to training mostly confirm previous findings. What we do not find are any larger returns to training when combined with new technology adoption. In contrast, there is evidence that the combined occurrence of new technology adoption and of training participation does not make individuals better off in terms of wages or job stability compared to individuals experiencing neither training nor new technology adoption. This casts doubt on whether increased training participation in the future that is required by technological change will come from a larger willingness of employees to pay for training.

Furthermore, we find that individuals on average do not profit from new technologies at their workplace in terms of wage or job mobility aspects. At the same time, however, new technologies on average do not pose a threat to wages (conditional on staying employed). Yet, similar to Cortes (2016) we find heterogeneous effects between highly educated individuals who benefit from technological change and medium-educated individuals who seem to be harmed. Moreover, there might be other benefits to new technologies at work apart from wage or job mobility. These could be safer work environments, changes in the working time or the outsourcing of tedious or repetitive tasks. Antón et al. (2020) look at the effect of robots on non-monetary working conditions and find an increase in the domain of work intensity and no impact on physical environment or skills. Since robots are a very special technology and measures for their adoption are only available on the industry level, there is still room for more micro-level research.

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Appendix

Table A.1 – Distribution of the frequency of training and new technology in 4-year period

	Training participation	New Technology	Training & New Technology
… in 0 of 4 years	0.452	0.492	0.748
… in 1 of 4 years	0.177	0.253	0.151
… in 2 of 4 years	0.130	0.144	0.065
… in 3 of 4 years	0.120	0.077	0.026
… in 4 of 4 years	0.121	0.035	0.010
Observations	5473	5473	5473

Descriptive statistics for individuals observed in all four waves.

Table A.2 – Selection into training and new technology adoption in terms of unobservables

	(1) Individual fixed effect	(2) Individual time trend
Training in 1 of 4 years	0.135***	0.009**
	(0.019)	(0.004)
Training in 2 of 4 years	0.162***	0.001
	(0.023)	(0.005)
Training in 3 of 4 years	0.171***	0.002
	(0.025)	(0.005)
Training in 4 of 4 years	0.168***	-0.005
	(0.027)	(0.005)
New Technology in 1 of 4 years	0.088***	0.001
	(0.018)	(0.004)
New Technology in 2 of 4 years	0.157***	0.007
	(0.024)	(0.005)
New Technology in 3 of 4 years	0.177***	0.008
	(0.032)	(0.006)
New Technology in 4 of 4 years	0.157***	0.010
	(0.047)	(0.010)
Training & New Technology in 1 of 4 years	-0.010	0.004
	(0.025)	(0.005)
Training & New Technology in 2 of 4 years	-0.034	0.004
	(0.037)	(0.007)
Training & New Technology in 3 of 4 years	-0.089	-0.009
	(0.055)	(0.011)
Training & New Technology in 4 of 4 years	-0.025	-0.024
	(0.087)	(0.018)
Female	-0.274***	
	(0.013)	
Migrant	0.074***	
	(0.016)	
Constant	-0.035**	0.010***
	(0.014)	(0.002)
Observations	5473	5473
R^2	0.119	0.004

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Dependent variable in column (1) is the predicted fixed effect from Specification (3) of Table 3 and in column (2) the estimated individual time trend from Specification (1) of Table 5. Reference category of the explanatory variables is no training and no new technology in all 4 years.

Table A.3 – Heterogeneity of returns by gender

	(1) Log Hourly Wage	(2) Job Change	(3) Promotion
Training	0.005	-0.009	0.001
	(0.004)	(0.007)	(0.002)
New Technology	-0.000	0.001	0.002
	(0.005)	(0.008)	(0.002)
Training x New Technology	0.001	0.010	0.001
	(0.009)	(0.014)	(0.004)
Female Interactions:			
Female x Training	0.007	-0.003	-0.003
	(0.005)	(0.008)	(0.002)
Female x New Technology	0.007	-0.002	-0.001
	(0.007)	(0.011)	(0.003)
Female x Training x New Tech	-0.016	-0.000	-0.004
	(0.013)	(0.020)	(0.006)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Observations	44791	38204	38204
R^2	0.129	0.044	0.009

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Estimates of the reference category are for men.

Table A.4 – Heterogeneity of returns by level of education

	(1) Log Hourly Wage	(2) Job Change	(3) Promotion
Training	0.011**	-0.021***	0.000
	(0.005)	(0.007)	(0.001)
New Technology	-0.009*	0.003	0.003*
	(0.005)	(0.008)	(0.002)
Training x New Technology	0.000	0.028**	-0.000
	(0.009)	(0.013)	(0.003)
Low Edu. Interactions:			
Low Edu x Training	-0.014	0.051	0.003
	(0.021)	(0.033)	(0.006)
Low Edu x New Technology	0.016	0.013	-0.001
	(0.018)	(0.023)	(0.003)
Low Edu x Training x New Tech	-0.008	-0.051	-0.000
	(0.047)	(0.056)	(0.013)
High Edu. Interactions:			
High Edu x Training	-0.002	0.019**	-0.002
	(0.005)	(0.008)	(0.002)
High Edu x New Technology	0.034***	-0.011	-0.004
	(0.008)	(0.013)	(0.003)
High Edu x Training x New Tech	-0.027*	-0.026	0.002
	(0.014)	(0.021)	(0.007)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Observations	44791	38204	38204
R^2	0.129	0.044	0.009

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Estimates of the reference category are for medium education.

Table A.5 – Heterogeneity of returns between blue- and white-collar workers

	(1) Log Hourly Wage	(2) Job Change	(3) Promotion
Training	0.010***	-0.010**	-0.001
	(0.003)	(0.005)	(0.001)
New Technology	0.003	0.002	0.002
	(0.005)	(0.007)	(0.002)
Training x New Technology	-0.007	0.008	0.001
	(0.007)	(0.011)	(0.003)
Blue-collar Interactions:			
Blue-collar x Training	-0.005	-0.002	0.003
	(0.010)	(0.011)	(0.002)
Blue-collar x New Technology	0.003	-0.009	0.001
	(0.007)	(0.010)	(0.002)
Blue-collar x Training x New Tech	-0.007	0.015	-0.009**
	(0.017)	(0.022)	(0.004)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Observations	44791	38204	38204
R^2	0.133	0.044	0.009

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Estimates of the reference category are for white-collar workers.

Table A.6 – Heterogeneity of returns by firm size

	(1) Log Hourly Wage	(2) Job Change	(3) Promotion
Training	0.009**	-0.015**	0.001
	(0.004)	(0.007)	(0.001)
New Technology	0.008	0.000	0.002
	(0.006)	(0.010)	(0.002)
Training x New Technology	-0.013	0.015	-0.004
	(0.011)	(0.017)	(0.004)
Small Firm Interactions:			
Small Firm x Training	0.011	0.022*	-0.000
	(0.009)	(0.012)	(0.001)
Small Firm x New Technology	0.002	-0.018	-0.001
	(0.014)	(0.019)	(0.002)
Small Firm x Training x New Tech	-0.003	0.008	0.004
	(0.026)	(0.030)	(0.004)
Large Firm Interactions:			
Large Firm x Training	-0.001	0.005	-0.002
	(0.005)	(0.007)	(0.001)
Large Firm x New Technology	-0.009	0.003	-0.001
	(0.006)	(0.010)	(0.002)
Large Firm x Training x New Tech	0.010	-0.008	0.006
	(0.011)	(0.018)	(0.005)
Year dummies	Yes	Yes	Yes
Individual and job characteristics	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Observations	44791	38204	38204
R^2	0.129	0.044	0.009

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Estimates of the reference category are for employees in medium size firms.