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Training and Changes in Job Tasks

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Marcus Tamm[1]

Training and Changes in Job Tasks

Abstract

This study investigates the impact of non-formal training on job tasks of workers. The analysis is based on panel data from Germany covering detailed information on tasks performed at work at the level of individual workers. The results indicate that after training workers are more engaged in non-routine interactive tasks than they were before training. Analyses by topic of training reveal considerable heterogeneity in the impact of training on job tasks. In particular, it is "communication and soft skills" training which is associated with more non-routine interactive tasks.

JEL Classification: J24, J62, O33

Keywords: Job tasks; routinization; returns to education; training

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1 Marcus Tamm, RWI and IZA. *- This study uses the factually anonymous data of the Panel "WeLL" – Employee Survey for the Project "Further Training as a Part of Lifelong Learning", waves 1-4 and the weakly anonymous WeLL survey data linked to administrative data of the IAB (WeLL-ADIAB 75-12). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) (project number: 101565) and via on-site use and subsequently remote data access (project number: 1240). The author is grateful to Katja Görlitz and Ronald Bachmann for comments and suggestions. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Declaration of interest: none. –* *All correspondence to: Marcus Tamm, RWI, Invalidenstr. 112, 10115 Berlin, Germany, e-mail: marcus.tamm@rwi-essen.de*

1. Introduction

Routinization has led to a drastic change of the labor market during the last couple of decades (see, e.g., Autor et al. 2003 for the US, Spitz-Oener 2006 and Dustmann et al. 2009 for Germany, Goos and Manning 2007 for the UK and Goos et al. 2009 for several European countries). The number of jobs with routine tasks has fallen substantially while the number of jobs with non-routine tasks has increased. This change is likely to continue in the light of digitalization and automation (Autor 2015). Future developments of machine learning might also change our experience of what kind of tasks are subject to automation and thus at risk of being performed by machines instead of human workers (e.g. Brynjolfsson et al. 2018). At the individual level such a change of employment at the aggregate level may be due to some workers leaving the labor market and new cohorts of workers with different skills and task sets entering (e.g. Cortes et al. 2014). But part of the aggregate change is also due to workers adapting the type of job tasks they perform (e.g. Gathmann and Schönberg 2010, Cortes 2016, Smith 2013, Bachmann et al. 2018). One way to facilitate such a change in job tasks might be human capital investments and specifically training.

Relatively little, however, is known about the interrelation between training and job tasks. To the best of my knowledge, I am aware of only three articles, two of them analyzing determinants of training and one analyzing whether training leads to changes in the task set of workers. Görlitz and Tamm (2016a) show that training participation differs between workers performing different types of tasks. Workers performing many routine tasks receive less training. Using firm level data and focusing on training of low skilled workers, Mohr et al. (2016) confirm that employees performing non-routine tasks are more likely to receive training than those performing routine tasks. Furthermore, Görlitz and Tamm (2016b) find that participation in (partly) self-financed training that is co-financed by a government sponsored voucher significantly influences the tasks individuals perform after training. They show that after training the participants are more often engaged in non-routine analytic tasks.

Most training of workers is financed by firms and not by individuals themselves (Bassanini et al. 2007). In this paper I analyze the impact of training on tasks for training that is mostly financed by firms. Thus the paper can be seen as an extension of Görlitz and Tamm (2016b) to the type of training that is most often received by workers. This is an important extension because Booth and Bryan (2005) have shown considerable differences in wage returns between firm-financed training and self-financed training. I use German panel data and estimate regression models using first differences, to account for selectivity in training participation and its possible correlation with job tasks. Because the impact of training on tasks may be quite heterogeneous and might depend on the topic of training, I also present results separately by training topic.

The paper contributes to the literature in various ways. For the tasks literature the analysis shows that training is one of the mechanisms to facilitate that workers adapt to changes that arise from digitalization and automation. This also opens ground for politicians who aim at helping workers to cope with routinization. For the literature on the returns to training one contribution is that the paper looks at outcomes that received little attention so far, namely job tasks. Most other analyses focus on wages (e.g. Lynch 1992, Pischke 2001, Frazis and

Loewenstein 2005, Booth and Bryan 2005, Leuven and Oosterbeek 2008, Görlitz 2011, Görlitz and Tamm 2016b), employment and aspects of job mobility (e.g. Parent 1999, Picchio and van Ours 2011, Görlitz and Tamm 2016b) or on other non-monetary outcomes such as job satisfaction (e.g. Burgard and Görlitz 2014).[1] One way through which training could increase wages and employment might be through adapting the tasks workers perform at their job. Thus, analyzing the impact of training on job tasks might also reveal an important mechanism. A second contribution to the literature on the returns to training is that the paper presents heterogeneous impact estimates by topic of training. Most previous research focuses on average returns to training and does not differentiate by topic of training. The literature rather looks at differences between on-the-job training and off-the-job training (e.g. Lynch 1992) or it distinguishes who finances the training (e.g. Pischke 2001, Booth and Bryan 2005) or whether the training is accredited or not (e.g. Booth and Bryan 2005). An exception is Bartel (1995) who looks at wage returns by type of training and finds that employee development training and technical training have a larger impact on wages than training of management skills. While it may partly be justified to disregard differences by topic of training when looking at wages, it is a fundamental issue to look at these differences when analyzing tasks because what workers learn when participating in training is extremely heterogeneous. Different skills are required to perform certain tasks and the types of skills that are trained in a course heavily differ by topic of training.

The remainder of the paper is organized as follows: Section 2 describes the data and presents descriptive statistics. Section 3 discusses the estimation strategy. Results are presented in Section 4. The final section summarizes the findings and offers a conclusion.

2. Data

The analysis is based on the linked employer employee data "WeLL". WeLL is a longitudinal survey comprising four waves that was particularly designed to analyze employment biographies, changes in the work environment and training activities of employees in Germany (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).[2] Within firms, employees were sampled randomly. All four waves of the survey were conducted by telephone on an annual basis between 2007 and 2010. Descriptive statistics on the survey participants are provided in Table 1, separately for all survey participants and by training status.

[Table 1 around here]

Questions on job activities are covered in the survey in each of the four waves. For an overall of 12 activities employees respond whether they perform these activities frequently, occasionally or never. Following Spitz-Oener (2006) I use responses to define five task indices for routine manual, non-routine manual, routine cognitive, non-routine analytical and non-routine interactive tasks. Table 2 lists the 12 job activities and shows how they are assigned to

[1] There is also a rather separate literature analyzing the impact of training for the unemployed (see Card et al. 2010 for an overview).

[2] Owing to this particular sampling frame, the WeLL data is not representative for Germany as a whole but it represents a wide range of firms from different industries and of different size.

the task categories. The assignment represents – given the current technology – what is at risk to be subject to substitution by computers (i.e. the routine tasks) or not well defined and programmable such that computers are unlikely to perform these tasks in the very near future (i.e. the non-routine tasks). For each worker i, the task index is defined for each of the five task categories j based on the number of activities that are performed frequently:

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

This index measures the share of activities a worker performs frequently among all activities within the task category j.

[Table 2 around here]

Table 3 indicates the evolution of task indices over time focusing on the sample I use for the main analysis – because there I apply a model in first differences, the sample is restricted to individuals working in two successive waves. Overall, there is little movement in the average of the task indices over time. Only for routine cognitive tasks the index decreases slightly by 0.05 points. Notwithstanding this high stability in task indices at the aggregate level, there is considerable variability over time at the individual level. Figure 1 looks more deeply into changes at the individual level by presenting information on transitions between two consecutive waves. Because there is more than one pair of consecutive waves, the transitions between all consecutive waves have been pooled in the figure. The top left panel of Figure 1, for example, shows the sequence for routine manual tasks. At the point of origin (which are waves 2007, 2008 and 2009, respectively) 59% of employees do not perform any routine manual activity on a frequent level (and have a task index of 0), 27% perform one of the routine manual activities on a frequent level (and have a task index of 0.5) and 14% perform both routine manual activities on a frequent level (and have a task index of 1). In the following wave (which are waves 2008, 2009 and 2010, respectively) a fifth of individuals (20%) experienced a change, i.e. either a drop or an increase in the routine manual task index. Specifically, 6% of individuals moved from 0 to 0.5, 1% from 0 to 1, 6% from 0.5 to 0, 2% from 0.5 to 1, 1% from 1 to 0 and 3% from 1 to 0.5. The other individuals experienced no change (i.e. 52% of individuals had a task index of 0 in two successive waves, 18% a task index of 0.5 and 11% a task index of 1). Notwithstanding these changes, the overall share of individuals with a specific task index remains basically unchanged, which confirms the aggregate results. For the other task indices the share of employees experiencing either a drop or an increase are 24% for non-routine manual tasks, 20% for routine cognitive tasks, 25% for non-routine analytic tasks and 49% for non-routine interactive tasks. (Note that the number of activities differs between task categories. This partly explains why there are more changes in the non-routine interactive task index and fewer changes in the routine cognitive task index.) Overall, 79% of employees experience changes in at least one of the task indices between two consecutive waves. These numbers illustrate that changes in job tasks are quite common at the individual level.

[Table 3 around here]

[Figure 1 around here]

The WeLL survey asks about participation in any kind of work-related non-formal training such as classroom training, lectures or seminars during the preceding year. This is the type of non-formal education which receives a lot of attention in the training literature (see Bassanini et al. 2007). Note that this question was asked only in waves 2 to 4.[3] For up to three courses per year the data also covers information on the duration, content and financing. Summary statistics on the participation rate are presented in Table 1. Almost every second worker (49%) participated in training during the preceding year. Table 4 shows details on duration, financing and content of the training.[4] The average duration of a training course is 34 hours; the median is 14 hours. Close to 90% of the courses are fully or at least partly financed by the firm and most courses also take place during working hours (64%), even though only 15% of the courses provide mainly or exclusively firm specific knowledge. The most frequent topics of the courses are aspects of health/security (23%), technical content (16%), computer/ICT (15%), administrative content (14%) and communication/soft skills (10%).

[Table 4 around here]

Who participates in training and how is participation related to job tasks? To answer this question, Table 5 shows results of a linear probability model of training participation on a set of individual characteristics and the task indices. All of the covariates are used in lags, i.e. they refer to the preceding wave. When looking at participation in any kind of training (column 1 of Table 5), I find that years of schooling are positively correlated with training. In contrast, individuals who are older and foreigners on average participate less in training. This mainly confirms findings from previous studies on training participation (e.g. Bassanini et al. 2007). Most importantly, from the perspective of the research question, the table shows that individuals who perform non-routine interactive tasks and those who perform non-routine manual tasks are much more likely to participate in training, while routine manual tasks are associated with a lower training probability. This confirms findings in Görlitz and Tamm (2016a) and Mohr et al. (2016). When looking at training participation by topic of training, however, the table shows that there are considerable differences in the association between tasks (as well as the other covariates) and participation by type of training (see columns 2 to 7 of Table 5). To analyze this, I use information on the topic of the courses and differentiate the five most likely topics of training; all other topics are put together in a residual category. The results indicate that training on security and health aspects is very likely among workers with non-routine manual tasks (column 2). In contrast, ICT training is very likely among workers with non-routine analytic tasks and non-routine interactive tasks (column 4). Administrative content and quality management is frequent for workers with non-routine interactive tasks (column 5). Communication or soft skills training is more likely if workers perform non-routine manual, non-routine analytic or non-routine interactive tasks (column 6). Hence, workers in different jobs and with different task sets not only differ in their overall rate of training participation but also perform different types of training. These findings also illustrate that any analysis on the

[3] Wave 1 also covers a question on training but refers to training participation during the preceding two years. Thus, questions are not directly comparable.

[4] For individuals who participated in more than one training course during the preceding year the information in Table 4 refers to all courses they participated in for which the data provides detailed information, i.e. for up to three courses per individual. Some 18% of employees participated in more than one training course and 2% in more than three courses. The average number of courses among training participants is 1.6.

impact of training on tasks has to take into account differences in tasks that already prevail before training participation.

[Table 5 around here]

3. Estimation strategy

The literature has provided ample evidence that human capital investments are strongly related to unobserved characteristics of individuals which themselves have an influence on the outcomes (such as ability or motivation). Thus, simple OLS regressions of outcomes on indicators of human capital investments are very likely to return biased estimates. In the absence of an experimental design, panel regression models that exploit variation in training over time at the individual level have therefore been one of the standard strategies for estimating the returns to training (e.g. Lynch 1992, Pischke 2001, Frazis and Loewenstein 2005). I follow this literature and provide estimates in first differences.

In principle, I am interested in the following equation

$$Y_{it} = \tilde{\alpha} + \tilde{\theta}\mathrm{HC}_{it} + X_{it}{}'\tilde{\gamma} + \tilde{\pi}U_i + \tilde{\eta}_{it}, \qquad (1)$$

where *Y* represents the task indices of individual *i* at time *t*, *HC* is the stock of human capital, *X* comprises observable individual characteristics and *U* represents unobserved characteristics that are constant over time. One standard solution to remove the impact of *U* is to estimate fixed effects models. In the present context, however, the problem with fixed effects models is that the stock of human capital is not observable in the data, because for training there is no comprehensive summary measure covering the whole training biography. For training the data only captures information on training participation during the preceding year. This training indicator Train_{it} can be seen as a proxy for the change in human capital over time ($\Delta\mathrm{HC}_{it}$), i.e., assuming no depreciation of human capital, Train_{it} is equal to one if $\Delta\mathrm{HC}_{it}$ is positive and Train_{it} is equal to zero if $\Delta\mathrm{HC}_{it}$ is zero.

Instead of estimating a fixed effects model I use the following first difference model

$$\Delta Y_{it} = \alpha + \theta\mathrm{Train}_{it} + \Delta X_{it}{}'\gamma + \eta_{it}, \qquad (2)$$

where Train_{it} replaces $\Delta\mathrm{HC}_{it}$. In equation (2), the impact of unobserved characteristics that are constant over time (as well as of observed constant characteristics) is differenced out and the impact of training on the task indices is measured by θ. The estimate of θ will provide an unbiased measure of the impact of training on tasks as long as there are no time varying unobserved factors that correlate with both, training participation and task changes.

Using a first difference strategy has implications for the sample of analysis. Job tasks are only available for individuals who are working at the time of interview. Because the dependent variable measures the change in job tasks between waves, the analysis sample is restricted to individuals who are working in the current and in the preceding wave.

4. Results

The following section presents the results of the first difference regressions using the task indices as outcomes. I start by looking at the impact of work-related training in general. Results for training in general are presented in Table 6 for several specifications. In addition to the training indicator, the first specification only controls for wave dummies (panel A of Table 6). In a second specification the model also controls for a couple of individual and family related factors that may change over time, e.g. marital status, an indicator for having children and its interaction with gender (panel B of Table 6). In a third specification the model additionally controls for job related factors, e.g. an indicator for full-time employment, an indicator for having a temporary contract, an indicator for blue collar workers and tenure (panel C of Table 6). Note that the control factors included in the third and possibly also in the second specification may potentially be endogenous. Thus, I consider the parsimonious specification presented in panel A as the most preferred specification. Having said this, note that all specifications show very similar results. Specifically, I find that training is associated with a significant increase of non-routine interactive tasks. For all other task indices the estimates are insignificant. This implies that training enables workers to perform more non-routine interactive tasks but does not lead to a reduction of other job tasks. The effect size for the non-routine interactive tasks is 0.0072 which is rather small given that this is equal to a forties of the standard deviation of the task index. Taken at face-value the impact estimate implies that, due to training, every 28th training participant experiences a change in one of the five activities defining the non-routine interactive task index towards performing this activity frequently.

[Table 6 around here]

4.1 Robustness of the findings

This subsection tests the robustness of the findings by controlling for changes in log earnings and for firm fixed effects, respectively. Until now the first difference analysis controls for a limited set of covariates only. The identification strategy thus assumes that training participation is unrelated to other changes in the work environment that might simultaneously affect the tasks performed at work. However, in reality it might be that workers who experience specific employment shocks are more likely to participate in training and experience task changes at the same time. It also might be that workers who are employed in specific firm are exposed to different levels of training and to different changes in tasks.

Panel D of Table 6 presents results that control for changes in log labor earnings in preceding years. Such changes in earnings might pick up the impact of employment shocks. Specifically, I use information on earnings from administrative records[5] and control for the first difference of log labor earnings in the three years preceding each interview. This means that training participation between *t-1* and *t0* is regressed on the first difference of log earnings between *t-1* and *t-2*, on the first difference of log earnings between *t-2* and *t-3* and on the first

[5] Administrative records are available for 95% of the WeLL participants and are included in WeLL-ADIAB.

difference of log earnings between *t-3* and *t-4*. The results of the specification are very similar to the other results presented in Table 6.

As has been pointed out by Goux and Maurin (2000) and by Görlitz (2011) controlling for firm specific effects is important when estimating the wage returns to training. Firms that are more likely to train their workers may also be on a different track with respect to adapting to new technological changes or other challenges that lead to changes in workers' task composition. In order to test the robustness of the findings, Table 7 presents results of a specification that controls for firm fixed effects. I implement a highly flexible specification by allowing firm fixed effects to differ between waves.[6] Accordingly, equation (2) is amended to include a dummy variable set μ_{jt} indicating all individuals working in firm j at time *t*: $\Delta Y_{ijt} = \alpha + \theta \text{Train}_{it} + \Delta X_{it}'\gamma + \mu_{jt} + \eta_{it}$. Similar to Table 6, Table 7 shows results for four specifications that differ in the number of individual specific controls used. For all specifications, I find that training is associated with an increase of non-routine interactive tasks and no significant changes of the other tasks.

[Table 7 around here]

This subsection has shown that the first difference results are robust to controlling for changes in log earnings during preceding years and for firm fixed effects. Having said this, however, and similar to most other analyses relying on first differences or fixed-effects approaches to identify treatment effects, I cannot rule out that simultaneity is a problem. This means that time varying unobserved factors may be present that influence the task composition and training participation. While changes of earnings in preceding years might partly pick up such factors, the estimation strategy would not able to pick up the effect of a nearby promotion. For example, an individual might be announced to get promotion and this promotion leads to a change in tasks performed at work. To cope with these changes in tasks, the individual also participates in training. In such a situation training would not be the cause of the change of tasks. Rather, the interpretation would be that training helps the individual to successfully adapt to the new tasks. This implies that the results presented in this paper should be interpreted as associations and do not necessarily represent causal estimates.

4.2 Alternative measures of tasks

This subsection looks at an alternative task index and at the individual activities underlying the task index, respectively. I do so because changes in the task index suggested by Spitz-Oener (2006) that is used in the above analysis are somewhat difficult to interpret with respect to the economic meaning of the size of the coefficient. The alternative task index is supposed to approximate the time share each worker dedicates to specific tasks. It is defined as

$$\text{Task}_{ji}^{\text{time share}} = \frac{\text{Number of activities in task category } j \text{ performed by worker } i \text{ (weighted by frequency)}}{\text{Number of all activities performed by worker } i \text{ (weighted by frequency)}}$$

and takes into account the frequency of each activity. For activities that are performed frequently the index uses a weight of 1 and for activities that are performed occasionally the

[6] In each wave, there are an average of 21 workers per firm.

index uses a weight of 1/3. Instead of normalizing the number of activities from category j that worker i performs by the overall number of activities in category j this alternative index normalizes by the overall sum of activities worker i performs.[7] Sample means for this alternative task index are shown in Table 8. Results using the alternative task index as dependent variable are shown in Table 9 for specifications with and without firm fixed effects.[8] They confirm that training is associated with an increase of non-routine interactive tasks and is not significantly related to changes of the other tasks. Taken at face-value the point estimates imply that after training participation the share of overall working time dedicated to non-routine interactive tasks is higher by 0.5 to 0.6 percentage points.

[Table 8 around here]

[Table 9 around here]

Table 10 shows results for each of the 12 activities that were used to construct the task indices to provide a more detailed perspective on how classroom training affects tasks. In this setting the dependent variable is binary and indicates whether the activity is performed frequently. Results suggest that the increase of non-routine interactive tasks is mainly driven by an increase of the activity "informing and advising". Here the training indicator is positive and significant at the 10%-level. For three out of the remaining four activities that are used to construct the non-routine interactive task index the training indicator also has a positive point estimate but is insignificant. Furthermore, training appears to increase the activity "supervising and controlling machines", which belongs to the routine manual tasks. For the latter the estimate is not robust; it gets considerably smaller and turns insignificant when firm fixed effects are controlled for (compare panel A and panel A' of Table 10), so I consider this no contradiction to the insignificant finding for routine manual tasks in Table 7.

[Table 10 around here]

4.3 Heterogeneity by duration and by topic of training

Table 11 presents results taking into account that the number of training hours an individual experiences may differ. It would be plausible if individuals taking part in longer courses experience larger task changes than individuals who participate in training covering just few hours. For the analysis I distinguish between long and short training and define long training to comprise all training covering at least 25 hours and short training to comprise training of less than 25 hours.[9] Similar to the main specification there is a significantly positive association between training and non-routine interactive tasks but only for long training. The estimate for long training is almost double the size of the estimate for any training shown in

[7] Unfortunately the data does not include any information on actual time use for the activities that would allow to test whether the time share generated by the alternative index is a good approximation. Overall, the assumptions that are necessary to interpret the alternative task index to represent time shares are quite strong.

[8] In the following, the tables focuses on results using the preferred specification. Results are generally very similar when controlling for additional covariates.

[9] The findings are similar when using alternative definition of long and short training, e.g. when using 40 hours of training as cutoff. Long training has a significantly positive impact on non-routine interactive tasks, the effect of short training is smaller in size and insignificant and the effects on the other task indices are always insignificant as well.

Table 6. In contrast, the estimate for short training on non-routine interactive tasks is small in size and statistically insignificant.

[Table 11 around here]

Next, the analysis looks at estimates by topic of training. The results on the task indices are shown in Table 12. There are no significant estimates for training covering security or health aspects and for training on computer or ICT aspects. In contrast, communication or soft skills training and training covering other topics are associated with more non-routine interactive tasks. Both point estimates are significant at the 5%-level when controlling for firm-fixed effects. Communication or soft skills training also is associated with a reduction of routine cognitive tasks (significant at the 10%-level). The estimate for training covering technical content on non-routine manual tasks is positive as well, but only marginally significant and it is negative for training covering administrative content or aspects of quality management. Training covering administrative content or aspects of quality management also has a marginally significant positive impact on routine manual tasks. These results clearly show that different kinds of training have different impacts on jobs tasks.

[Table 12 around here]

5. Conclusion

Labor markets around the world experience tremendous changes in the composition of their workforce. Fewer workers perform routine tasks and the number of workers engaged in non-routine tasks is on the rise. For workers, one strategy to adapt to these changes might be through training. Using panel data from Germany, the analysis investigates whether training participation actually does affect tasks. I find that training is a successful route to more non-routine tasks for workers. Specifically, I find that after training workers are more engaged in non-routine interactive tasks than they were before training. However, given the nature of the data analyzed, I cannot rule out that the findings in this paper are contaminated by unobserved third factors leading to changes in tasks and to participation in training. If this were the case, the interpretation would not be that training leads to task changes but rather that training helps individuals to successfully adapt to the new tasks.

The results also show that the topic of training is key to the changes in jobs tasks. Different kinds of training differently affect the job tasks performed by workers. This also explains why I find that training in general leads to more non-routine interactive tasks, while Görlitz and Tamm (2016b) find that training increases non-routine analytic tasks. Both studies probably look at training comprising different kinds of topics. With respect to the impact of training by topic, I find that non-routine interactive tasks specifically benefit from communication and soft skills training and from training on other topics, while training on security or health aspects, training on technical content, training on computer and ICT aspects and training on administrative content are not significantly associated with changes in the non-routine interactive task index that is used in the analysis. Furthermore, training on technical content is associated with more engagement in non-routine manual tasks, while none of the other types of training is.

This clearly has policy implications. The European Union and its individual member states, for example, are strongly committed to increase participation rates in lifelong learning activities such as training (e.g. as formulated in the strategic framework for European cooperation in education and training 'ET 2020'). Among others, this is motivated by the challenges of technical change. Yet, most country specific strategies and interventions apply a broad definition of training and do not focus on specific topics. According to the results of this paper, such lack in specificity is likely to be inefficient. Any strategy designed to improve the adaptability of workers to the challenges of digitalization and automation by shifting a larger fraction of labor to non-routine tasks will have to focus on specific topics of training rather than any kind of training.

The analysis also shows that training participation is very unequally distributed among the workforce, favoring those with more education and those who already perform relatively more non-routine tasks. Thus, workers who are most at risk of being replaced by machines generally show lower rates of training participation. This calls into question whether firm-financed training or training financed by individuals self-selves will be an avenue also for low skilled individuals and if so, how policy measures should be designed to boost participation especially among those most in need. Findings in Görlitz and Tamm (2016a), for example, document that training differentials between skills groups are even larger when looking at self-initiated training rather than training initiated by employers.

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Tables and Figures

Table 1 – Sample means

	All	Non-participants in training	Participants in training
Training in the classroom, in a seminar, a lecture or a course	0.486		
Male	0.634	0.655	0.611
Birth year before 1952	0.119	0.138	0.099
Birth year 1952 - 1961	0.389	0.401	0.377
Birth year 1962 - 1971	0.333	0.320	0.347
Birth year after 1971	0.159	0.141	0.177
Foreigner	0.047	0.054	0.039
Married	0.744	0.748	0.740
Living with kids	0.363	0.348	0.378
Years of schooling	13.2	12.8	13.7
Full-time employment	0.830	0.834	0.826
Temporary contract	0.050	0.050	0.050
Blue collar worker	0.314	0.422	0.201
Tenure in years	17.9	18.6	17.1
Log daily labor earnings (1 year lag)	4.545	4.468	4.625
Log daily labor earnings (2 year lag)	4.519	4.449	4.590
Log daily labor earnings (3 year lag)	4.490	4.428	4.553
Log daily labor earnings (4 year lag)	4.469	4.407	4.534

Note: Descriptive statistics (sample means) are presented for the main analysis sample (i.e. individuals employed in the current and the preceding wave; N=10,492 person-year observations). Training participation refers to the preceding 12 months.

Table 2 – Assignment of job activities to task categories

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

Table 3 – Evolution of tasks over time

	Year 2007	Year 2008	Year 2009	Year 2010
Routine manual tasks	0.286	0.283	0.283	0.265
Non-routine manual tasks	0.328	0.327	0.338	0.315
Routine cognitive tasks	0.463	0.436	0.473	0.415
Non-routine analytic tasks	0.358	0.337	0.362	0.354
Non-routine interactive tasks	0.380	0.367	0.395	0.380
Observations	4038	4038	3337	3117

Note: Task indices as defined in Spitz-Oener (2006) using the assignment of job activities to task categories shown in Table 2. Descriptive statistics are presented for the analysis sample (i.e. individuals employed in the current and the preceding wave, for 2007 those employed in 2007 and 2008).

Table 4 – Duration, financing and topic of training

Characteristic of the training course	Mean
Duration in hours	34.2
Partly or fully employer financed training	0.888
Training fully taking place during working hours	0.643
Training given in the firm	0.640
Training providing certificate	0.695
Training providing (mainly/exclusively) firm-specific knowledge	0.147
Topic of training …	
security or health aspects	0.231
technical content	0.160
computer, ICT	0.152
administrative content, quality management	0.141
communication or soft skills training	0.101
manager and executive training	0.074
foreign language	0.033
environmental aspects	0.010
other content	0.099

Note: Descriptive statistics are presented for courses of training participants in the analysis sample (i.e. individuals employed in the current and the preceding wave). For individuals who participated in more than one training during the preceding year the information refers to all courses with detailed information. Whether training provides firm-specific knowledge rather than knowledge of general nature is rated by employees.

Table 5 – Determinants of training by topic of training

	Training (in any type of course) (1)	Training on security or health aspects (2)	Training on technical content (3)	Training on computer, ICT aspects (4)	Training on administrative content or quality management (5)	Communication or soft skills training (6)	Training on other topic (7)
Male	-0.0399***	-0.0826***	0.0903***	-0.0152*	-0.0288***	-0.0244***	-0.0047
	[0.0143]	[0.0102]	[0.0081]	[0.0090]	[0.0085]	[0.0072]	[0.0094]
Birth year 1952 - 1961	0.0747***	0.0118	0.0284***	0.0104	0.0124	0.0126	0.0206*
	[0.0179]	[0.0111]	[0.0099]	[0.0111]	[0.0091]	[0.0083]	[0.0113]
Birth year 1962 - 1971	0.1047***	0.0173	0.0393***	0.0244*	0.0277**	-0.0027	0.0451***
	[0.0201]	[0.0131]	[0.0112]	[0.0129]	[0.0108]	[0.0093]	[0.0132]
Birth year after 1971	0.1420***	0.0532***	0.0306**	0.0252*	0.0308**	0.0044	0.0373**
	[0.0225]	[0.0152]	[0.0126]	[0.0143]	[0.0123]	[0.0105]	[0.0147]
Foreigner	0.0455*	0.0106	0.0265**	0.0008	0.0174	-0.0086	-0.0106
	[0.0251]	[0.0171]	[0.0133]	[0.0148]	[0.0115]	[0.0114]	[0.0171]
Married	0.0028	-0.0053	-0.0085	0.0146*	-0.0043	-0.0090	-0.0003
	[0.0139]	[0.0100]	[0.0082]	[0.0084]	[0.0077]	[0.0068]	[0.0094]
Living with kids	-0.0254	0.0443***	-0.0037	-0.0329***	-0.0263**	0.0056	-0.0287**
	[0.0192]	[0.0164]	[0.0087]	[0.0120]	[0.0118]	[0.0106]	[0.0135]
Living with kids x male	0.0246	-0.0466***	-0.0170	0.0185	0.0281**	0.0186	0.0341**
	[0.0225]	[0.0174]	[0.0124]	[0.0136]	[0.0131]	[0.0117]	[0.0153]
Years of schooling	0.0197***	0.0056***	0.0005	0.0026*	0.0042***	-0.0009	0.0137***
	[0.0023]	[0.0018]	[0.0014]	[0.0015]	[0.0014]	[0.0013]	[0.0017]
Routine manual tasks	-0.0806***	-0.0163	0.0107	-0.0253***	-0.0354***	-0.0331***	-0.0028
	[0.0168]	[0.0107]	[0.0109]	[0.0092]	[0.0087]	[0.0070]	[0.0103]
Non-routine manual tasks	0.1556***	0.1756***	0.0420***	-0.0333***	-0.0213**	0.0468***	0.0098
	[0.0187]	[0.0118]	[0.0122]	[0.0113]	[0.0101]	[0.0085]	[0.0123]
Routine cognitive tasks	0.0007	0.0419***	0.0303***	-0.0242***	0.0122*	-0.0227***	-0.0220***
	[0.0111]	[0.0077]	[0.0070]	[0.0066]	[0.0067]	[0.0054]	[0.0077]
Non-routine analytic tasks	0.0854***	-0.0347***	0.0459***	0.0767***	-0.0215**	0.0207**	0.0228*
	[0.0188]	[0.0120]	[0.0122]	[0.0121]	[0.0098]	[0.0092]	[0.0131]
Non-routine interactive tasks	0.2701***	0.0374***	-0.0354**	0.0611***	0.1444***	0.0652***	0.1448***
	[0.0222]	[0.0144]	[0.0142]	[0.0145]	[0.0135]	[0.0115]	[0.0156]
R^2	0.0966	0.0628	0.0301	0.0246	0.0315	0.0254	0.0438
Obs.	10479	10479	10479	10479	10479	10479	10479

*Note: Table provides coefficients of a linear probability model using training participation as dependent variable. Training indicates course participation in preceding 12 months. Covariates also include: dummies for waves. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 6 – Impact of training on job tasks

	Routine manual tasks	Non-routine manual tasks	Routine cognitive tasks	Non-routine analytic tasks	Non-routine interactive tasks
Panel A					
Training	0.0035	-0.0004	0.0066	-0.0012	0.0072**
	[0.0045]	[0.0045]	[0.0082]	[0.0049]	[0.0035]
R^2	0.0017	0.0032	0.0076	0.0054	0.0098
Observations	10492	10492	10492	10492	10492
Panel B					
Training	0.0035	-0.0006	0.0067	-0.0013	0.0072**
	[0.0045]	[0.0045]	[0.0082]	[0.0049]	[0.0035]
R^2	0.0029	0.0036	0.0084	0.0055	0.0102
Observations	10479	10479	10479	10479	10479
Panel C					
Training	0.0038	-0.0000	0.0061	-0.0024	0.0072**
	[0.0045]	[0.0045]	[0.0083]	[0.0050]	[0.0035]
R^2	0.0038	0.0035	0.0083	0.0056	0.0112
Observations	10222	10222	10222	10222	10222
Panel D					
Training	0.0038	0.0008	0.0062	-0.0022	0.0070*
	[0.0046]	[0.0046]	[0.0084]	[0.0050]	[0.0036]
R^2	0.0044	0.0039	0.0084	0.0058	0.0123
Observations	10055	10055	10055	10055	10055

*Note: Task indices as defined in Spitz-Oener (2006). Training indicates course participation in preceding 12 months. Covariates in panel A include: dummies for waves. Covariates in panel B include: those of panel A and the first difference of years of schooling, of marital status, of having children and of having children interacted with gender. Covariates in panel C include: those of panel B and the first difference of full-time employment, of having a temporary contract, of being blue collar worker and of tenure. Covariates in panel D include: those of panel C and the first difference of log earnings in the three years preceding each interview. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 7 – Impact of training on job tasks controlling for firm fixed effects

	Routine manual tasks	Non-routine manual tasks	Routine cognitive tasks	Non-routine analytic tasks	Non-routine interactive tasks
Panel A'					
Training	0.0009	-0.0013	0.0085	-0.0011	0.0093**
	[0.0049]	[0.0049]	[0.0089]	[0.0054]	[0.0039]
R^2	0.0450	0.0416	0.0489	0.0478	0.0530
Observations	10492	10492	10492	10492	10492
Panel B'					
Training	0.0009	-0.0013	0.0089	-0.0012	0.0092**
	[0.0049]	[0.0049]	[0.0089]	[0.0054]	[0.0039]
R^2	0.0462	0.0419	0.0499	0.0477	0.0534
Observations	10479	10479	10479	10479	10479
Panel C'					
Training	0.0006	-0.0010	0.0080	-0.0027	0.0087**
	[0.0050]	[0.0050]	[0.0090]	[0.0055]	[0.0039]
R^2	0.0481	0.0432	0.0509	0.0492	0.0561
Observations	10222	10222	10222	10222	10222
Panel D'					
Training	0.0005	-0.0005	0.0082	-0.0028	0.0086**
	[0.0050]	[0.0050]	[0.0091]	[0.0056]	[0.0039]
R^2	0.0490	0.0438	0.0519	0.0497	0.0573
Observations	10055	10055	10055	10055	10055

*Note: Task indices as defined in Spitz-Oener (2006). Training indicates course participation in preceding 12 months. Covariates in panel A' include: dummies for waves and wave specific firm fixed effects. Covariates in panel B' include: those of panel A' and the first difference of years of schooling, of marital status, of having children and of having children interacted with gender. Covariates in panel C' include: those of panel B' and the first difference of full-time employment, of having a temporary contract, of being blue collar worker and of tenure. Covariates in panel D' include: those of panel C' and the first difference of log earnings in the three years preceding each interview. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 8 – Sample means for alternative task index

	All	Non-participants in training	Participants in training
Time share routine manual tasks	0.129	0.165	0.091
Time share non-routine manual tasks	0.158	0.160	0.156
Time share routine cognitive tasks	0.100	0.111	0.088
Time share non-routine analytic tasks	0.165	0.153	0.178
Time share non-routine interactive tasks	0.449	0.412	0.486

Note: Sample means for the alternative task index (defined in section 4.2) are presented for the main analysis sample (i.e. individuals employed in the current and the preceding wave; N=10,492 person-year observations).

Table 9 – Impact of training on tasks measured using an alternative task index

	Time share routine manual tasks	Time share non-routine manual tasks	Time share routine cognitive tasks	Time share non-routine analytic tasks	Time share non-routine interactive tasks
Panel A					
Training	-0.0007	-0.0034	-0.0009	0.0004	0.0045*
	[0.0021]	[0.0021]	[0.0016]	[0.0019]	[0.0026]
R^2	0.0004	0.0008	0.0023	0.0001	0.0007
Observations	10288	10288	10288	10288	10288
Panel A'					
Training	-0.0019	-0.0033	-0.0021	0.0010	0.0064**
	[0.0023]	[0.0023]	[0.0017]	[0.0021]	[0.0028]
R^2	0.0490	0.0439	0.0487	0.0371	0.0500
Observations	10288	10288	10288	10288	10288

*Note: Task indices as defined in section 4.2. Training indicates course participation in preceding 12 months. Covariates in panel A include: dummies for waves. Covariates in panel A' include: those of panel A and wave specific firm fixed effects. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 10 – Impact of training on job activities

	Routine manual tasks		Non-routine manual		Routine cognitive	Non-routine analytic		Non-routine interactive				
	Fabricating, producing goods	Supervi-sing, controlling machines	Repairing, patching	Nursing, serving, healing	Measuring, controlling, quality checks	Develo-ping, researching	Gathering informa-tion, investiga-ting	Informing, advising	Training, teaching, educating	Organizing, planning	Negotiating	Buying, providing, selling
Panel A												
Training	-0.0073	0.0143**	-0.0030	0.0022	0.0066	-0.0032	0.0008	0.0137*	0.0098	-0.0021	0.0111	0.0036
	[0.0050]	[0.0070]	[0.0048]	[0.0077]	[0.0082]	[0.0045]	[0.0083]	[0.0080]	[0.0069]	[0.0076]	[0.0069]	[0.0061]
R^2	0.0003	0.0025	0.0003	0.0030	0.0076	0.0013	0.0047	0.0040	0.0032	0.0017	0.0023	0.0017
Obs.	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492
Panel A'												
Training	-0.0075	0.0092	-0.0034	0.0008	0.0085	-0.0043	0.0020	0.0169*	0.0108	0.0001	0.0116	0.0071
	[0.0055]	[0.0076]	[0.0052]	[0.0084]	[0.0089]	[0.0050]	[0.0091]	[0.0087]	[0.0075]	[0.0083]	[0.0075]	[0.0068]
R^2	0.0457	0.0493	0.0447	0.0460	0.0489	0.0458	0.0458	0.0459	0.0418	0.0445	0.0446	0.0380
Obs.	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492	10492

*Note: Training indicates course participation in preceding 12 months. Covariates in panel A include: dummies for waves. Covariates in panel A' include: those of panel A and wave specific firm fixed effects. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 11 – Impact of training on job tasks by duration of training

	Routine manual tasks	Non-routine manual tasks	Routine cognitive tasks	Non-routine analytic tasks	Non-routine interactive tasks
Panel A					
Long training	0.0003	0.0024	0.0063	0.0034	0.0139***
	[0.0059]	[0.0059]	[0.0104]	[0.0064]	[0.0047]
Short training	0.0076	-0.0010	0.0065	-0.0051	0.0018
	[0.0051]	[0.0053]	[0.0100]	[0.0058]	[0.0042]
R^2	0.0019	0.0032	0.0076	0.0055	0.0103
Observations	10492	10492	10492	10492	10492
Panel A'					
Long training	-0.0013	0.0023	0.0088	0.0022	0.0163***
	[0.0062]	[0.0063]	[0.0110]	[0.0068]	[0.0050]
Short training	0.0041	-0.0026	0.0074	-0.0037	0.0035
	[0.0056]	[0.0058]	[0.0107]	[0.0065]	[0.0046]
R^2	0.0451	0.0416	0.0489	0.0478	0.0536
Observations	10492	10492	10492	10492	10492

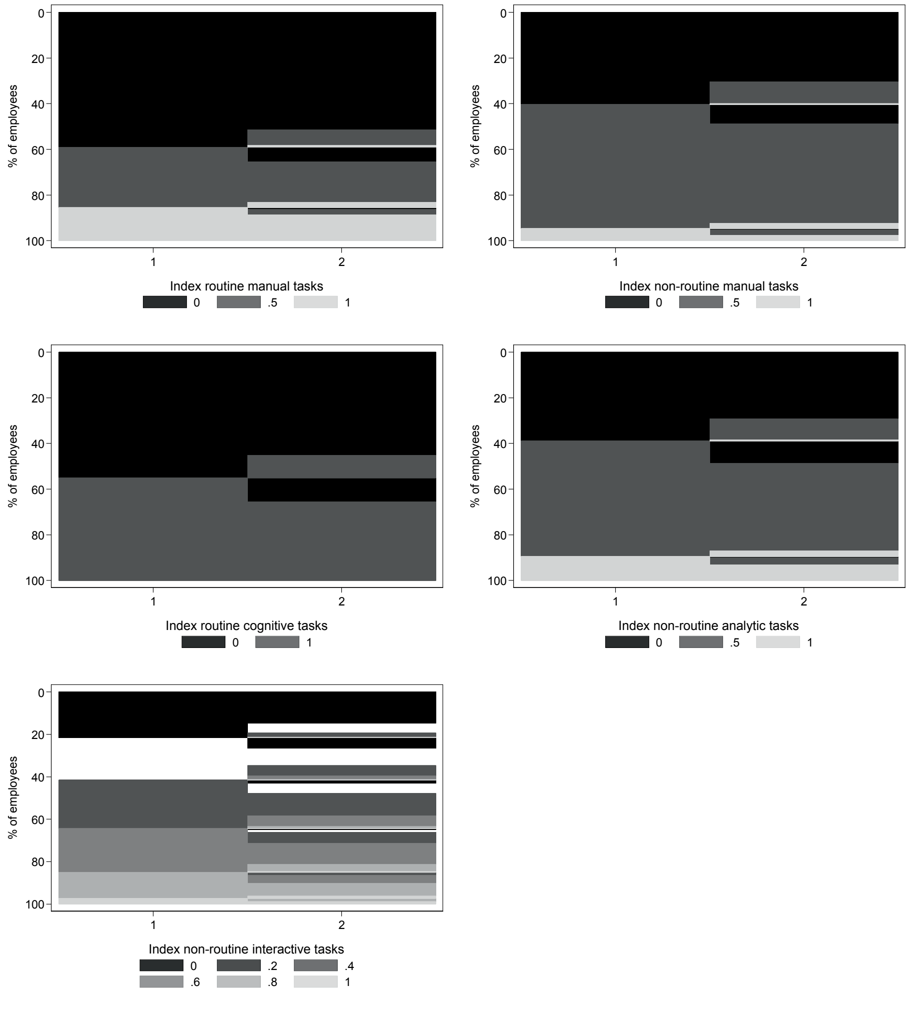
*Note: Task indices as defined in Spitz-Oener (2006). Long training indicates course participation in preceding 12 months of at least 25 hours and short training indicates course participation of less than 25 hours. Covariates in panel A include: dummies for waves. Covariates in panel A' include: those of panel A and wave specific firm fixed effects. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.*

Table 12 – Impact of training on job tasks by topic of training

	Routine manual tasks	Non-routine manual tasks	Routine cognitive tasks	Non-routine analytic tasks	Non-routine interactive tasks
Panel A					
Training on security or health aspects	0.0018	-0.0008	-0.0076	-0.0072	-0.0030
	[0.0068]	[0.0058]	[0.0130]	[0.0079]	[0.0055]
Training on technical content	0.0056	0.0156*	-0.0044	0.0055	0.0026
	[0.0086]	[0.0089]	[0.0146]	[0.0083]	[0.0062]
Training on computer, ICT aspects	-0.0032	-0.0034	-0.0026	-0.0052	0.0073
	[0.0072]	[0.0078]	[0.0130]	[0.0085]	[0.0062]
Training on administrative content or quality management	0.0144**	-0.0141*	0.0155	0.0051	-0.0018
	[0.0070]	[0.0080]	[0.0137]	[0.0083]	[0.0063]
Communication or soft skills training	-0.0021	0.0154*	-0.0344**	-0.0008	0.0150*
	[0.0078]	[0.0092]	[0.0167]	[0.0103]	[0.0077]
Training on other topic	-0.0035	-0.0110	0.0181	-0.0078	0.0099*
	[0.0065]	[0.0068]	[0.0122]	[0.0073]	[0.0053]
R^2	0.0021	0.0042	0.0083	0.0057	0.0103
Observations	10492	10492	10492	10492	10492
Panel A’					
Training on security or health aspects	-0.0031	-0.0007	-0.0025	-0.0070	-0.0045
	[0.0079]	[0.0067]	[0.0146]	[0.0088]	[0.0061]
Training on technical content	0.0059	0.0176*	-0.0075	0.0040	0.0066
	[0.0088]	[0.0093]	[0.0153]	[0.0086]	[0.0065]
Training on computer, ICT aspects	-0.0041	-0.0041	-0.0048	-0.0061	0.0080
	[0.0076]	[0.0083]	[0.0137]	[0.0089]	[0.0064]
Training on administrative content or quality management	0.0124*	-0.0148*	0.0140	0.0041	0.0002
	[0.0074]	[0.0082]	[0.0141]	[0.0089]	[0.0066]
Communication or soft skills training	-0.0027	0.0133	-0.0299*	-0.0005	0.0169**
	[0.0083]	[0.0098]	[0.0177]	[0.0106]	[0.0082]
Training on other topic	-0.0069	-0.0111	0.0193	-0.0096	0.0110**
	[0.0068]	[0.0070]	[0.0127]	[0.0075]	[0.0055]
R^2	0.0454	0.0426	0.0494	0.0480	0.0536
Observations	10492	10492	10492	10492	10492

*Note: Task indices as defined in Spitz-Oener (2006). Training indicates course participation in preceding 12 months. Covariates in panel A include: dummies for waves. Covariates in panel A’ include: those of panel A and wave specific firm fixed effects. Standard errors accounting for clustering at the worker level in brackets. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.*

Figure 1 – Transitions of task indices over time



Note: Transitions are shown for the main analysis sample (i.e. individuals employed in two consecutive waves; N=10,492 person-year observations).