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No Future, No Training? Explaining Cross-national Variation in the Effect of Job Tasks On Training Participation

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Abstract Access to further training among adults on the labor market is unequally distributed. In particular, workers in occupations that are likely to be replaced by machines in the future participate less in training. This is mainly because of the job tasks they conduct: workers conducting routine tasks are more likely both to be replaced and to receive less training. As a consequence, technological change may lead to further polarization on the labor market. However, this trend may be cushioned by educational and labor market institutions. In this article, to assess the impact of institutions, the association between job tasks and participation in non-formal job-related training is analyzed in 24 countries from the first and second rounds of the Program for the International Assessment of Adult Competencies (PIAAC). Multilevel regression analysis is applied to test the influence of macro variables on the task gradient in training. The results reveal that tasks are important predictors of training participation in all countries. Comparing the effects across countries, it is found that tracking in initial education increases inequality in training participation owing to abstract tasks. Vocational orientation, on the other hand, reduces the effect. Furthermore, collective bargaining coverage decreases the effects of tasks on training, whereas strong employment protection legislation increases them. This indicates that the inclusiveness of lifelong learning is already influenced by the initial educational system. Strong unions and dynamic labor markets further enhance access to additional training among vulnerable workers.

Keywords Lifelong learning · Social inequality · Technological change · PIAAC · Educational systems

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Keine Zukunft, keine Weiterbildung? Zur Erklärung von Länderunterschieden im Effekt von Tätigkeiten auf die Weiterbildungsbeteiligung

Zusammenfassung Der Zugang zu Weiterbildung auf dem Arbeitsmarkt ist ungleich verteilt. Insbesondere Beschäftigte in Berufen, die durch Maschinen ersetzt werden können, nehmen seltener an Kursen teil. Dies liegt an den von ihnen ausgeführten Tätigkeiten: Beschäftigte mit Routinetätigkeiten werden mit größerer Wahrscheinlichkeit ersetzt und erhalten auch weniger Weiterbildung. Somit kann der technologische Wandel zu einer weiteren Polarisierung auf dem Arbeitsmarkt führen. Dieser Trend könnte von Bildungs- und Arbeitsmarktinstitutionen abgefedert werden. Um die Auswirkungen von Institutionen zu erforschen, wird in diesem Beitrag der Zusammenhang zwischen Tätigkeiten und der Teilnahme an non-formalen berufsbezogenen Weiterbildungen in 24 Ländern aus den ersten beiden Runden des „Program for the International Assessment of Adult Competencies" (PIAAC) analysiert. Es wird eine Mehrebenenregressionsanalyse angewendet, um den Einfluss von Makrovariablen auf den Tätigkeitsgradienten in der Weiterbildungsteilnahme zu testen. Die Ergebnisse zeigen, dass Tätigkeiten wichtige Prädiktoren für die Teilnahme an Weiterbildungskursen in allen Ländern sind. Im Ländervergleich wird deutlich, dass die frühe Zuordnung zu Schulzweigen die Ungleichheit bei der Teilnahme an Weiterbildung, die durch Tätigkeiten entsteht, erhöht. Eine Ausrichtung auf Berufsausbildung hingegen mindert den Effekt. Darüber hinaus werden die Auswirkungen von Tätigkeiten auf die Weiterbildungsteilnahme durch Tarifbindung verringert, während sie durch Kündigungsschutz verschärft werden. Dies zeigt, dass die Ungleichheit beim lebenslangen Lernen bereits durch das Erstausbildungssystem beeinflusst wird. Außerdem verbessern Gewerkschaften und dynamische Arbeitsmärkte den Zugang von schwachen Beschäftigtengruppen zu Weiterbildung.

Schlüsselwörter Lebenslanges Lernen · Technologischer Wandel · Soziale Ungleichheit · PIAAC · Bildungssystem

1 Introduction

Recent technological developments, such as machine learning, big data analysis, and mobile robots, have the potential to change labor markets profoundly. Occupations may change or even disappear completely because certain job tasks become automated. Therefore, politicians and pundits alike advocate lifelong learning to ensure the employability of the affected workers. Yet, research consistently shows that training opportunities are unequally distributed (Blossfeld et al. 2014). This has often been attributed to inequalities in initial education: those who received little initial schooling also receive less further training. However, recent research challenged this interpretation by showing that participation in further training is mainly determined by characteristics of workplaces and occupations and less by individual resources (Schindler et al. 2011; Görlitz and Tamm 2016; Saar and Räis 2017).

The question about who will be most affected by technological change recently received considerable attention. Following the pioneering work by Autor et al. (2003), a number of studies argued that workers conducting routine tasks are most likely to lose their jobs because their tasks can be easily codified and programmed (Spitz-Oener 2006; Dengler and Matthes 2018). Recent technological developments, however, suggest that the division into routine and non-routine tasks is no longer informative regarding the future of an occupation (Frey and Osborne 2017). The speed at which the development of artificial intelligence proceeds suggests that many non-routine tasks may be substituted in the near future. However, there seem to be certain "bottlenecks" that may hamper the development of algorithms for these tasks. These include complex perception and manipulation as well as creative and social intelligence.

Research on training participation revealed that workers in jobs with a high substitution potential face a double disadvantage: they are likely to lose their jobs to computers and have less access to further training (OECD 2019). This is because of the job tasks these workers conduct: the probability of training participation is lower among workers conducting routine tasks, who are most likely to be replaced by machines (Görlitz and Tamm 2016; Kleinert and Wölfel 2018). Nevertheless, current technological change also generates new jobs (Bessen 2015; Autor 2015). However, these jobs presumably require skills that affected workers currently do not have, such as interpersonal skills or creativity (Frey and Osborne 2017). Thus, those most in need of new skills get the least training.

In this article, the aim is to find out whether the effect of tasks on training differs between countries. Thereby, I want to inquire whether policy measures can lead to more equality in training participation. My research question is: do institutions mediate the effect of tasks on training participation? The literature about the influence of educational systems on inequality showed that certain features of educational systems such as early tracking are related to inequalities in academic achievement among students (Van de Werfhorst and Mijs 2010). Furthermore, the influence of institutions continues after schooling is finished. The literature about institutional influences on training participation among adults showed that there are systematic differences between countries both in the level and in the inequality of training (Saar et al. 2013; Bills and van de Werfhorst 2018). Yet, little is known so far about the international variation in the effect of tasks on further training participation.

I focus my analyses on work-related non-formal further training courses because they are the most common form of lifelong learning in advanced capitalist societies. Non-formal further training comprises structured learning after initial training during prime working age. Compared with formal further training, non-formal courses do not lead to a recognized certificate such as a college or vocational training degree. Thus, non-formal courses are usually short and narrow in scope. Examples include computer courses, language courses, courses teaching soft skills, or courses about new products or machines. In the EU-28, about 37% of the adult population participated in non-formal courses whereas only about 6% participated in formal courses. Among the participants in non-formal courses, 84% stated that the course was job-related (Cedefop 2015). In the remainder of this article, I refer to work-

related non-formal further training courses as "further training" for the sake of brevity.

The article contributes to several strands of research on lifelong learning. It is the first to show the association between tasks and further training from an international comparative perspective using high-quality data from the "Program for the International Assessment of Adult Competencies" (PIAAC). Thereby, it advances the literature on the influence of educational and labor market institutions on inequality by providing evidence for cross-national differences in the effects of tasks on training participation among adults. This perspective also sheds light on the mechanisms behind the association between tasks and training. Additionally, it provides better estimates of the effect of tasks on training participation because of the wide set of available control variables in this data set, such as competencies.

2 Previous Research

Research on the influence of job tasks on training participation so far mainly attempted to explain the training gap between workers with different educational credentials or labor market positions. It is a well-established finding that workers with low educational credentials, low skills, and low-class positions participate less in further training (Blossfeld et al. 2014; Cedefop 2015; OECD 2019). Using German survey data, Schindler et al. (2011) show that job tasks explain a large part of the training gap between social classes. Görlitz and Tamm (2016) also use German data and find that the training gap between tertiary educated workers and workers with lower education is largely due to differences in job tasks. They further reveal that training participation is especially low among workers conducting routine tasks. Analytic and interactive tasks, on the other hand, are correlated with higher training participation. This finding has been reproduced using another German data set (Kleinert and Wölfel 2018). Mohr et al. (2016) also find evidence for the influence of tasks on training among less-qualified workers using data from German firm-level data.

A recent study by the OECD revealed that training participation is lower in jobs that have a higher risk of substitution through machines (OECD 2019, p. 248 f). The authors calculate the risk of automation on the occupational level based on data from Frey and Osborne (2017). These occupational data have been extended to other countries using the task measures in the PIAAC (Nedelkoska and Quintini 2018). However, they calculate substitution potentials for whole occupations and thus underestimate the variation of tasks within occupations (Dengler and Matthes 2018). Furthermore, I argue that the direct assessment of task effects on training facilitates the development of a theoretical framework for context effects. Therefore, I use direct measurements of tasks and not the estimated automation potential in these analyses.

So far, there is no evidence for cross-national variation in the effect of tasks on training participation because the available studies focused solely on Germany. This may influence the conclusions because Germany has specific educational and labor market institutions. The finding that training provision is strongly connected

to job content may be due to close links between initial education and occupations in Germany (DiPrete et al. 2017; Schindler et al. 2011). This leads to the acquisition of specific skills and thus potentially high costs for employers to retrain workers for new jobs. Also, vocational training in Germany leads to strong barriers between occupations and thus less occupational mobility over the life course (Allmendinger 1989; DiPrete et al. 1997). This may result in a reluctance to train routine and non-abstract workers for new prospective tasks and occupations.

Research on the influence of educational systems on inequality revealed that the structure of schools influence the distribution of skills in a society (Van de Werfhorst and Mijs 2010). For example, Hanushek and Wößmann (2006) compare a large number of countries and show that early tracking, i.e., the sorting of students into tracks based on ability, increases the dispersion of math test scores. Tracking also increases the influence of family background on educational outcomes, as Brunello and Checchi (2007) show in a comparative analysis. Other institutional features seem to reduce inequality. Bol et al. (2014) show that countries with central examinations feature lower educational inequality. The vocational orientation of a country, i.e., the degree to which initial education already prepares students for specific occupations, does not seem to influence inequality among students (Bol and van de Werfhorst 2013). Among adults, vocational education systems even have lower skill gaps than general education systems (Heisig and Solga 2015).

So far, we know only little about institutional influences on the inequality in access to further training among adults (Bills and van de Werfhorst 2018; Saar et al. 2013). There is ample evidence for cross-national differences in levels of training partic-ipation. The studies reveal that training incidence is higher in educational systems without tracking and in systems that provide higher average levels of schooling (e.g., Bassanini et al. 2005; O'Connell and Jungblut 2008; Wolbers 2005; Vogtenhuber 2015). Research on inequality in participation, on the other hand, is much scarcer. Most of these studies considered gaps between educational groups and found that they are larger in countries with early tracking (Brunello 2004; Roosmaa and Saar 2010). Martin and Rüber (2016) further showed that the gaps decrease with higher public spending on education.

To my knowledge, only one study so far has considered institutional influences on inequalities due to workplace characteristics (Saar and Räis 2017). However, unlike in the present study, the authors only considered reading tasks. This precludes the integration of the findings with the literature on the substitution of tasks through computers. Also, the authors only compare six countries and are therefore not able to statistically test hypotheses at the macro level. Nevertheless, they find substantial country differences in the effect of reading tasks on training. In line with the con-siderations above, they find that Germany exhibits the largest inequality in training participation owing to reading tasks in their sample.

3 Theoretical Considerations

3.1 The Association Between Tasks and Further Training

In this study, I analyze the impact of routine and abstract tasks on training participation. This categorization of tasks follows a scheme proposed by Autor et al. (2003) to study skill-biased technological change. It takes on a "'machine's eye' view" (Autor et al. 2003, p. 1282) to find out which tasks machines can conduct. According to the model, all tasks that are repetitive and based on clearly defined rules can be replaced by machines. They accordingly label these tasks as routine and all tasks that cannot be easily codified as non-routine. Examples for routine tasks that are likely to be substituted are jobs on assembly lines or repetitive customer services. Typical non-routine tasks, on the other hand, range from janitorial services to management jobs. In both jobs, workers often have to adapt to novel or unforeseen situations. The second dimension that Autor et al. (2003) consider is whether a task involves manual or cognitive work. Combining these dimensions, they arrive at four types of tasks: routine manual, routine cognitive, non-routine manual, and non-routine cognitive.

In this paper, I use a more parsimonious version of the task scheme introduced by Autor et al. (2006). They collapsed the two routine categories from the initial model because they assume a similar substitution potential for both. Consequently, they arrive at three types of tasks: routine, (non-routine) manual, and abstract (non-routine cognitive). The engineering bottlenecks identified by Frey and Osborne (2017), which include tasks that will be difficult to automate even in the near future, can also be related to these task categories. Manual tasks, conducted for example by janitors or waiters, often deal with unstructured objects or environments that computers still have difficulties in handling. Abstract tasks, such as managing or consulting, often involve interactions with people and complex problem solving. Computers are unlikely to match human capabilities in terms of creative and social intelligence needed for these tasks in the near future.

The individual-level mechanisms behind the association between tasks and training are mostly derived from human capital theory (Becker 1975). According to this approach, workers and employers only invest in training if the returns are larger than the investments. Consequently, investment in further training is especially likely if either the costs of training are low or the returns are high (or both). Schindler et al. (2011) describe two mechanisms that link the investment logic of human capital theory and job tasks. Their first argument is that jobs with complex tasks require specific skills that are rare on the labor market. Consequently, employees hired for such positions often do not possess all of the required skills and have to learn them through further training to become productive in their position. Thus, further training alleviates mismatches on the labor market due to underskilled workers (Ferreira et al. 2017). The second argument is that some tasks demand skills that become outdated quickly. It is therefore necessary to invest in training to keep productivity stable. This should lead to higher training participation in occupations that use new technologies (Bresnahan et al. 2002).

Skill mismatch and task-specific skill depreciation both relate directly to two categories in the task scheme introduced above: abstract tasks and routine tasks. Abstract tasks are likely to be skill intensive and possibly also subject to skill depreciation. For example, jobs involving complex problem solving usually require the use of a plethora of skills, many of which workers have to learn on the job. At the same time, work content may change substantively depending on the nature of the problems addressed, which should increase the need for constant skill updating. Routine tasks, on the other hand, usually do not require many skills and updating of knowledge. Once workers know how to conduct a routine task, they can perform it continuously without further training. It is also likely that workers already possess the required skills when hired. Finally, manual tasks, the third category in the model, are difficult to relate to the two mechanisms. Therefore, I do not take into account these tasks in the theoretical considerations below.

It is plausible to assume that employers' considerations about productivity are the main drivers of the effect of tasks on training. Employers are the main providers of training in all countries considered in this study. For example, in the EU-28, 89% of all participants in job-related non-formal further training received financial support for the course from their employers (Cedefop 2015).

Given these considerations, the important question is: under which circumstances do employers train routine and non-abstract workers, even though their job tasks lead to low incentives to do so? If firms are rational actors they only train if the payoffs exceed the investments. Based on the considerations above, payoffs among routine and non-abstract workers are likely to be smaller than among abstract workers. Yet, the required investments may differ between countries. In the following section, I argue that the institutional context and in particular, education systems, may play a role in the investment decisions by influencing training costs.

3.2 Institutions and Inequality in Further Training Participation

The first important institutional factor is the initial educational system. In this study, I consider two aspects of educational systems: stratification and vocational orientation (Allmendinger 1989; Shavit and Müller 1998). Stratification indicates the degree to which students are separated into different tracks. Vocational orientation describes the degree to which the initial schooling system already provides occupation-specific knowledge.

Given the theoretical considerations about training costs in the previous section, it seems likely that initial inequalities are exacerbated by further training. This may be due to larger skill gaps between students in tracked systems (Hanushek and Wößmann 2006). Consequently, workers in routine or non-abstract jobs, who usually come from the lower tracks, often have lower skills. Assuming that learning new skills is more difficult among the less-skilled, they are much more costly to train (Heckman 2000). Moreover, employers may even anticipate this and design routine as well as non-abstract jobs in stratified systems so that training requirements are lower. As a result, skill barriers between occupations increase. These mechanisms should be less prevalent in comprehensive systems with more equal skill

distributions. Therefore, I expect that stratification increases inequality in training participation between workers conducting different tasks:

H1 The effect of routine and abstract tasks on training participation is larger in countries with highly stratified initial school systems.

Vocational orientation may lead to larger inequalities in training participation. Hanushek et al. (2017) argue that vocational systems lead to large gaps in general skills because upper secondary vocational programs teach specialized skills, whereas tertiary programs teach general skills. At the same time, this setup may lead to the sorting of vocational graduates into routine jobs. Tertiary graduates, on the other hand, are likely to go into abstract jobs. Consequently, the effect of tasks on further training should be large in systems with a large vocational sector. In such systems, barriers between occupations based on specific credentials may hamper employer investment in training routine and non-abstract workers because it is relatively costly to teach them new skills. Educational systems that mainly teach general skills, on the other hand, decrease skill polarization between workers. Therefore, training is cheaper for employers regardless of what task the worker is conducting. This should lead to lower effects of tasks on training. Thus, I formulate my second hypothesis:

H2 The effect of routine and abstract tasks on training participation is larger in vocational education systems.

Yet, it may also be the case that vocational systems lead to lower effects of tasks on training. This would be the case if vocational training leads to lower skill polarization than general education. Vocational training programs may teach skills beyond the ones directly required for a certain task. In line with this, Heisig and Solga (2015) show that general skills of workers with upper-secondary education do not differ between systems with strong vocational orientation and systems with general education. Thus, workers with vocational qualifications usually possess both general and vocational skills. Moreover, vocational skills in such systems usually extend beyond firm-specific knowledge because training is centrally organized by the state. This may lead to jobs with higher task complexity because employers know that workers possess a variety of skills. In this case, employers can implement "high-performance work practices" such as job rotation, team working, or employee participation in decision making. These firm policies are associated with higher training participation (O'Connell and Byrne 2012). In general education systems on the other hand, vocational skills are obtained on the job. Thus, if vocational systems teach both a wide range of general and vocational skills, workers in general education systems are likely to possess a narrower range of vocational skills than workers in vocational systems. Consequently, skills in general education systems are more polarized and geared toward certain tasks. This may make training investments in workers conducting routine or non-abstract tasks more costly for employers. According to these considerations, I formulate my third hypothesis, which predicts the opposite of H2:

H3 The effect of routine and abstract tasks on training participation is smaller in vocational education systems.

In addition, labor market institutions may also influence the task gradient in training participation. One important factor may be employment protection legislation (EPL). If dismissals are costly, firms may decide to hire only high-skilled workers for permanent positions. Less-skilled individuals then either become employed on temporary contracts or even unemployed. Thus, EPL generates strong labor market segmentation into a primary segment with permanent positions and a secondary segment with temporary positions (Gebel and Giesecke 2011). It is likely that this segmentation runs along the boundaries of routine and abstract jobs. Routine and non-abstract workers are more likely to be in the secondary segment because their jobs require fewer skills and they can therefore be replaced more easily. Since it is not profitable for employers to invest in temporary workers because of the lower pay-off period, the effect of tasks on training may increase. Thus, my fourth hypothesis is:

H4 The effect of routine and abstract tasks on training participation is larger if EPL is strong.

On the other hand, it is possible that EPL influences the task gradient in the opposite direction. The investment decision of employers may be influenced by the opportunities to lay off workers. If the firm needs new skills, the management can decide to either hire new workers or train the existing workforce (Bellmann et al. 2014). If it is difficult to dismiss incumbent workers, employers may decide to train them even if their skills are low. This would imply that firing costs exceed the costs of training. Thus, given that companies employ some routine and non-abstract workers on permanent contracts despite labor market segmentation, the opposite of H4 is also plausible:

H5 The effect of routine and abstract tasks on training participation is smaller if EPL is strong.

Unions may be important drivers of equalized training opportunities. Booth et al. (2003) show that union-covered workers in the UK receive more training. Thus, larger union influence in the whole economy may decrease inequalities in training. This may be because collective bargaining leads to wage compression. Thus, wages are more equal among workers and depend less on skills. In this case, it is rational for employers to train all workers so that their productivity matches the wages (Acemoglu and Pischke 1999). This may be especially beneficial for routine and non-abstract workers' training opportunities. If collective agreements set their wages above their productivity, employers have an incentive to train them. Another reason may be that unions negotiate equal training chances for all workers in collective bargaining agreements. Thus, they counteract the employers' investment logic. Therefore, I assume that:

Table 1 Summary of the Hypotheses

| | Hypothesized direction of interaction | |
	Task effect increases because	Task effect decreases because
Educational system		
Tracking	H1: skill gaps between tracks	–
Vocational orientation	H2: low general skills in vocational education	H3: high general skills in vocational education
Labor market institutions		
Employment protection legislation	H4: short investment horizon (temporary contract)	H5: training cheaper than dismissal
Collective bargaining coverage	–	H6: low wage differentials and training negotiated
Active labor market policies	–	H7: state funded

H6 The effect of routine and abstract tasks on training participation is smaller if collective bargaining is widespread.

Finally, government activities in the form of active labor market programs (ALMP) may also influence inequality in training. Since governments do not consider training costs when investing in training, the provision of state funded training through ALMPs should be much more equally distributed. Moreover, governments may even have the goal to train the low-skilled to reduce social inequality. Therefore, my final hypothesis is:

H7 The effect of routine and abstract tasks on training participation is smaller if ALMP expenditure on training is high.

The hypotheses formulated in this section describe an interaction between the effect of tasks on training at the individual level and the institutions at the country level. Thus, I assume that the influence of routine tasks and abstract tasks is smaller or larger in a country depending on the institutional setup. Table 1 summarizes the hypotheses by institution and direction of the interaction and briefly summarizes the proposed mechanism.

In addition to the institutions discussed so far, skill demand in an economy may also influence the effect of tasks on training. If an economy relies more on recent technology and knowledge-intensive services, there are more abstract jobs. On the one hand, this may lead to more training, even for routine and non-abstract workers, to teach them the required skills for abstract jobs. On the other hand, it may also lead to a polarization of the labor force in terms of training because employers only invest in workers already conducting abstract tasks. Either way, this influence may confound the institutional influences theorized above because economic structure also correlates with certain institutions. For example, liberal market economies with low EPL, weak unions, and a general education system usually have an economy with more radical innovations (Hall and Soskice 2001). This may result in higher

demand for abstract skills. Therefore, I control for the level of innovation when testing the hypotheses about institutional influences.

4 Data and Methods

I use data from the first two rounds of the "Program for the International Assessment of Adult Competencies" (PIAAC) to test my hypotheses (OECD 2016). I restrict the sample to individuals aged between 25 and 65 who are currently in dependent employment and not enrolled in formal education. The restriction to this age group minimizes bias due to different initial training and retirement regimes. Furthermore, I only include respondents who attained their most recent educational degree in the country they are surveyed in. This ensures that the country-specific educational system had an impact on their labor market careers. I further exclude data from Russia and Cyprus because of low quality and five more countries because of missing macro variables. After deleting all cases with missing values on the relevant variables, the analysis data set contains 24 countries and 66,976 individuals.

The dependent variable is participation in non-formal job-related training courses during the 12 months prior to the interview. It is coded as one for participation in one or more courses and zero for non-participation. I use the generated indicator variable supplied with the data.[1] It uses surveyed information about participation in open and distance education, sessions for on-the-job training, seminars and workshops, as well as courses and private lessons. The survey participants report themselves whether the activity was job-related.

The main independent variables on the individual level are job tasks. Following Autor et al. (2006), I categorize the tasks as abstract, routine, and manual tasks. Empirically, I build on the work of De La Rica and Gortazar (2017), who operationalized this model using the PIAAC data. As described in Table 2, the measure for abstract tasks consists of items about complex reading and writing, problem solving, and communication tasks, as proposed by the authors.

Table 2 Operationalization of tasks

Task	Used PIAAC items for index construction (question no.)
Abstract	Read diagrams, maps or schematics (G_Q01h)
	Write reports (G_Q02c)
	Faced complex problems >30 min (F_Q05b)
	Persuading/influencing people (F_Q04a)
	Negotiating with people (F_Q04b)
Routine	Change sequence of task (D_Q11a)
	Change how to do work (D_Q11b)
	Change speed of work (D_Q11c)
	Change working hours (D_Q11d)
Manual	Physical work (F_Q06b)

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[1] The name of the variable in the public use files is NFE12JR.

However, I depart from the approach by De La Rica and Gortazar (2017) to measuring routine tasks. The authors use items about task discretion, learning at work, and manual dexterity. I only use task discretion because the other two concepts are not well suited to my analysis. Learning at work is directly related to my dependent variable and may blur the results. Manual dexterity may not refer to routine tasks in a strict sense because tasks involving accuracy with hands or fingers may also be non-routine.[2] Moreover, Frey and Osborne (2017) identify dexterity with hands and fingers as a potential bottleneck for automation. This renders its inclusion into an indicator for routine tasks problematic.[3] Unfortunately, the PIAAC data do not provide more detailed information about routine tasks such as questions about repetitive tasks. Yet, task discretion at work is a good proxy for standard routine tasks such as supervising machines or measuring. To construct my indicator for routine tasks, I reverse the items used in the scale for task discretion, which is provided in the PIAAC data (Perry et al. 2017). See Table 2 for details.

I generate indicators for abstract and routine tasks using principal component analysis on the mentioned items and extracted the first factor. The factor loadings of the individual items are depicted in the Online Appendix. Figure 1 plots the two indicators and shows that routine and abstract tasks are not opposites. Although there is a negative correlation between the two indicators ($r = -0.34$), there are many cases with rather high scores on both. This indicates that the constructs measure distinct task dimensions that may also occur together.
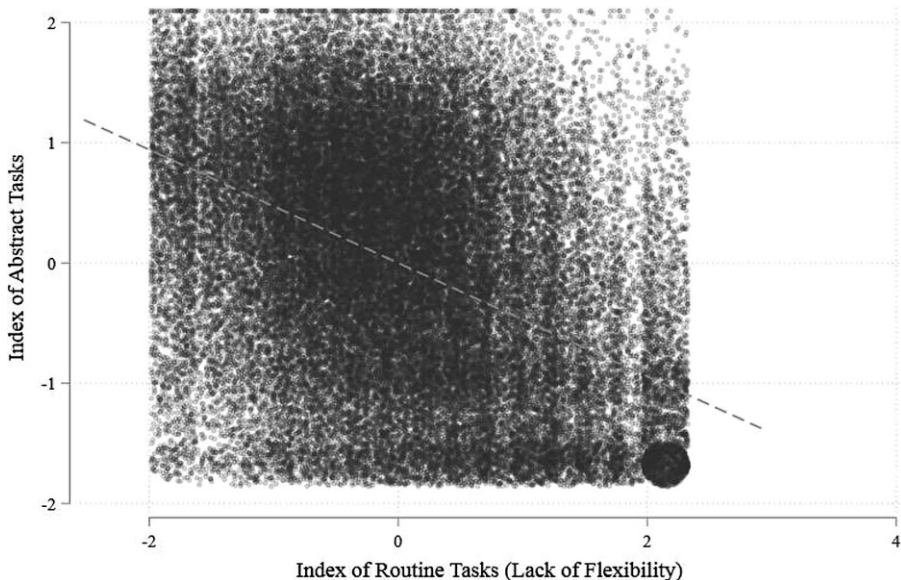

Fig. 1 Scatterplot of the abstract and routine task indexes. (Source: PIAAC, own calculations)

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[2] The exact wording is "How often does your job usually involve using skill or accuracy with your hands or fingers?"

[3] However, I still include it as a control variable in the models because of its importance for automation.

I further use a wide set of control variables to address confounding between tasks and training and obtain an unbiased estimate of the effect of tasks on training. The variables are measured at the individual level and comprise individual, job, and firm level characteristics (see full regression tables in the Online Appendix). Previous research showed that these factors predict both training participation and job tasks (Schindler et al. 2011; Görlitz and Tamm 2016). In terms of job content, I also control for manual accuracy tasks (hand/finger accuracy), and manual tasks in general (physical work). Also, I add measures of literacy and numeracy to the models. Since these indicators are provided in the form of ten plausible values, I estimate my models once for each plausible value and combine the results using Rubin's rules (Rubin 1987; Perry et al. 2017). To combine the estimates, I use the R package *mitml* (Grund et al. 2016). Nevertheless, there may still be unmeasured confounders that may bias the results.

At the country level, I add information about the initial education system from the Educational Systems Database, version 4 (Bol and van de Werfhorst 2011). External differentiation is a composite indicator consisting of three variables. Bol and van de Werfhorst (2011) compile the information about age at first selection and the tracks available at age 15 from OECD reports. They further include the length of tracked education from a study by Brunello and Checchi (2007). The three variables have been converted into an index using principle component analysis (for further details, see Bol and van de Werfhorst (2011, p. 13 f.)). Vocational orientation is measured as the proportion of students in upper-secondary education who are enrolled in a vocational program. Bol and van de Werfhorst (2011) created this measure by combining OECD and UNESCO data using principle component analysis (for further details, see Bol and van de Werfhorst (2011, p. 14 f.)).

The labor market indicators on the macro level are all measured at the time of the survey. This was 2011 for the first round and 2014 for the second round of the PIAAC. I use the latest OECD measure for employment protection legislation of regular employment contracts (version 3) (OECD 2013). I further operationalize government-funded training measures using the indicator about expenditure on training programs as part of active labor market programs provided by the OECD (Grubb and Puymoyen 2008). I use expenditure as the percentage of gross domestic product. Collective bargaining coverage is measured as the ratio of employees covered by collective agreements, divided by all wage earners with the right to bargain. The data are provided by the OECD and are based on the ICTWSS Database (Visser 2016). To control for differences in skill demand, I also add a variable containing expenditure on research and development as a percentage of gross domestic product provided by the OECD (OECD 2015). Although this does not capture the demand for skills directly, it is a good and widely available proxy for the degree to which economies are innovative and based on knowledge-intensive production. For example, it is an integral part of the European Innovation Scoreboard (European Union 2019). All variables in the models are z-standardized within the analysis sample. Table 3 shows the macro data used in the analyses.

Table 4 shows the correlation between the macro indicators used in the analysis. Tracking and vocational orientation correlate highly and significantly but not perfectly, indicating that they often occur together. Moreover, EPL correlates sig-

Table 3 Macro data used in the analyses

	External differentiation index[a]	Vocational orientation index[b]	EPL index[c]	Collective bargaining coverage[d]	ALMP expenditure on training as % of GDP[e]	Expenditure on R&D as % of GDP[f]
Austria	1.82	1.70	2.44	98	0.44	2.68
Belgium	1.02	0.94	3.13	96	0.15	2.16
Canada	−1.32	−1.72	1.51	31	0.10	1.80
Chile	0.32	−0.16	1.80	19.33	0.04	0.38
Czech Republic	1.62	1.74	2.75	49.21	0.01	1.56
Denmark	−0.87	0.46	2.32	83	0.64	2.97
Finland	−0.87	0.74	2.17	90	0.50	3.64
France	−0.47	0.39	2.82	98	0.37	2.19
Germany	1.86	0.89	2.84	58.9	0.25	2.80
Greece	−0.47	−0.31	2.44	40	0.13	0.84
Ireland	−0.30	−0.35	1.98	40.49	0.42	1.53
Israel	−0.06	−0.27	2.22	26.1	0.06	4.11
Italy	0.17	0.95	3.03	80	0.14	1.21
Japan	−0.47	−0.73	2.09	17.8	0.05	3.38
Korea	0.07	−0.55	2.17	11.53	0.03	3.74
Netherlands	0.94	1.26	2.88	87.17	0.12	1.90
Norway	−1.04	0.88	2.31	67.96	0.18	1.63
Poland	−0.08	0.30	2.39	14.86	0.01	0.75
Slovak Republic	1.62	1.49	2.63	35	0.00	0.66
Slovenia	0.12	1.06	2.67	65	0.06	2.39
Spain	−1.02	0.00	2.56	76.98	0.19	1.33
Sweden	−0.87	0.69	2.52	88	0.09	3.25
United Kingdom	−1.04	0.47	1.76	31.2	0.01	1.69
United States	−1.32	−1.84	1.17	13	0.04	2.76

[a]Source: Bol and van de Werfhorst (2011, p. 13 f)
[b]Source: Bol and van de Werfhorst (2011, p. 14 f)
[c]Source: OECD (2013)
[d]Source: Visser (2016)
[e]Source: Grubb and Puymoyen (2008)
[f]Source: OECD (2015)

nificantly with tracking, vocational orientation, and collective bargaining coverage. This combination is typical for coordinated market economies such as Germany. Nevertheless, none of the correlations is close to perfect, indicating that there is the possibility of partialling out estimates for individual institutions.

I use mixed-effects logistic regression to jointly estimate the coefficients at the micro and at the macro level. The models include random slopes for both routine and abstract tasks to arrive at valid estimates of the standard error for the interactions with the macro level variables. I test for the need to include further random slopes

Table 4 Correlation matrix of the macro indicators, $N = 24$. (Sources: see Table 3)

	Tracking	Vocational orientation	EPL	Collective bargaining coverage	ALMP training expenditure	R&D expenditure
Tracking	1	–	–	–	–	–
Vocational orientation	0.657***	1	–	–	–	–
EPL	0.586**	0.767***	1	–	–	–
Collective bargaining coverage	0.156	0.612**	0.641***	1	–	–
ALMP training expenditure	–0.0805	0.169	0.108	0.605**	1	–
R&D expenditure	–0.134	–0.149	–0.107	0.120	0.261	1

$^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

on micro level variables by comparing the Bayesian information criterion (BIC) between various specifications (Heisig et al. 2017). The procedure reveals that model-fit improves if random slopes on literacy and employment in the public sector are added. I approximate the degrees of freedom used to obtain the p values for the estimates using the m-l-1 rule, as suggested by Elff et al. (2019). Here, m is the number of groups (countries) and l the number of contextual effects. This method proved to be superior to standard methods of obtaining p values if the number of
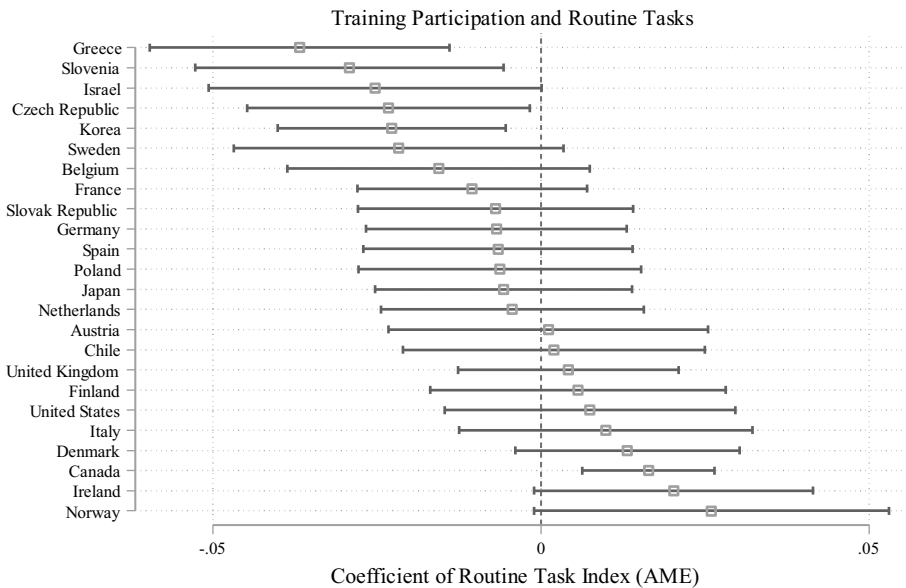

Fig. 2 Average marginal effects and 95% confidence intervals for routine tasks on training participation from country-level logistic regressions including all control variables. (Source: PIAAC, own calculations)

groups is low, as in my case. I estimate the models using the R package *lme4* (Bates et al. 2015).

To interpret the results of the logistic regressions, I use predicted probability plots. This is necessary because the point estimates of interaction effects in logistic regressions may be misleading (Mize 2019). The predicted probability plots are generated using the R package *sjPlot* (Lüdecke 2018), which relies on the package *ggplot2* for the output (Wickham 2016). As suggested by Mize (2019), I also estimate predicted probabilities for all small and non-significant interaction effects. The analyses show that the predicted probabilities are all in line with the coefficients from the model.

5 Results

Before I turn to the hypotheses, I first show evidence that tasks are important predictors of training participation in all of the countries studied here. Figure 2 shows that routine tasks are significantly associated with the probability of training participation in about a quarter of the countries. I also find considerable cross-national variation and both negative and positive point estimates. Compared with the large negative associations between routine tasks and training shown in previous research for Germany by Görlitz and Tamm (2016), as well as Kleinert and Wölfel (2018), this is surprising. Yet, it is probably due to the operationalization of routine tasks in this study, which only includes task discretion because the PIAAC lacks more information, as discussed in the previous section.
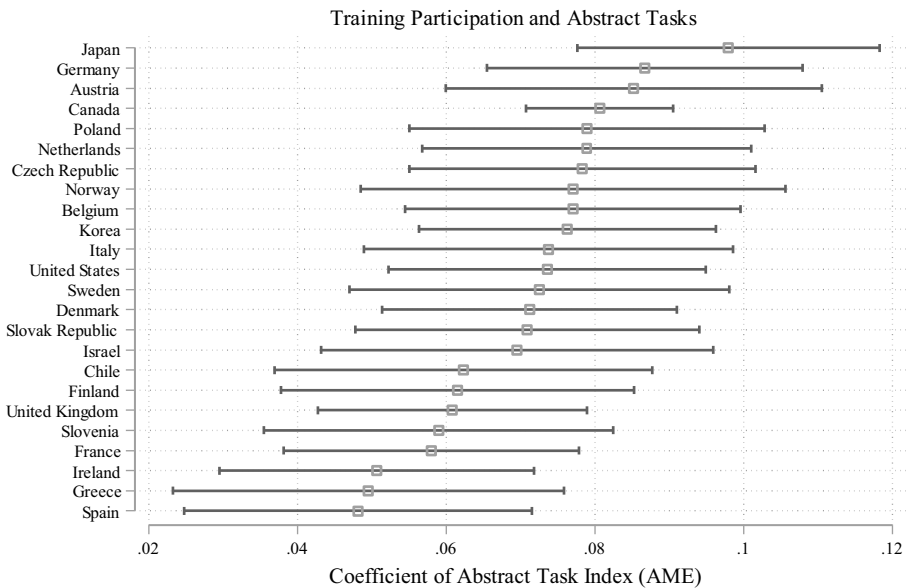

Fig. 3 Average marginal effects and 95% confidence intervals for abstract tasks on training participation from country-level logistic regressions including all control variables. (Source: PIAAC, own calculations)

Table 5 Cross-level interactions of routine tasks with indicators for educational systems from the mixed effects logistic regression model of training participation. Full model is shown in the Online Appendix. (Source: PIAAC, own calculations)

	Model 1	Model 2	Model 3	Model 4
Routine tasks	–0.02	–0.02	–0.02	–0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Tracking	–0.00	–	–0.06	–0.05
	(0.06)		(0.08)	(0.08)
Routine* tracking	–0.01	–	–0.01	–0.01
	(0.02)		(0.03)	(0.02)
Vocational orientation	–	0.06	0.11	0.09
		(0.07)	(0.09)	(0.09)
Routine* vocational orientation	–	–0.02	–0.01	–0.01
		(0.02)	(0.03)	(0.02)
R&D expenditure	–	–	–	0.07
				(0.05)
Routine* R&D expenditure	–	–	–	–0.02
				(0.01)
Number of jobs	66,891	66,891	66,891	66,891
Number of groups	24	24	24	24

$^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6 Cross-level interactions of routine tasks with indicators for labor market institutions from the mixed effects logistic regression model of training participation. Full model in the Online Appendix. (Source: PIAAC, own calculations)

	Model 1	Model 2	Model 3	Model 4	Model 5
Routine tasks	–0.02	–0.02	–0.02	–0.01	–0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
EPL	–0.06	–	–	–0.18*	–0.19***
	(0.07)			(0.08)	(0.09)
Routine* EPL	–0.04*	–	–	–0.06*	–0.07**
	(0.02)			(0.02)	(0.02)
Collective bargaining	–	0.10	–	0.18$^+$	0.20$^+$
		(0.06)		(0.09)	(0.10)
Routine* collective bargaining	–	–0.00	–	0.01	0.03
		(0.02)		(0.03)	(0.02)
ALMP training	–	–	0.09	0.00	–0.01
			(0.06)	(0.07)	(0.08)
Routine* ALMP	–	–	0.02	0.02	0.02
			(0.02)	(0.02)	(0.02)
R&D expenditure	–	–	–	–	–0.00
					(0.05)
Routine* R&D expenditure	–	–	–	–	–0.04**
					(0.01)
Number of jobs	66,891	66,891	66,891	66,891	66,891
Number of groups	24	24	24	24	24

$^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

On the other hand, I find positive and significant associations between abstract tasks and training participation in all of the countries in Fig. 3. Still, the point estimates vary substantively between countries. These first analyses show that the task content of occupations plays a role in training participation in many countries, though with varying intensity. This is even the case after controlling for competencies. Therefore, the speculation by Görlitz and Tamm (2016) that the correlation between tasks and training may be confounded by ability does not seem to be warranted.

Turning to the impact of the macro level indicators, Table 5 depicts the interactions between the educational system and the effect of routine tasks on training as being weak. The coefficient for routine tasks shows that the association with training participation is slightly negative on average across the countries in my sample. However, the estimate is not significantly different from zero. The interactions with the macro-level indicators are also small and not statistically significant. Thus, there is no systematic difference in the effect of routine tasks on training due to educational systems. Therefore, none of my theoretical considerations about the influence of the educational system gains support in the case of routine tasks. The full models in the Online Appendix show that the control variables all point in the expected directions. This also applies to the further models below.
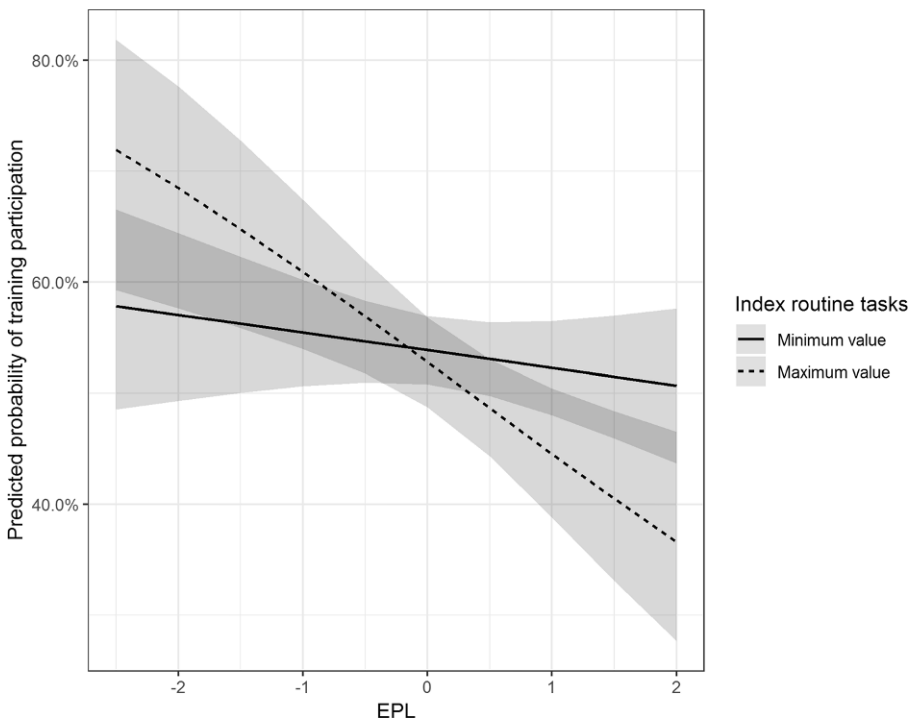

Fig. 4 Predicted probabilities of training participation at different levels of the routine task index and EPL. (Source: PIAAC, own calculations based on Model 5 in Table 6. All other covariates in the model are set to their respective means for the predictions)

Table 6, on the other hand, shows that EPL increases the negative effect of routine tasks. Thus, it increases the inequality in training participation between routine and non-routine workers. The association even holds after including other labor market institutions and skill demand in the models. This is in line with Hypothesis 4, predicting that EPL will lead to a separation of training opportunities between insiders in non-routine and outsiders in routine jobs. The analyses suggest that employers invest less in routine workers if there is strong EPL. This may be due to the short investment horizon of temporary workers in such systems. Also, it may be that employers are reluctant to train workers on the secondary labor market for positions in the primary segment. Beyond this, neither ALMP nor collective bargaining coverage shows any substantial association with the effect of routine tasks on training. Since interaction effects in logistic regressions are difficult to interpret in substantive terms, I plotted the predicted probabilities of training participation at different levels of the routine task and the EPL indicators. The predictions are based on Model 5 in Table 6, holding all other variables in the model at their respective means.

Figure 4 shows that routine workers, i.e., those with a high value on the routine task index, have substantially lower probabilities of training participation than non-routine workers in countries with strong EPL. The difference in predicted probabilities at the maximum value of EPL in the data amounts to more than 10 percentage points. However, the picture is reversed in countries with low EPL. Here, the model predicts that training participation among routine workers is even higher than among non-routine workers. One reason behind this may be that training investments in countries with low EPL reflect the structural changes on the labor market much more. It may be that workers in countries with highly dynamic labor markets, such

Table 7 Cross-level interactions of abstract tasks with indicators for educational systems from the mixed effects logistic regression model of training participation. Full model in the Online Appendix. (Source: PIAAC, own calculations)

	Model 1	Model 2	Model 3	Model 4
Abstract tasks	0.37^{***}	0.38^{***}	0.38^{***}	0.38^{***}
	(0.02)	(0.02)	(0.02)	(0.01)
Tracking	0.03	–	–0.03	–0.03
	(0.05)		(0.07)	(0.06)
Abstract * tracking	0.01	–	0.04^{+}	0.04^{*}
	(0.02)		(0.02)	(0.02)
Vocational orientation	–	0.09	0.11	0.10
		(0.06)	(0.08)	(0.07)
Abstract * vocational orientation	–	–0.02	$–0.05^{*}$	$–0.05^{*}$
		(0.02)	(0.02)	(0.02)
R&D expenditure	–	–	–	0.12^{*}
				(0.04)
Abstract * R&D expenditure	–	–	–	0.04^{**}
				(0.01)
Number of jobs	66,891	66,891	66,891	66,891
Number of groups	24	24	24	24

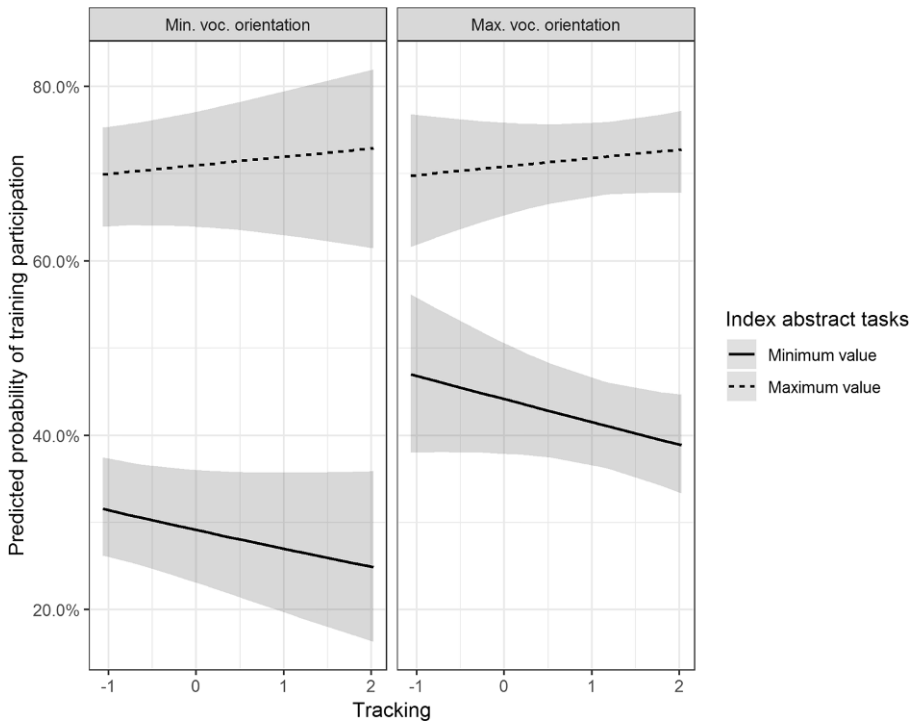$+p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Fig. 5 Predicted probabilities of training participation at different levels of the abstract task index, tracking, and vocational orientation. (Source: PIAAC, own calculations based on Model 4 in Table 7. All other covariates in the model are set to their respective means for the prediction)

as the USA or Canada, are more likely to transition from routine to abstract jobs and therefore receive more even more training to acquire the needed skills.

Next, I show that the effect of abstract tasks on training varies substantially between different educational systems. Table 7 reveals that there is a positive interaction between tracking and the effect of abstract tasks on training. Since the coefficient of abstract tasks on training is positive, this implies an inequality increasing influence. Vocational orientation, on the other hand, is associated with lower effects of abstract tasks. These two coefficients are both significant in Model 3 when both interactions are included. This suggests that the strong correlation between tracking and vocational orientation masks the countervailing associations. The inclusion of skill demand measured as R&D expenditure in Model 4 does not change the results. Thus, the analysis shows evidence in favor of both hypothesis 1 and hypothesis 3. Tracking increases the effect of abstract tasks on training, presumably because it increases skill gaps between jobs. Yet, the vocational orientation of a system seems to counteract this tendency. This may be due to higher skill levels and task complexity across occupations.

To interpret the results from Table 7 in substantive terms, I again turn to predicted probabilities. The two panels in Fig. 5 show that tracking and vocational orientation mainly influence the training participation of non-abstract workers, which have

Table 8 Cross-level interactions of abstract tasks with indicators for labor market institutions from the mixed effects logistic regression model of training participation. Source: PIAAC, own calculations. (Full model in the Online Appendix)

	Model 1	Model 2	Model 3	Model 4	Model 5
Abstract tasks	0.38***	0.38***	0.38***	0.38***	0.37***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
EPL	0.03	–	–	–0.09	–0.03
	(0.06)			(0.08)	(0.07)
Abstract * EPL	–0.01	–	–	0.01	0.03+
	(0.02)			(0.02)	(0.02)
Collective bargaining	–	0.09+	–	0.15	0.09
		(0.05)		(0.09)	(0.08)
Abstract * collective bargaining	–	–0.02	–	–0.03	–0.05+
		(0.02)		(0.03)	(0.02)
ALMP training	–	–	0.06	–0.02	–0.03
			(0.05)	(0.07)	(0.06)
Abstract * ALMP	–	–	–0.01	0.01	–0.00
			(0.02)	(0.02)	(0.02)
R&D expenditure	–	–	–	–	0.12*
					(0.04)
Abstract * R&D expenditure	–	–	–	–	0.05**
					(0.01)
Number of jobs	66,891	66,891	66,891	66,891	66,891
Number of groups	24	24	24	24	24

$^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

a low value on the abstract job task index. The right panel of the figure shows the predicted probabilities if the vocational orientation of the system is high. For these countries, the model predicts a participation rate of 40% of non-abstract workers in tracked systems and almost 50% in comprehensive systems. Thus, less stratified systems improve the training chances of non-abstract workers substantively. The left panel shows the same relationship in systems with low vocational orientation. Here, non-abstract workers profit from comprehensive schools as well. Yet, their predicted probabilities remain at a lower level in comparison. Taken together, the model shows that comprehensive systems with vocational orientation generate the lowest inequalities in training between workers with different tasks. Such systems exist in the Scandinavian countries in my sample (Denmark, Sweden, Norway, and Finland) as well as in the UK (see Table 3). The countries mainly achieve this by increasing training probabilities for non-abstract workers whereas the probabilities among abstract workers remain unchanged. Thus, reducing skill gaps through comprehensive schooling and providing broad vocational skills seems to be a way of including more vulnerable workers in training measures.

Finally, Table 8 suggests that there is also an influence of labor market institutions on the effect of abstract tasks on training. However, I only find substantial and significant coefficients after controlling for all institutions as well as for skill demand in Model 5. The results suggest that EPL increases the effect of abstract tasks on training. Thus, as for routine tasks, I also find that strong EPL is associated with higher inequality in training participation, as suggested by Hypothesis 4. In addition,
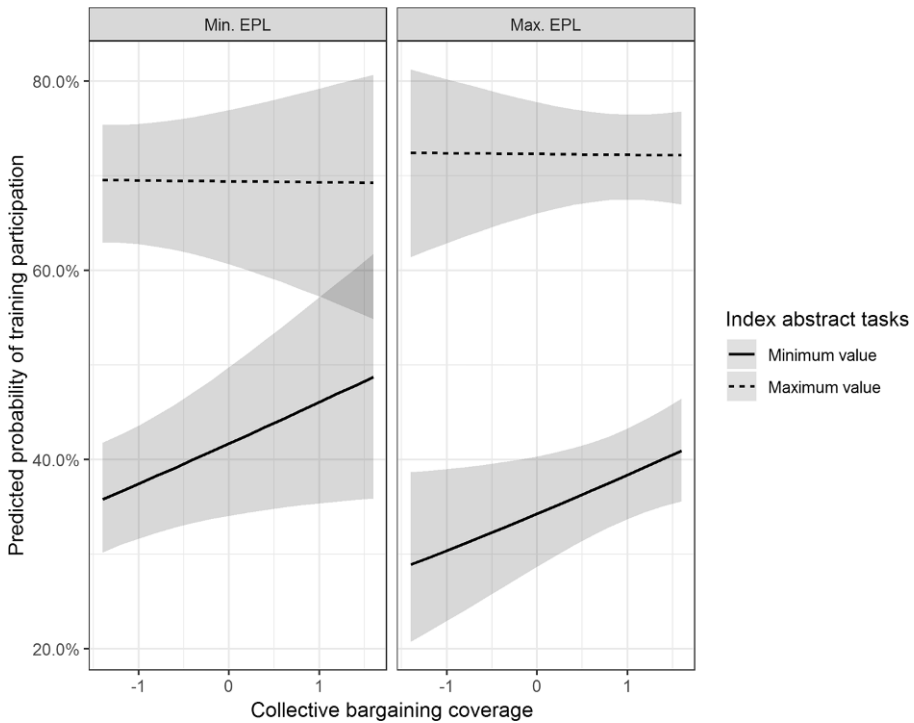
Fig. 6 Predicted probabilities of training participation at different levels of the abstract task index, collective bargaining coverage, and EPL. (Source: PIAAC, own calculations based on Model 5 in Table 8. All other covariates in the model set to their respective means for the predictions)

Model 5 also shows that collective bargaining coverage reduces the effect of abstract tasks net of the other institutions. Thus, as predicted by Hypothesis 6, unions may reduce inequality in training participation.

To take a closer look at the influence of EPL and unions, I again plotted the predicted probabilities of training participation in Fig. 6. The two panels show that strong unions increase the training chances of non-abstract workers. Thus, as expected, they improve training chances for workers in weaker positions on the labor market. The right panel in Fig. 6 further shows that strong EPL increases the gap between abstract and non-abstract workers. Thus, the model predicts that inequality in training between abstract and non-abstract workers is lowest in countries with strong unions and weak EPL. Among the countries studied, this applies to Finland, Norway, and Denmark (see Table 3).

6 Conclusion

Technological change will have a substantial impact on the labor market. Many workers will either have to update their skills or change their jobs entirely in the near future if they want to avoid unemployment (Autor 2015; Frey and Osborne

2017; Dengler and Matthes 2018). Yet, how can adults acquire new skills? Empirical research on education and training during adulthood often showed that the opportunities to learn are unequally distributed (Blossfeld et al. 2014). Therefore, it is unclear whether the workers most in need of training get access.

In this article, I show that exactly those job tasks that have a high chance of being replaced by machines in the future are associated with lower training probabilities in many countries. Especially workers conducting abstract tasks such as complex problem solving or negotiating receive much more training than other workers. This confirms earlier findings from Germany (Mohr et al. 2016; Görlitz and Tamm 2016; Kleinert and Wölfel 2018). Routine tasks, on the other hand, are not associated with lower training participation in most countries according to my analyses. However, this may be due to the imperfect measurement of routine tasks in the PIAAC data I use.

The cross-national analyses reveal that the effect of abstract tasks on training varies with educational institutions. Thus, the extent to which lifelong learning is realized for all workers regardless of their tasks and occupations depends on the setup of the initial schooling system. In countries with a comprehensive school system, non-abstract workers receive much more training than in countries with a tracked school system. This suggests that the early separation of students in school solidifies skills gaps and boundaries between abstract and non-abstract jobs (Heisig and Solga 2015). Thus, the results extend the knowledge about the effect of educational systems on inequality by showing that early tracking also affects educational inequalities later in life (Van de Werfhorst and Mijs 2010).

In contrast, vocational orientation of the schooling system leads to more equal training participation. This disproves recent claims that such systems do not prepare workers for changes on the labor market (Hanushek et al. 2017). Instead it seems that vocational orientation equips workers with skills that ensure trainability. Consequently, employers can design more complex and thus training-intensive jobs, even for workers conducting non-abstract tasks. Taken together, I find the lowest effect of abstract tasks on training participation in systems with little tracking and high vocational orientation. The effect of routine tasks on training, on the other hand, does not vary between educational systems in my analyses.

The analyses also indicate that employment protection legislation (EPL) and unions influence inequality in training participation because of job tasks. EPL increases the effect of both abstract and routine tasks on training. This suggests that insider–outsider structures on the labor market, which EPL fosters, translate into lower training chances among non-abstract and also routine workers. Accordingly, strong EPL may generate even stronger inequalities on the labor market in times of rapid technological change. The outsiders' skills will become less aligned with the requirements of jobs on the primary labor market. Collective bargaining coverage, on the other hand, is associated with less inequality in training participation between abstract and non-abstract workers. This may be due to wage compression, which makes training non-abstract workers more profitable for employers. Another reason may be collective agreements that include training opportunities for all workers. Thus, the combination of strong unions and low employment protection is associ-

ated with the lowest inequality in training participation between workers conducting abstract and non-abstract tasks.

Taken together, the results suggest that countries with comprehensive schools, vocational education, strong unions, and little employment protection offer the best circumstances to prepare all workers for the repercussions of technological change. This combination ensures that workers receive sufficient skills during initial education to be able to acquire new skills later on. As a consequence, barriers between jobs on the labor market are low enough to ensure changing tasks and occupations later in life. Also, wage compression leads to high incentives to invest and ensure equal training chances for all. In reality, however, a country case with this configuration does not exist. In my sample, the Scandinavian countries come closest to this combination. Nevertheless, the models predict lower training probabilities for non-abstract workers even under the most favorable conditions. Thus, workers most affected by technological change still have less access to lifelong learning.

An important limitation of this study is that I cannot test the proposed mechanisms directly with the data at hand. Also, it remains debatable whether the macro-level effects are indeed causal. The low number of country cases inhibits the inclusion of control variables. Thus, the conclusions drawn from the analysis have to be treated with caution. Furthermore, I cannot ascertain that training is actually beneficial for vulnerable workers. Even though a recent study by Tamm (2018) suggests that training leads to taking over more analytic tasks, it is not clear whether this applies to workers in all occupations. It may be that routine workers are still learning skills for their current tasks. Nevertheless, it is plausible that regular training participation also increases learning of skills that may become important once workers have to change into more learning-intensive jobs. In line with this, research consistently showed that training participation decreases the risk of unemployment (Dieckhoff 2007; Ebner and Ehlert 2018).

Even though there are important limitations, a few tentative policy conclusions can be drawn. According to the results, governments have only little leverage in the short run to decrease inequalities in training participation due to tasks. The analyses suggest that "lifelong learning" is more than a buzzword to promote adult education. Policy makers have to consider the life-wide dimension of education to address inequalities in further training participation. Consequently, reforms of educational systems toward more comprehensive systems with vocational elements cannot tackle today's inequalities among adults. Yet, they may help future generations to cope with technological change. A direct remedy of the inequalities through government investment in active labor market policy, on the other hand, does not seem to help. Yet, governments may foster union power to generate more equal training chances. Also, a liberalization of employment protection legislation may be an option, but it may prove difficult to implement if many workers fear losing their jobs to machines.

To ascertain these implications, future research should study the relationship between job tasks and further training from a life course perspective in different countries. Longitudinal analyses of workers' educational and labor market careers in different contexts should be used to scrutinize the presented findings. Such analyses may also reveal further avenues for policy change toward more inclusive adult learning participation. Also, the question of which types of learning are beneficial in

this process should be addressed. It may be that organized learning on non-formal courses is not the only way to ensure employability in times of rapid technological change. Future research should therefore also consider informal activities such as self-administered learning. The goal should be to arrive at a better understanding of how educational and labor market careers interact and how this generates social inequality in times of technological change. The present article provides some first evidence in this regard.

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