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ROA Universiteit Maastricht

TiU Stichting Katholieke Universiteit Brabant

UOXF The Chancellor, Masters and Scholars of the University of Oxford

CE Cambridge Econometrics Ltd.

SOFI Stockholms University

WZB Wissenschaftszentrum Berlin für Sozialforschung GGmbH

EUI European University Institute

TU Tallinn University



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Description of deliverable (100 words)

Deliverable 3.6 assesses whether adult education can reduce inequalities that emerge because of technological change. First, we analyse the determinants of access to adult education and training. Our focus is specifically on inequalities between workers at different risk of automation. Furthermore, we focus on differences between educational groups and between men and women in different households. Second, we assess the consequences of training participation for future learning and future careers. All of the analyses compare two or more countries to learn about the influence of institutions. The results shed light on favourable conditions for lifelong learning and policies that increase the inclusiveness of adult education.



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Chapter 1: Introduction and Conclusions

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Due to technological change, skill needs in the labor market are rapidly changing, leading to a growth in the importance of education and training during adulthood. While it is important to reconceptualize initial education to prepare future generations, as described in Deliverables 3.3 and 3.4, adults' skill needs need to be considered in the short term. Much of today's workforce left initial education a long time ago and now face structural changes that may render their skills obsolete. In this case, they will need to acquire new skills through adult education and training. In this deliverable we aim to find out whether and how adult education and training can remedy the inequalities caused by technological change outlined in WP 1 and WP 2.

To study the role of adult education and training in reducing inequality, we ask three research questions:

What determines participation in adult education and training? We analyze the impact of workplaces and careers on participation in adult training and investigate differences between gender and family types.

What are the consequences of a lack of learning competencies and participation in further training?

How do education systems and labor market institutions shape opportunities for skill acquisition "against the odds"?

We address these questions from a country-comparative perspective to examine the impact of institutions and derive policy implications. This chapter introduces our analyses and findings, and the policy implications drawn from these findings.

We conducted several analyses to understand *the role of workplaces and careers in inequalities in adult training participation*. In **Chapter 2**, we investigate cross-country variations in the relationship between job tasks and nonformal training participation. Using PIAAC data and multilevel analyses, we show that job tasks with higher automation risks are associated with lower training rates in many countries. In contrast, workers conducting abstract tasks, such as complex problem solving or negotiating, have considerably higher training participation rates than other workers. While training participation depends on job tasks across countries, there is also considerable country variation in the training disadvantages faced by routine and nonabstract workers. Some countries are apparently better at reducing the inequalities between workers in different jobs.

Chapter 3 examines the role of job tasks and other job characteristics on participation, compared to workers' skills and motivation to learn. Moreover, the analyses focus on the group most vulnerable to technological change—less-educated workers (defined as those with less than upper secondary

education). Using PIAAC data, the two-step multilevel approach, and Shapley decompositions, we examine to extent to which the disadvantage of less-educated workers in job-related nonformal training can be explained by simply having different jobs to better-educated workers. The analyses show that less-educated workers have the lowest training participation rates in all 27 countries studied. Job placement—measured by job tasks, job characteristics, and company characteristics—is the most important factor in differences in training participation between less- and intermediate-educated workers in every country except Sweden. Differences in job allocation by educational attainment contribute significantly to the training disadvantage of less-educated workers, above and beyond skills differentials and other worker characteristics. The subset of job characteristics (including company tenure, occupational status, and part-time employment) has the highest explanatory power in the majority of countries. Moreover, accounting for country differences in job allocation and workers' skills markedly reduces cross-national variation in less-educated workers' training disadvantage.

Chapter 4 examines the accumulation of training participation; whether training begets training. The role of previous training experiences is compared with individual and environmental conditions in the fostering or prevention of training participation. Germany and the UK are compared, using data from the German National Education Panel Study (NEPS) and Understanding Society for the UK. The analysis shows that “training begets training” in both countries. But the conditions that already influence first training participation—skills and early job placement—have a greater explanatory power concerning later training participation than previous training experiences. Moreover, the analyses reveal educational differences: High- and medium-educated workers benefit most (and to a comparable extent) from previous training participation, while less-educated workers seem to be less affected (UK) or even unaffected (DE) by previous training participation.

Chapters 6, 7, and 8 investigate the *role of family trajectories on gender differences in adult training participation*. In **Chapter 6**, the authors analyze the gender gap in ICT-related training participation, which may be especially important in combatting inequality due to technological change. To explain this, the authors compare the role of workplace-related characteristics with household characteristics. Cross-sectional Adult Education Survey data from 2016 is analyzed using multilevel models. This shows that women are somewhat disadvantaged in ICT training participation, partly due to occupational and sectoral gender segregation. However, there is also a considerable gender gap in ICT training participation for men and women working in the same occupation and sector: the ICT gender training gap is larger in high-skilled white-collar jobs, in professional, scientific, and technical sectors, and in retail, accommodation, and catering. It is lower, or even to female advantage, in low-skilled white-collar positions, construction, mining, manufacturing, and transportation, and in smaller companies. A potential explanation for this finding is that the content of training differs between occupation and sectors; training might be targeted to improve customer service, database structure,

or programming. The household context—and in particular having younger children (<13 years)—is not significantly associated with ICT training participation for men or women.

Chapter 7 focuses on the role of family formation and dissolution in nonformal training participation: The impact of the transition to parenthood on training gaps between men and women (Chapter 7A), and the impact of family dissolution on women's and men's participation in further education (Chapter 7B). The analyses are based on longitudinal data from Germany and the UK, two countries with different family policies. Concerning the *transition to parenthood*, the analyses show that women suffer a substantial motherhood penalty in job-related training participation, while men seem to be rather weakly affected by parenthood. This female *transition to parenthood* penalty decreases once children are 3 years old. Thus, we find a temporary decrease in training participation among women after childbirth. This was not visible in the cross-sectional data analyzed in Chapter 6, as the dynamics of the penalty could not be assessed. Concerning family dissolution, we find that men and women's participation in further training declines following divorce in both countries.

Chapter 8 focuses on the impact of family formation on gender differences in participation in *formal* education. Using longitudinal register data from Finland and Understanding Society survey data for the UK, we examine whether family life (number of children in household, age of children, and marital status) is associated with differences in participation in formal adult education, and how this varies between different institutional contexts. Similar to the results for nonformal training in Chapter 7A and B, there are significant gender differences in how family life affects enrolment in formal adult education in both countries: Women seem to be more restrained than men in obtaining further educational qualifications when they have children in the household. Among married and high-income men, having children actually increases participation in formal adult education.

We also studied the benefits of training participation in Chapters 4 and 5 to assess *the consequences of a lack of learning competencies and participation in further training*. In **Chapter 4**, we show that training participation in the past leads to further training participation. This effect is small in comparison to the impact of the workplace. Nevertheless, one benefit of taking part in training at one time is that it leads to continuous training participation for some. This also implies that those who do not participate in training have a lower probability of participating in training in the future.

In **Chapter 5**, we analyze whether further training helps vulnerable workers to transition to new jobs, using NEPS data from Germany and Understanding Society data from the UK. Data on automation risk from WP1 is added to the survey data. The results show that job-related training prevents unemployment for employees in both Germany and the UK. Yet, job-related training is not associated in either country with increased within- or between-company mobility, or occupational changes. There are hardly any differences in the effect of further training on occupational mobility from the occupational risk of substitution by automation. Thus, training works as a safety net providing protection from unemployment, but it does not assist in the transition to new jobs, even when the current job has no future.

Throughout, we provide our insights on *how education systems and labor market institutions shape opportunities for skill acquisition “against the odds”*, through careful country comparison. These results provide a basis for our policy recommendations, providing hints on “best practice” country cases.

Chapter 2 shows 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. In these cases, the gaps between workers conducting different job tasks are smallest. This ensures that workers learn enough skills during initial education to be able to acquire new skills later on. As a consequence, barriers between jobs in the labor market are low enough to ensure that people can change tasks and occupations later in life. Also, wage compression leads to high incentives to invest and ensure equal training opportunities for all. In reality, however, a country case with this configuration does not exist. In the sample, the Scandinavian countries come closest to this combination. Nevertheless, the models predict lower training probabilities for vulnerable workers even under the most favorable conditions, albeit at a lower level.

Chapter 3 looks at the perspective of less-educated workers and provides evidence that educational and labor market institutions play a role in the inequality of training participation. Institutions primarily contribute to cross-national variation in less-educated workers’ training disadvantage by moderating the impact of individual-level predictors; in particular, job allocation factors. For example, high wage inequality increases the training disadvantage of less-educated employees, as companies profit more from investing in further training for intermediate-educated employees. Union density has an ambiguous influence on the training disadvantage. Less-educated workers seem to benefit from higher trade union density by being allocated ‘better’ jobs, such as skill-intensive jobs and/or jobs in training-active firms. However, within similar work environments, higher trade union density is associated with a larger training disadvantage for less-educated workers, suggesting that trade unions strategically focus more on skilled employees than less-educated workers in their commitment to further training. This somewhat qualifies the positive assessment of unions in training participation in Chapter 2. In line with the results in Chapter 2, the training disadvantage of less-educated workers is larger in countries with stratified secondary education and higher differences in the mean skills between less- and intermediate-educated adults, possibly because of the higher skill transparency of educational credentials, which is consequential for job placement.

The results outlined in **Chapter 4** suggest that institutions also have an impact on training dynamics over the life course. In the UK, where initial education is more geared towards general skills and internal labor markets (ILM) are more common, training more often leads to future training. Workers seem to benefit more from the cross-fertilizing dynamic of training courses over time. In Germany, however, where there is a greater focus on vocational education and occupational labor markets (OLM) are more common, the effect of training on future training is smaller, especially among the

least educated. This might be because the more heterogeneous skill profiles of workers in ILMs demand more regular training, fostering greater cognitive connectivity between courses. Thus, a one-time training participation is more likely to kick off a chain of training participation in the UK than in Germany, even for workers who are otherwise unlikely to train.

Unlike the results from other chapters, the results outlined in **Chapter 5** show no significant differences in the benefits of training participation between Germany and the UK. Training is a safety net that protects against unemployment in both countries. In contrast, there is no impact on moving to new jobs in either country. This is particularly interesting because we do find that many more workers change their jobs in the UK; this is as expected because of the much more fluid labor market. Yet, acquiring a new job, especially when the previous role is likely to be automated in the future, is not more likely after training in the UK, nor is it in Germany. Thus, even if workers participate in training “against the odds” in vulnerable positions, they apparently do not acquire the skills to enable them to switch jobs. Labor market institutions do not seem to influence this.

In **Chapter 6**, we examine cross-country differences in the gender gap in ICT training and show that women have the highest ICT participation rates in Norway, Spain, Germany, France, Austria, Belgium, Sweden, and the Netherlands. Moreover, it appears that the gender gap in ICT training courses in favor of men tends to be higher in countries with high overall ICT participation rates, such as Norway, Luxembourg, the Netherlands, Switzerland, and the United Kingdom. Evidence of differences between countries in training predictors is less straightforward. Still, the gender culture and overall gender inequality index (GII)—comprising health, empowerment, and economic status indicators—tends to modify the gendered ICT training gap. Participation in ICT training is higher in countries with a more egalitarian gender culture, but this effect is stronger for men, so the participation gap is relatively high. Similarly, participation in ICT courses is higher in countries with a lower GII and a lower level of gender inequalities in different spheres of life, and again the effect is stronger for men. It may be that in less gender-equal countries, women are more likely to engage in the fields of science, technology, engineering, and mathematics, to find a way out of difficult living conditions. Accordingly, young women might be pressured to use new technologies and acquire ICT skills, possibly explaining why the gendered ICT training gap is higher in more gender-egalitarian countries.

In **Chapter 7A**, we show how work-family policies have an impact on mothers’ training participation. In conservative welfare regimes such as Germany, policies are aimed at the male breadwinner norm, fostering a motherhood training penalty, even in the long term. Mothers with young children enjoy longer maternity leave but face a lack of childcare options prior to kindergarten. Additionally, social policy discourages paid employment among women as secondary earners, thereby fostering the traditional family model. In liberal welfare regimes, such as the UK, policies promote the “one and a half earner” model. The motherhood training penalty is smaller and only of short duration, because women are encouraged to engage in part-time work and use public part-time childcare services.

Moreover, flexible work schedules have become a policy tool that companies have adopted to attract and retain working parents.

The findings in **Chapter 7B** add to a more nuanced picture of institutional influences by considering training participation after divorce in the UK and Germany. Both men and women's participation in further training declines following divorce in the UK, while further training participation does not change following divorce in Germany. For many German women, this may be connected to the need to take up work after divorce in a traditional family model and the ensuing need for training. In the UK, on the other hand, most women are already in work, and the effect of lost partner support emerges. In this case, family policies in both countries do not seem to help.

Chapter 8 provides some further evidence of institutional influences on gender differences in formal adult education participation. In the UK, enrolment in formal adult education is less affected by family life for men, while mothers (particularly with young children) bear the burden of family responsibilities, preventing their *formal* adult education enrolment. In contrast, in Finland, both men and women with young children have a higher likelihood of enrolling, and among women this is even more so for low-income and single-parent women. This suggests that mothers in deprived situations (in terms of finances and relationships) have a high need for further education and hence enroll in formal adult education. The Finnish adult education system provides opportunities that do not have high financial or time constraints and may promote the livelihoods of individuals from more disadvantaged situations. The labor market protection and universal family policies may provide additional support, providing more equal opportunities for mothers and fathers to enroll in formal adult education programs. In the UK, formal adult education requires large financial and time resources, and enrolment opportunities are limited for those with low attainment of these resources. Weak labor market protection may boost this effect, as individuals are not able to take up formal (full-time) education for fear of losing labor market standing. In addition to the lack of family support, having children reduces opportunities even further. This all suggests that there is a 'Matthew effect' in the UK; the middle classes and those who already have large resources benefit most from formal adult education, updating and upgrading their skills and qualifications in a labor market that is changing due to technological innovations.

Taken together, these results suggest several **policy implications**: First and foremost, policies should be targeted at enhancing training opportunities for knowledge-poor workplaces. This would also facilitate the "training begets training" mechanism and further increase training rates. However, the focus should be both on public provision of training courses outside of companies and on improving learning conditions in workplaces. Therefore, governments should focus on improving educational leave and providing financial support and incentives. These should be especially targeted towards vulnerable workers, such as those in atypical employment. Governments should also provide guidance and financial incentives for employers to train their workforce, hold them accountable to

grant and finance educational leave, and constantly encourage career guidance, skill validation, and learning opportunities, either via collective agreements or bilateral agreements. Governments could also increase the cognitive connectivity between courses by, for example, integrating modular learning and partial qualifications as a structural feature of adult training. Furthermore, to increase cognitive and meta-cognitive skills, educational policy should build and maintain a positive foundation for meta learning as part of education and training curricula, e.g., learning-to-learn. Finally, educational reforms must contribute to the vision and norm of “lifelong learning.” Such training policies are not only likely to include more of the workers in jobs at risk of automation, but are also likely to help workers move to emerging jobs. Most current training measures are not very effective, according to our analyses.

To address the gender training gap, gendered work tasks and work organization differentials—that is, poor learning environments in female-dominated occupations and sectors—need to be targeted by training policies. Moreover, universal childcare provision, especially for very young children, is a “training-enhancing policy”; it can increase mothers’ training participation, which in turn decreases the gender training gap. Further training programs should also become more flexible, with shorter or modular training courses that allow women with children to reduce the time needed away from work or home. Further training programs should also aim to promote the return of women to work, either after childbirth, following a period of parental leave, or as a result of long-term unemployment due to unpaid family care responsibilities. Instructors and managers of training institutions should receive gender awareness training to raise and address gender issues and avoid stereotypes. This can sensitize employers and encourage them to offer further job training to both women and men, especially women with children. Employers and training providers all have roles to play in creating a supportive and motivating environment that is conducive to the recruitment of mothers into further training participation.

Chapter 2: Institutional effects on inequalities in training participation - Explaining cross-national variation in the effect of job tasks on further training¹

Author: Martin Ehlert (WZB)

Extended Summary

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. 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. This is due to the job tasks these workers conduct: The probability of training participation is lower among workers conducting routine tasks, which are most likely to be replaced by machines. Nevertheless, current technological change also generates new jobs. However, these jobs presumably require skills that affected workers currently do not have, such as interpersonal skills or creativity. Thus, those most in need of new skills get the least training.

In this chapter, I aim 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. The research question is: Do institutions mediate the effect of tasks on training participation? So far, little is known so far about the international variation in the effect of tasks on further training participation. The therefore chapter contributes to several strands of research on lifelong learning. It is the first to show the association between tasks and further training in an international comparative perspective using high quality data from the “Programme for the International Assessment of Adult Competencies” (PIAAC). Thereby, it advances the literature about the influence of educational and labor market institutions on inequality by providing evidence about 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.

¹ This chapter was also published as Ehlert, Martin. 2020. “No Future, No Training? Explaining Cross-National Variation in the Effect of Job Tasks On Training Participation.” *KZfSS Kölner Zeitschrift Für Soziologie Und Sozialpsychologie* 72 (1): 483–510.

The results confirm 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. 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 international comparison further reveals that some countries are better at reducing the inequalities between workers on different jobs. 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, albeit at a lower level.

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 due to the job tasks these workers conduct: The probability of training participation is lower among workers conducting routine tasks, which 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 chapter, I aim 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 to 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 while 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 chapter, I will refer to work-related non-formal further training courses as “further training” for the sake of brevity.

The chapter contributes to several strands of research on lifelong learning. It is the first to show the association between tasks and further training in an international comparative perspective

using high quality data from the “Programme for the International Assessment of Adult Competencies” (PIAAC). Thereby, it advances the literature about the influence of educational and labor market institutions on inequality by providing evidence about 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.248f). The authors calculate the risk of automation on the occupational level based on data from Frey and Osborne (2017). This occupational data has been extended to other countries using the task measures in 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 will use direct measurements of tasks and not the estimated automation potential in my 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 tight linkages 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 participation. The studies reveal that training incidence is higher in educational systems without tracking and systems that provide higher average levels of schooling (e.g.: Bassanini et al., 2005; O’Connell and Jungblut, 2008; Wolbers, 2005; Vogtenhiber, 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 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 on the macro level. Nevertheless, they find substantial country differences in the effect of reading tasks on training. In line with the considerations above, they find that Germany exhibits the largest inequality in training participation due 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, which are likely to be substituted, are jobs in 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 chapter, 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 consider 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 for 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 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 payoff 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:

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 on the individual level and the institutions on 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.

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 voc. edu.	H3: High general skills in voc. edu.
Labor market institutions		
Employment protection legislation	H4: Short investment horizon (temp. cont.)	H5: Training cheaper than dismissal
Collective bargaining coverage	-	H6: Low wage differentials & training negotiated
Active labor market policies	-	H7: State funded

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 is also correlated 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 “Programme 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 data 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 in 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.² 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.

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 do work (D_Q11b) Change speed of work (D_Q11c) Change working hours (D_Q11d)
Manual	Physical work (F_Q06b)

² The name of the variable in the public use files is NFE12JR.

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.

However, I depart from the approach by De La Rica and Gortazar (2017) of 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 for 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.³ 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.⁴ Unfortunately the PIAAC data does 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 reversed 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.

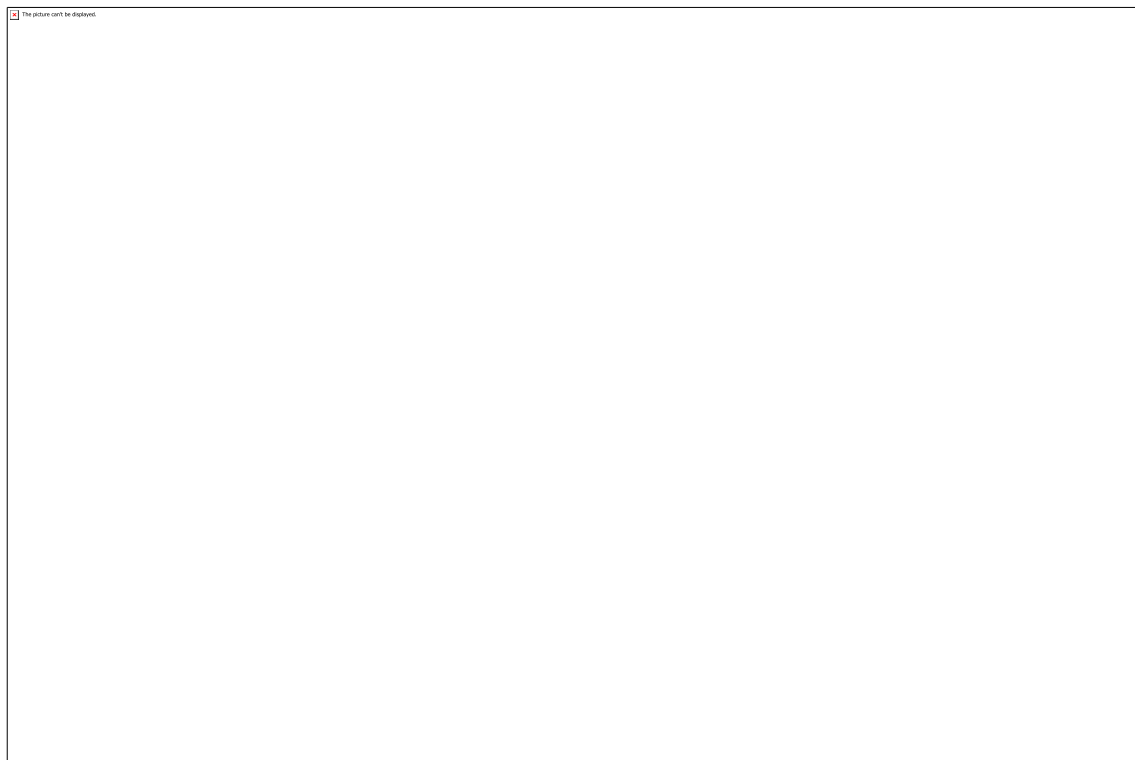
I further use a wide set of control variables to address confounding between tasks and training and obtain an unbiased estimate of the effect of tasks on training. The variables are measured on the individual level and comprise individual, job, and firm level characteristics (see full regression tables 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 added measures of literacy and numeracy to the models. Since these indicators are provided in the form of 10 plausible values, I estimate my models once for each

3 The exact wording is “How often does your job usually involve using skill or accuracy with your hands or fingers?”

4 However, I still included it as a control variable in the models because of its importance for automation.

plausible value and combined 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.

Figure 1: Scatterplot of the abstract and routine tasks indexes. Source: PIAAC, own calculations



On the country level, I added 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) compiled the information about age of 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.13f)). 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.14f)).

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 PIAAC. I use the latest OECD measure for employment protection legislation of regular employment contracts (version 3) (OECD, 2013). I further operationalized 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 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 right to bargain. The data are provided by the OECD and are based on the ICTWSS Data base (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). While 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 are highly and significantly but not perfectly correlated indicating that they often occur together. Moreover, EPL is significantly correlated 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 to partial out estimates for individual institutions.

I use mixed-effects logistic regression to jointly estimate the coefficients on the micro and 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 tested for the need to include further random slopes on micro level variables by comparing the bayesian information criterion (BIC) between different specifications (Heisig et al., 2017). The procedure revealed 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-I-1** rule as suggested by Elff et al. (2019). Here, **m** is the number of groups (countries) and **I** the number of contextual effects. This method proved to be superior to standard methods of obtaining p-values if the number of 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** (Lüdtke, 2018), which relies on the package **ggplot2** for the output (Wickham, 2016). As suggested by Mize (2019), I also estimated 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.

Table 3: Macro data used in the analyses.

	External differentiation index5	Vocational orientation index6	EPL index7	Collective bargaining coverage8	ALMP expenditure for training as % of GDP9	Expenditure for R&D as % of GDP10
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

5 Source: Bol and van de Werfhorst (2011, p.13f)

6 Source: Bol and van de Werfhorst (2011, p.14f)

7 Source: OECD (2013)

8 Source: Visser (2016)

9 Source: Grubb and Puymoyen (2008)

10 Source: OECD (2015)

Table 4: Correlation matrix of the macro indicators, N = 24. Sources: See Table 3

	Tracking	Voc. orient.	EPL	Coll. barg. cov.	ALMP training exp.	R&D exp.
Tracking	1					
Voc. orient.	0.657***	1				
EPL	0.586**	0.767***	1			
Coll. barg. cov.	0.156	0.612**	0.641***	1		
ALMP training exp.	-0.0805	0.169	0.108	0.605**	1	
R&D exp.	-0.134	-0.149	-0.107	0.120	0.261	1

p < 0.005, ** p < 0.001, *** p < 0.001

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 to 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 PIAAC lacks more information as discussed in the previous section. On the other hand, I find positive and significant associations between abstract tasks and training participation in all of the countries in Figure 3. Still, the point estimates vary substantively between countries. These first analyses show that the task content of occupations plays a role for 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 that the interactions between the educational system and the effect of routine tasks on training are 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.

Figure 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.

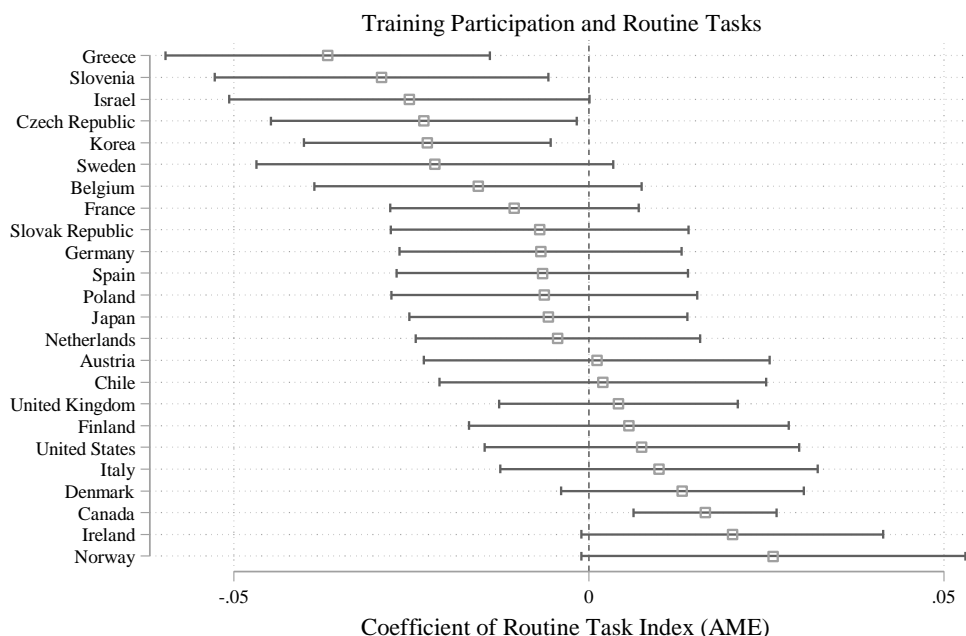


Table 6, on the other hand, shows that EPL increases the negative effect of routine tasks. Thus, it increases the inequality in training participation between routine and non-routine workers. The association even holds after including other labor market institutions and skill demand into the models. 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 show 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 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.

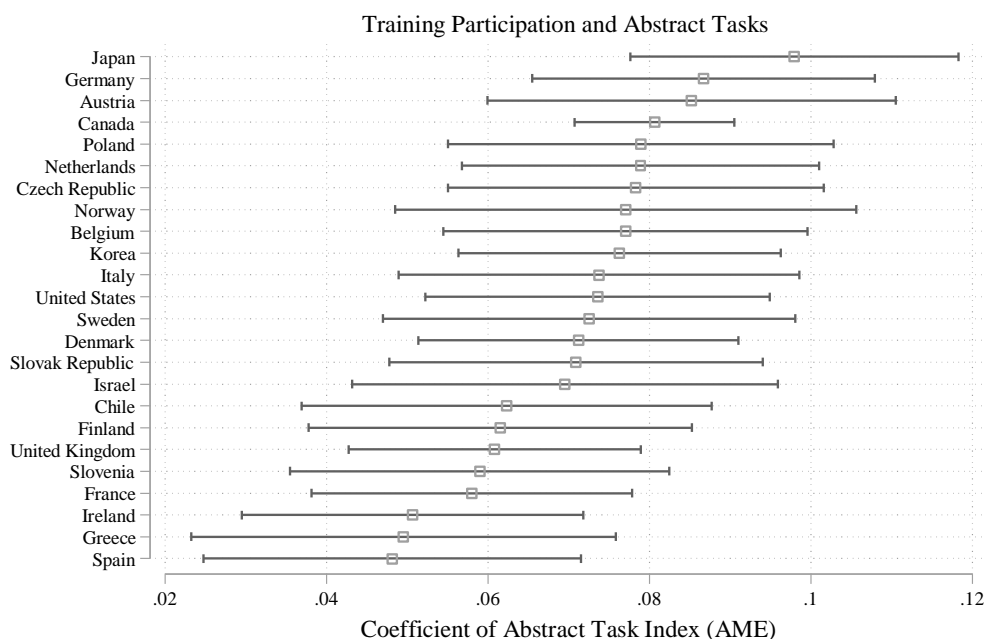


Figure 4 shows that routine workers, i.e. those with a high value on the routine task index, have substantially lower probabilities of training participation than non-routine workers in countries with strong EPL. The difference in predicted probabilities at the maximum value of EPL in the data amounts 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 as the US 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 expenditures in Model 4 does not change the results. Thus, the analysis shows evidence in favor of both hypothesis 1 and 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 Figure 5 show that tracking and vocational orientation mainly influence the training participation of non-abstract workers, which have a low value on the abstract job task index. The right panel the figure shows the predicted probabilities if the vocational orientation of the system is high. For these countries, model predicts a participation rate of 40 per cent of non-abstract workers in tracked systems and almost 50 per cent in comprehensive systems. Thus, less stratified systems improve 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 as well from comprehensive schools.

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 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)		-0.06 (0.08)	-0.05 (0.08)
Rout. * Tracking	-0.01 (0.02)		-0.01 (0.03)	-0.01 (0.02)
Voc. Orientation		0.06 (0.07)	0.11 (0.09)	0.09 (0.09)
Rout. * Voc. Orient.		-0.02 (0.02)	-0.01 (0.03)	-0.01 (0.02)
R&D Expenditure				0.07 (0.05)
Rout. * R&D Exp.				-0.02 (0.01)
Num. obs.	66891	66891	66891	66891
Num. groups:	24	24	24	24

***p < 0.001, **p < 0.01, *p < 0.05, +p < 0.1

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.

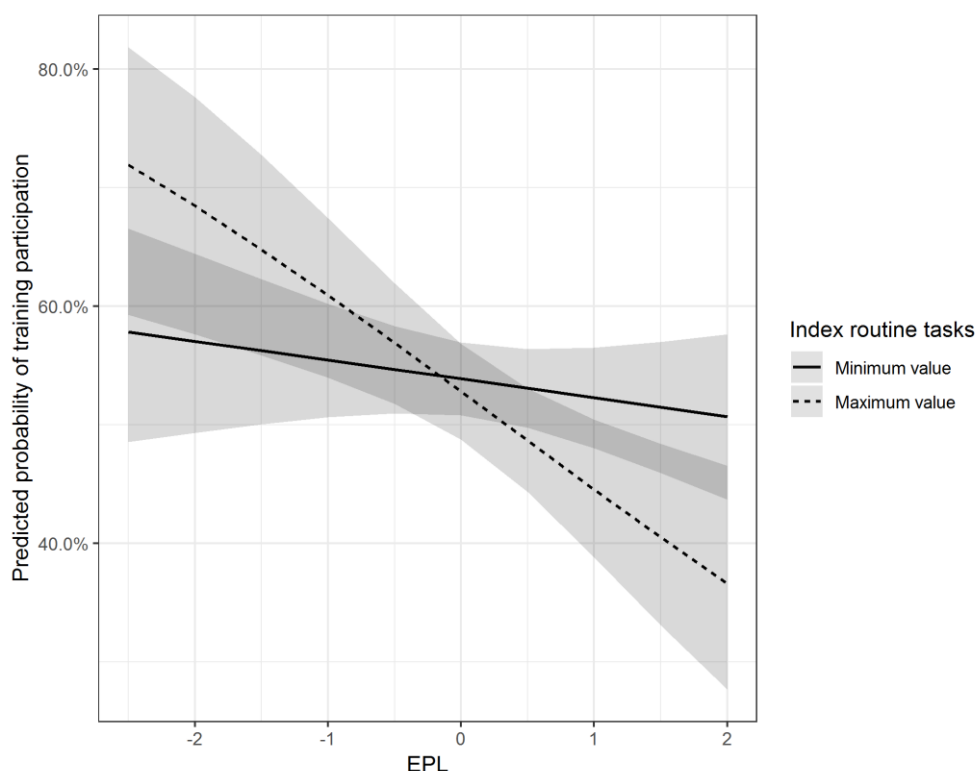
	Model 1	Model 2	Model 3	Model 4	Model 5
Routine tasks	-0.02 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.01)	-0.01 (0.01)
EPL	-0.06 (0.07)			-0.18* (0.08)	-0.19* (0.09)
Rout. * EPL	-0.04* (0.02)			-0.06* (0.02)	-0.07** (0.02)
Col. bargaining		0.10 (0.06)		0.18+ (0.09)	0.20+ (0.10)
Rout. * Col. barg.		-0.00 (0.02)		0.01 (0.03)	0.03 (0.02)
ALMP training			0.09 (0.06)	0.00 (0.07)	-0.01 (0.08)
Rout. * ALMP			0.02 (0.02)	0.02 (0.02)	0.02 (0.02)
R&D Expenditure					-0.00 (0.05)
Rout. * R&D Exp.					-0.04** (0.01)
Num. obs.	66891	66891	66891	66891	66891
Num. groups:	24	24	24	24	24

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Yet, their predicted probabilities remain on 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 while the probabilities among abstract workers remain unchanged. Thus, reducing skill gaps through comprehensive schooling and providing broad vocational skills seems to be a way to include 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, like for routine tasks I also find that strong EPL is associated with higher inequality in training participation as suggested by hypothesis 4. In addition, 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.

Figure 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 set to their respective means for the predictions.



To take a closer look at the influence of EPL and unions, I again plotted the predicted probabilities of training participation in Figure 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 Figure 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).

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.

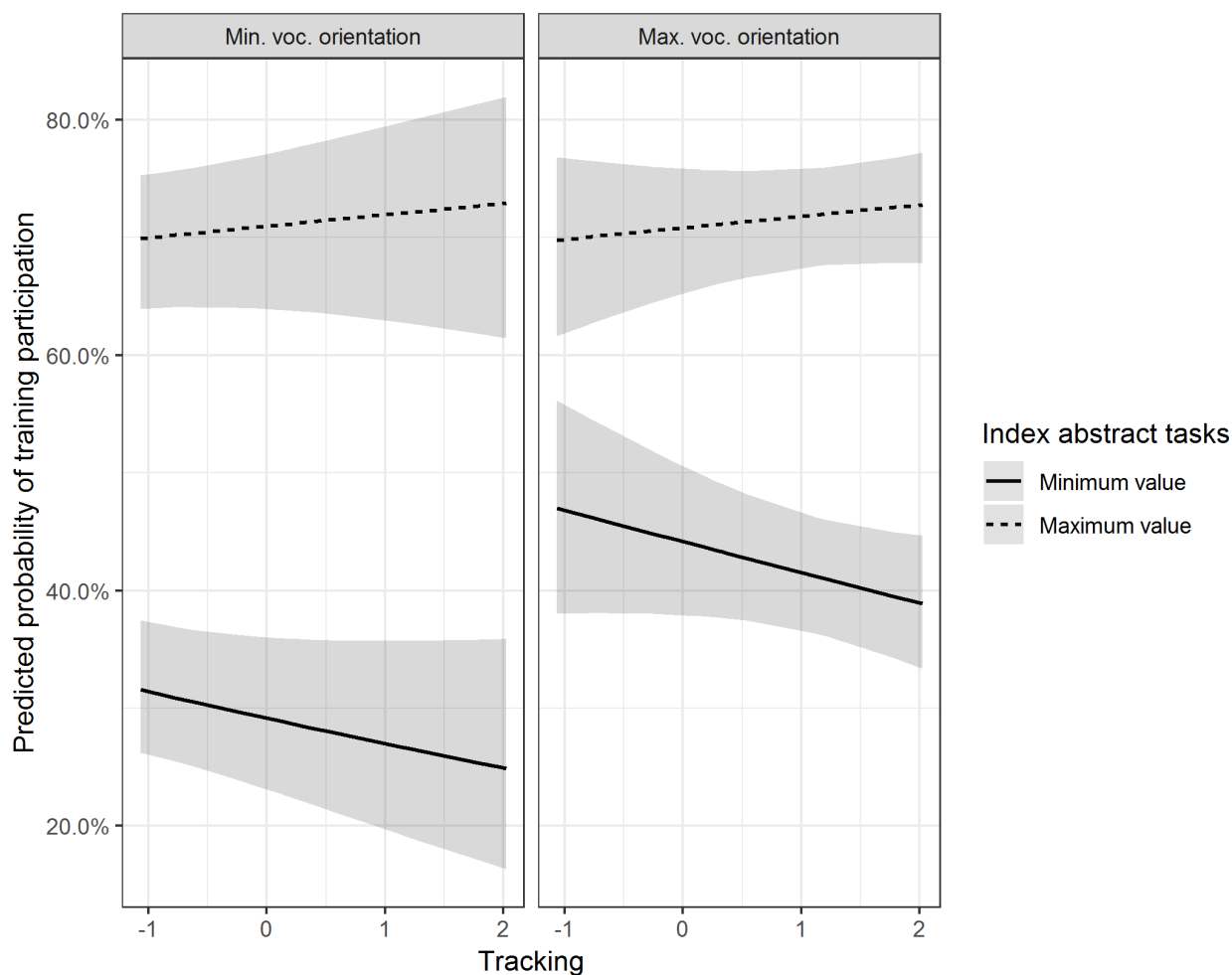
	Model 1	Model 2	Model 3	Model 4
Abstract tasks	0.37*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.38*** (0.01)
Tracking	0.03 (0.05)		-0.03 (0.07)	-0.03 (0.06)
Abst. * Tracking	0.01 (0.02)		0.04+ (0.02)	0.04* (0.02)
Voc. Orientation		0.09 (0.06)	0.11 (0.08)	0.10 (0.07)
Abst. * Voc. Orient.		-0.02 (0.02)	-0.05* (0.02)	-0.05* (0.02)
R&D Expenditure				0.12* (0.04)
Abst. * R&D Exp.				0.04** (0.01)
Num. obs.	66891	66891	66891	66891
Num. groups:	24	24	24	24

***p < 0.001, **p < 0.01, *p < 0.05, +p < 0.1

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 chapter 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.

Figure 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 set to their respective means for the predic



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 suggest 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).

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 Append

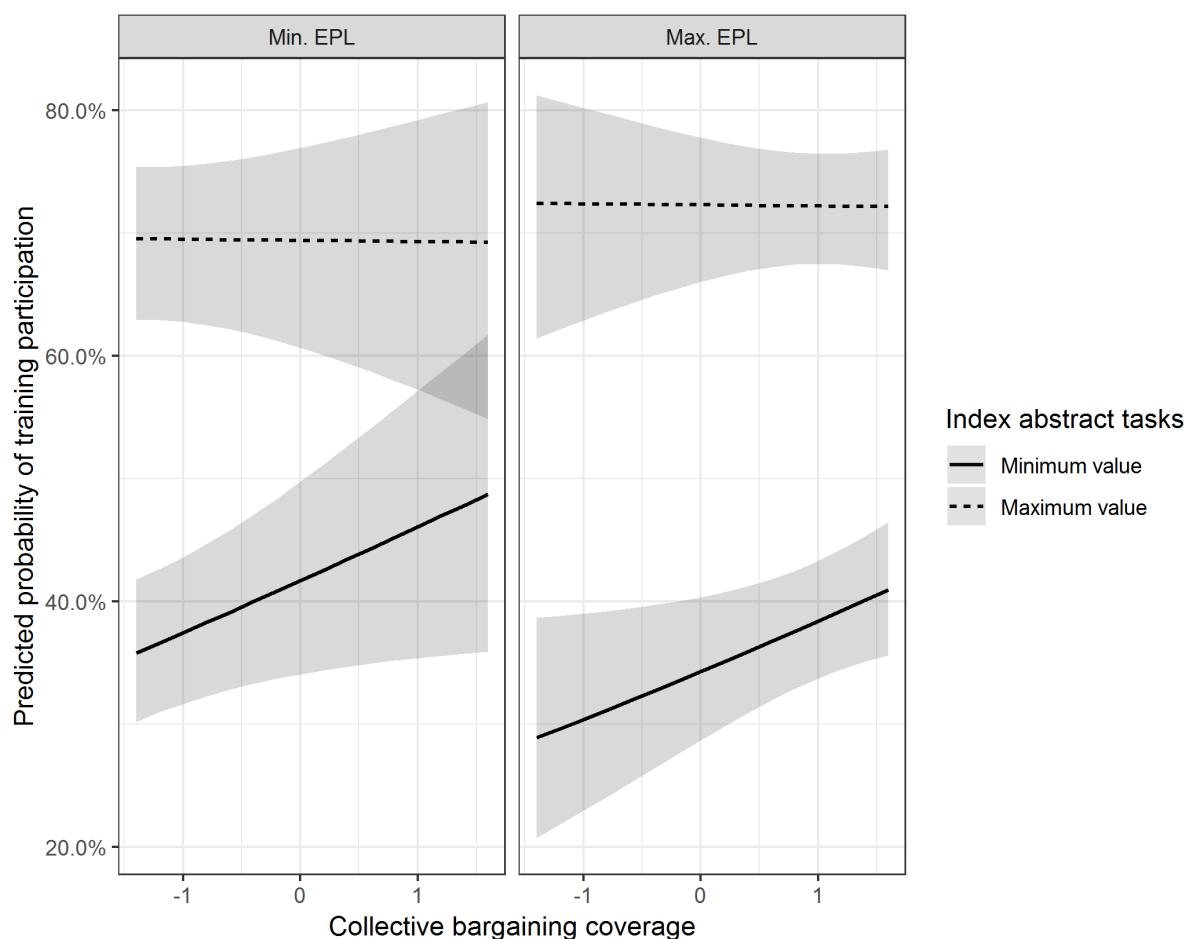
	Model 1	Model 2	Model 3	Model 4	Model 5
Abstract tasks	0.38*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.37*** (0.01)
EPL	0.03 (0.06)			-0.09 (0.08)	-0.03 (0.07)
Abst. * EPL	-0.01 (0.02)			0.01 (0.02)	0.03+ (0.02)
Col. bargaining		0.09+ (0.05)		0.15 (0.09)	0.09 (0.08)
Abst. * Col. barg.		-0.02 (0.02)		-0.03 (0.03)	-0.05+ (0.02)
ALMP training			0.06 (0.05)	-0.02 (0.07)	-0.03 (0.06)
Abst. * ALMP			-0.01 (0.02)	0.01 (0.02)	-0.00 (0.02)
R&D Expenditure					0.12* (0.04)
Abst. * R&D Exp.					0.05** (0.01)
Num. obs.	66891	66891	66891	66891	66891
Num. groups:	24	24	24	24	24

*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1

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 due to 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 that 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 associated with the lowest inequality in training participation between workers conducting abstract and non-abstract tasks.

Figure 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.



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 still rather learn skills for their current tasks. Nevertheless, it is plausible that regular training participation also increases learning 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 policy conclusions can be drawn. 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 towards more comprehensive systems with vocational elements cannot tackle today’s inequalities among adults. Yet, they may help future generations to cope with technological change.

In terms of more short-run remedies, the analyses suggest that inequalities are likely to remain large if firms are the main providers of training and this is not counterbalanced. On the one hand, the inequality may be reduced by strong unions as the results suggest. On the other hand, governments could provide more training. However, the findings in this chapter suggest that existing active labor market programs do not achieve this. Therefore, new ways of public training provision have to be developed. Future research should assess how to target such programs for the most vulnerable workers.

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Appendix

Table A1: Factor loadings for the principal components analysis for abstract tasks. Source: PIAAC, own calculations.

	e(L) Factor1
Skill use work - Literacy - Read diagrams maps or schematics	.6000276
Skill use work - Literacy - Write reports	.6076515
Skill use work - Problem solving - Complex problems	.7058553
Skill use work - How often - Influencing people	.7517783
Skill use work - How often - Negotiating with people	.7623874

	e(L) Factor1
Current work - Work flexibility - Sequence of tasks	.8520544
Current work - Work flexibility - How to do the work	.8590716
Current work - Work flexibility - Speed of work	.8138378
Current work - Work flexibility - Working hours	.6919284

Table A2: Factor loadings for the principal components analysis for routine tasks. 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)		-0.06 (0.08)	-0.05 (0.08)
Rout. * Tracking	-0.01 (0.02)		-0.01 (0.03)	-0.01 (0.02)
Voc. Orientation		0.06 (0.07)	0.11 (0.09)	0.09 (0.09)
Rout. * Voc. Orient.		-0.02 (0.02)	-0.01 (0.03)	-0.01 (0.02)
R&D Expenditure				0.07 (0.05)
Abst. * R&D Expenditure				-0.02 (0.01)
Abstract tasks	0.38*** (0.02)	0.38*** (0.02)	0.37*** (0.02)	0.37*** (0.02)
Manual accuracy tasks	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Manual tasks	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)
Computer use	0.48*** (0.03)	0.48*** (0.03)	0.48*** (0.03)	0.48*** (0.03)
Age (Ref.: 25-29)				
30-34	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
35-39	-0.08* (0.04)	-0.08* (0.04)	-0.08* (0.04)	-0.08* (0.04)

TECHNEQUALITY Deliverable D3.6

	(0.04)	(0.04)	(0.04)	(0.04)
40-44	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
45-49	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
50-54	-0.19***	-0.19***	-0.19**	-0.19**
	(0.05)	(0.05)	(0.05)	(0.05)
55-59	-0.34***	-0.34***	-0.34***	-0.34***
	(0.06)	(0.06)	(0.06)	(0.06)
60-65	-0.60***	-0.60***	-0.60***	-0.60***
	(0.07)	(0.07)	(0.07)	(0.07)
Education (Ref.: ISCED 0-2)				
ISCED 3a	0.15***	0.15***	0.15***	0.15***
	(0.03)	(0.03)	(0.03)	(0.03)
ISCED 3b	0.24***	0.24***	0.24***	0.24***
	(0.03)	(0.03)	(0.03)	(0.03)
ISCED 5long/6	0.36***	0.36***	0.36***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)
Professionals	0.06	0.06	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.04)
Occupation (ISCO, Ref.: Managers)				
Technicians and ass. prof.	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
Clerks	-0.40***	-0.40***	-0.40***	-0.40***
	(0.04)	(0.04)	(0.04)	(0.04)
Service and sales	-0.17***	-0.17***	-0.17***	-0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Skilled agricultural and fishery	-0.30*	-0.30*	-0.30*	-0.30*
	(0.11)	(0.11)	(0.11)	(0.11)
Craft and related trades	-0.23***	-0.23***	-0.23***	-0.23***
	(0.05)	(0.05)	(0.05)	(0.05)
Machine op. and assemblers	-0.15**	-0.15**	-0.16**	-0.16**
	(0.05)	(0.05)	(0.05)	(0.05)
Elementary occupations	-0.51***	-0.51***	-0.51***	-0.51***
	(0.05)	(0.05)	(0.05)	(0.05)
Literacy	0.06	0.06	0.06	0.06
	(0.03)	(0.04)	(0.04)	(0.04)
Numeracy	0.03	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Gender: Men (Ref.: Women)	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
11-50 people	0.35***	0.35***	0.35***	0.35***
	(0.02)	(0.02)	(0.02)	(0.02)
Firm size (Ref.: 1-10 people)				
51-250 people	0.55***	0.55***	0.55***	0.55***
	(0.03)	(0.03)	(0.03)	(0.03)
More than 1000 people	0.69***	0.69***	0.69***	0.69***
	(0.04)	(0.04)	(0.04)	(0.04)
Public Sector	0.33***	0.33***	0.33***	0.33***



	(0.05)	(0.05)	(0.05)	(0.05)
Mining	0.51***	0.51***	0.51***	0.51***
	(0.13)	(0.13)	(0.13)	(0.13)
Sector (Ref.: Agriculture)				
Manufacturing	-0.05	-0.05	-0.05	-0.05
	(0.09)	(0.09)	(0.09)	(0.09)
Electricity/Water supply	0.43***	0.43***	0.43***	0.43***
	(0.11)	(0.11)	(0.11)	(0.11)
Construction	-0.02	-0.02	-0.02	-0.02
	(0.09)	(0.09)	(0.09)	(0.09)
Commerce	-0.02	-0.02	-0.02	-0.02
	(0.09)	(0.09)	(0.09)	(0.09)
Transport	0.23*	0.23*	0.23*	0.23*
	(0.09)	(0.09)	(0.09)	(0.09)
Services	0.29**	0.29**	0.29**	0.29**
	(0.08)	(0.08)	(0.08)	(0.08)
Native-born and foreign-language	-0.03	-0.03	-0.03	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)
Migration status (Ref.:Native)				
Foreign-born and native-language	-0.10 ⁺	-0.10 ⁺	-0.10 ⁺	-0.10 ⁺
	(0.05)	(0.05)	(0.05)	(0.05)
Foreign-born and foreign-language	-0.20***	-0.20***	-0.19***	-0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Fulltime employed	0.25***	0.25***	0.25***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)
Work experience	0.10***	0.10***	0.10***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
Employer tenure	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Num. obs.	66891	66891	66891	66891
Num. groups:	24	24	24	24

	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)
Rout. * EPL	-0.04*			-0.06*	-0.07**
	(0.02)			(0.02)	(0.02)
Col. bargaining		0.10		0.18 ⁺	0.20 ⁺
		(0.06)		(0.09)	(0.10)
Rout. * Col. barg.		-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)
Abst. * ALMP			0.02	0.02	0.02
			(0.02)	(0.02)	(0.02)
R&D Expenditure					-0.00
					(0.05)

Abst. * R&D Exp.					-0.04** (0.01)
Abstract tasks	0.37*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.37*** (0.02)	0.37*** (0.02)
Manual accuracy tasks	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Manual tasks	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)	0.03* (0.01)
Computer use	0.48*** (0.03)	0.48*** (0.03)	0.48*** (0.03)	0.48*** (0.03)	0.48*** (0.03)
Age (Ref.: 25-29)					
30-34	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
35-39	-0.08* (0.04)	-0.08* (0.04)	-0.08* (0.04)	-0.08* (0.04)	-0.08* (0.04)
40-44	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
45-49	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
50-54	-0.19*** (0.05)	-0.19*** (0.05)	-0.19*** (0.05)	-0.19** (0.05)	-0.19** (0.05)
55-59	-0.34*** (0.06)	-0.34*** (0.06)	-0.34*** (0.06)	-0.34*** (0.06)	-0.34*** (0.06)
60-65	-0.60*** (0.07)	-0.60*** (0.07)	-0.60*** (0.07)	-0.60*** (0.07)	-0.60*** (0.07)
Education (Ref.: ISCED 0-2)					
ISCED 3a	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)
ISCED 3b	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)
ISCED 5long/6	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)
Professionals	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)
Occupation (ISCO, Ref.: Managers)					
Technicians and ass. prof.	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
Clerks	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)
Service and sales	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)
Skilled agricultural and fishery	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)
Craft and related trades	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)
Machine op. and assemblers	-0.16** (0.05)	-0.16** (0.05)	-0.16** (0.05)	-0.15** (0.05)	-0.15** (0.05)
Elementary occupations	-0.51*** (0.05)	-0.51*** (0.05)	-0.51*** (0.05)	-0.51*** (0.05)	-0.50*** (0.05)



Literacy	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)
Numeracy	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
Gender: Men (Ref.: Women)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)
11-50 people	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)
Firm size (Ref.: 1-10 people)					
51-250 people	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)
More than 1000 people	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)
Public Sector	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)
Mining	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)
Sector (Ref.: Agriculture)					
Manufacturing	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)
Electricity/Water supply	0.43*** (0.11)	0.43*** (0.11)	0.43*** (0.11)	0.43*** (0.11)	0.44*** (0.11)
Construction	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)
Commerce	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)
Transport	0.23* (0.09)	0.23* (0.09)	0.23* (0.09)	0.23* (0.09)	0.23* (0.09)
Services	0.29** (0.08)	0.29** (0.08)	0.29** (0.08)	0.29** (0.08)	0.29** (0.08)
Native-born and foreign-language	-0.03 (0.05)	-0.03 (0.05)	-0.03 (0.05)	-0.03 (0.05)	-0.03 (0.05)
Migration status (Ref.:Native)					
Foreign-born and native-language	-0.10+ (0.05)	-0.10+ (0.05)	-0.10+ (0.05)	-0.10+ (0.05)	-0.10+ (0.05)
Foreign-born and foreign-language	-0.20*** (0.04)	-0.20*** (0.04)	-0.20*** (0.04)	-0.20*** (0.04)	-0.20*** (0.04)
Fulltime employed	0.25*** (0.03)	0.25*** (0.03)	0.25*** (0.03)	0.25*** (0.03)	0.25*** (0.03)
Work experience	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)	0.10*** (0.02)
Employer tenure	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Num. obs.	66891	66891	66891	66891	66891
Num. groups:	24	24	24	24	24

	Model 1	Model 2	Model 3	Model 4
Abstract tasks	0.37*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.38*** (0.01)
Tracking	0.03		-0.03	-0.03

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	(0.05)		(0.07)	(0.06)
Abst. * Tracking	0.01		0.04*	0.04*
	(0.02)		(0.02)	(0.02)
Voc. Orientation		0.09	0.11	0.10
		(0.06)	(0.08)	(0.07)
Abst. * Voc. Orient.		-0.02	-0.05*	-0.05*
		(0.02)	(0.02)	(0.02)
R&D Expenditure				0.12*
				(0.04)
Abst. * R&D Exp.				0.04**
				(0.01)
Routine Tasks	-0.02	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Manual accuracy tasks	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Manual tasks	0.03*	0.03*	0.03*	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)
Computer use	0.48***	0.48***	0.48***	0.48***
	(0.03)	(0.03)	(0.03)	(0.03)
Age (Ref.: 25-29)				
30-34	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
35-39	-0.08*	-0.08*	-0.08*	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)
40-44	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
45-49	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
50-54	-0.19***	-0.19***	-0.19**	-0.19**
	(0.05)	(0.05)	(0.05)	(0.05)
55-59	-0.34***	-0.34***	-0.34***	-0.34***
	(0.06)	(0.06)	(0.06)	(0.06)
60-65	-0.60***	-0.60***	-0.60***	-0.60***
	(0.07)	(0.07)	(0.07)	(0.07)
Education (Ref.: ISCED 0-2)				
ISCED 3a	0.15***	0.15***	0.15***	0.15***
	(0.03)	(0.03)	(0.03)	(0.03)
ISCED 3b	0.24***	0.24***	0.24***	0.24***
	(0.03)	(0.03)	(0.03)	(0.03)
ISCED 5long/6	0.36***	0.36***	0.36***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)
Professionals	0.06	0.06	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.04)
Occupation (ISCO, Ref.: Managers)				
Technicians and ass. prof.	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
Clerks	-0.40***	-0.40***	-0.40***	-0.40***
	(0.04)	(0.04)	(0.04)	(0.04)
Service and sales	-0.17***	-0.17***	-0.17***	-0.17***

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	(0.04)	(0.04)	(0.04)	(0.04)
Skilled agricultural and fishery	-0.30*	-0.30*	-0.30*	-0.30*
	(0.11)	(0.11)	(0.11)	(0.11)
Craft and related trades	-0.23***	-0.23***	-0.23***	-0.23***
	(0.05)	(0.05)	(0.05)	(0.05)
Machine op. and assemblers	-0.15**	-0.16**	-0.16**	-0.16**
	(0.05)	(0.05)	(0.05)	(0.05)
Elementary occupations	-0.50***	-0.51***	-0.51***	-0.51***
	(0.05)	(0.05)	(0.05)	(0.05)
Literacy	0.06	0.06	0.06	0.06
	(0.03)	(0.04)	(0.04)	(0.04)
Numeracy	0.03	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Gender: Men (Ref.: Women)	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
11-50 people	0.35***	0.35***	0.35***	0.35***
	(0.02)	(0.02)	(0.02)	(0.02)
Firm size (Ref.: 1-10 people)				
51-250 people	0.55***	0.55***	0.55***	0.55***
	(0.03)	(0.03)	(0.03)	(0.03)
More than 1000 people	0.69***	0.69***	0.69***	0.69***
	(0.04)	(0.04)	(0.04)	(0.04)
Public Sector	0.33***	0.33***	0.33***	0.33***
	(0.05)	(0.05)	(0.05)	(0.05)
Mining	0.51***	0.51***	0.51***	0.51***
	(0.13)	(0.13)	(0.13)	(0.13)
Sector (Ref.: Agriculture)				
Manufacturing	-0.05	-0.05	-0.05	-0.05
	(0.09)	(0.09)	(0.09)	(0.09)
Electricity/Water supply	0.43***	0.43***	0.43***	0.44***
	(0.11)	(0.11)	(0.11)	(0.11)
Construction	-0.02	-0.02	-0.02	-0.02
	(0.09)	(0.09)	(0.09)	(0.09)
Commerce	-0.02	-0.02	-0.02	-0.02
	(0.09)	(0.09)	(0.09)	(0.09)
Transport	0.23*	0.23*	0.23*	0.23*
	(0.09)	(0.09)	(0.09)	(0.09)
Services	0.29**	0.29**	0.29**	0.29**
	(0.08)	(0.08)	(0.08)	(0.08)
Native-born and foreign-language	-0.03	-0.03	-0.03	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)
Migration status (Ref.:Native)				
Foreign-born and native-language	-0.10+	-0.10+	-0.10+	-0.10+
	(0.05)	(0.05)	(0.05)	(0.05)
Foreign-born and foreign-language	-0.20***	-0.19***	-0.20***	-0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Fulltime employed	0.25***	0.25***	0.25***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)
Work experience	0.10***	0.10***	0.10***	0.10***

	(0.02)	(0.02)	(0.02)	(0.02)
Employer tenure	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Num. obs.	66891	66891	66891	66891
Num. groups:	24	24	24	24

	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)
Abst. * EPL	-0.01			0.01	0.03+
	(0.02)			(0.02)	(0.02)
Col. bargaining		0.09+		0.15	0.09
		(0.05)		(0.09)	(0.08)
Abst. * Col. barg.		-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)
Abst. * ALMP			-0.01	0.01	-0.00
			(0.02)	(0.02)	(0.02)
R&D Expenditure					0.12*
					(0.04)
Abst. * R&D Exp.					0.05**
					(0.01)
Routine Tasks	-0.03	-0.03	-0.03	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Manual accuracy tasks	0.05***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Manual tasks	0.03*	0.03*	0.03*	0.03*	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Computer use	0.48***	0.48***	0.48***	0.47***	0.48***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age (Ref.: 25-29)					
30-34	-0.05	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
35-39	-0.08*	-0.08*	-0.08*	-0.08*	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
40-44	-0.05	-0.05	-0.05	-0.05	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
45-49	-0.05	-0.05	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
50-54	-0.19***	-0.19***	-0.19***	-0.19**	-0.20**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
55-59	-0.34***	-0.34***	-0.34***	-0.34***	-0.34***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
60-65	-0.60***	-0.60***	-0.60***	-0.60***	-0.60***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Education (Ref.: ISCED 0-2)					

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ISCED 3a	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)	0.15*** (0.03)
ISCED 3b	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)	0.24*** (0.03)
ISCED 5long/6	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)	0.36*** (0.04)
Professionals	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)	0.06 (0.04)
Occupation (ISCO, Ref.: Managers) Technicians and ass. prof.	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)	-0.05 (0.04)
Clerks	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)	-0.40*** (0.04)
Service and sales	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)	-0.17*** (0.04)
Skilled agricultural and fishery	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)	-0.30* (0.11)
Craft and related trades	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)	-0.23*** (0.05)
Machine op. and assemblers	-0.16** (0.05)	-0.16** (0.05)	-0.16** (0.05)	-0.16** (0.05)	-0.16** (0.05)
Elementary occupations	-0.51*** (0.05)	-0.51*** (0.05)	-0.51*** (0.05)	-0.51*** (0.05)	-0.51*** (0.05)
Literacy	0.06 (0.03)	0.06 (0.04)	0.06 (0.03)	0.06 (0.04)	0.06 (0.04)
Numeracy	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
Gender: Men (Ref.: Women)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)
11-50 people	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)	0.35*** (0.02)
Firm size (Ref.: 1-10 people) 51-250 people	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)	0.55*** (0.03)
More than 1000 people	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)	0.69*** (0.04)
Public Sector	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)	0.33*** (0.05)
Mining	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)	0.51*** (0.13)
Sector (Ref.: Agriculture) Manufacturing	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.05 (0.09)
Electricity/Water supply	0.43*** (0.11)	0.43*** (0.11)	0.43*** (0.11)	0.43*** (0.11)	0.44*** (0.11)
Construction	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)
Commerce	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)	-0.02 (0.09)

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Transport	0.23*	0.23*	0.23*	0.23*	0.24*
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Services	0.29**	0.29**	0.29**	0.29**	0.29**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Native-born and foreign-language	-0.03	-0.03	-0.03	-0.03	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Migration status (Ref.:Native)					
Foreign-born and native-language	-0.10 ⁺	-0.10 ⁺	-0.10 ⁺	-0.10 ⁺	-0.10 ⁺
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Foreign-born and foreign-language	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Fulltime employed	0.25***	0.25***	0.25***	0.25***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Work experience	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Employer tenure	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Num. obs.	66891	66891	66891	66891	66891
Num. groups:	24	24	24	24	24



Chapter 3: Training opportunities of less-skilled adults in international comparison

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Extended summary

In this extended summary, we embed our analyses into the larger Technequality framework, outline our main findings and derive policy implications.

The Technequality deliverables of WP1 have clearly illustrated that automation technologies (will) restructure the demand for labor and skills. Thus, maybe more than in the past, continuous skills enhancement and adaption will become a *necessity* to successfully respond to the impact of technological innovations on work and prevent adverse consequences for labor markets, such as increased skill shortages and increased risks of unemployment or over-qualification. Ensuring that all workers have access to education and training beyond the realm of initial education is and will be central for both sufficient skill supply and sustainability of employment careers. Chapter 2 (of Deliverable 3.6) has outlined that access to further training is unequally distributed among workers and that certain groups of workers, such as routine workers, are doubly vulnerable to automation: First, by holding jobs that are at high risk of being substituted by machines and algorithms, and second, by having less opportunities to participate in further training to reskill.

In this chapter, we focus on the training disadvantage of less-educated adults and the relative importance of job allocation vs. skills; more specifically of workers' general numeracy and literacy proficiency. These two key information-processing skill domains are prerequisites for successful training participation and, as shown in Deliverable 1.2, numeracy skills will be of growing demand in the future. We contribute to answer the following two questions from task 3.5 of the grant proposal: *What are consequences of a lack of learning competencies? And how do education and labor market institutions shape opportunities for skill acquisition "against the odds"?* – focusing on an international comparison of less-educated workers, using the PIAAC (Programme for the International Assessment of Adult Competencies) data from 27 countries (including 16 EU-member states). Answers to these questions also improve our knowledge about the employment environments that encourage or discourage less-educated workers from participating in training. The findings of this analysis in turn provide the basis for assessing and developing targeted measures/interventions that ensure training opportunities for less-educated workers' continuous skills enhancement and adaption in order to remain productive in changing labor markets.

In our analyses, we classify workers by their level of formal qualification rather than their skills (or competence proficiency) and compare less-educated workers (i.e., with less than upper secondary education, ISCED 0-2) with intermediate-educated workers (i.e., with upper secondary education or



non-tertiary post-secondary degree, ISCED 3-4). The advantage of this approach is that it allows assessing the role of workers' skills in comparison to their formal qualification and job allocation for inequalities in adult training participation more comprehensively: On the one hand, educational degrees constitute the most important predictor of general skills, such as literacy or numeracy proficiency, because later skill formation processes do not substitute but rather complement early educational attainment. Thus, less-educated adults are on average also less-skilled workers and their training disadvantage should be partly explained by individual competencies (and learning motivation). On the other hand, the signaling function of educational certificates determines workers' allocation to jobs and therefore further learning environments. So even after accounting for individual skills, less-educated workers might be disadvantaged in terms of training participation because of having been allocated to workplaces with no or only limited access to further training, while being more prone to the risk of automation at the same time (see Deliverables 1.4 and 1.5 and Chapter 2 of Deliverable 3.6). In sum, our approach to classify workers by educational attainment and to use skills as an additional key independent variable in our analyses allows assessing the relative role of both educational certificates and workers' skills vis-a-vis job allocation for access to adult training. Moreover, this approach is particularly interesting from a cross-country perspective: Country variation in mean (numeracy and literacy) skills is largest for the less-educated group compared to upper secondary and tertiary education (OECD 2013).

We focus on the difference in participation rates in job-related non-formal training between less-educated and intermediate-educated workers because it is the predominant form of adult education and training (Cedefop 2015). We first examine whether less-educated workers' training disadvantage is explained by the simple fact that they carry out different jobs than better-educated workers or rather by individual skills (i.e. numeracy and literacy proficiency) and workers' motivation to learn. Concerning cross-national variation, we then investigate the extent to which cross-country differences in job allocation and workers' skills, respectively, explain country differences in less-educated workers' training disadvantage. We also explore the role of education systems and labor market institutions in moderating the training disadvantage of less-educated workers by generating country differences in skills acquisition and job allocation.

Main findings

1. Less-educated workers show the lowest participation rates in adult training in all countries (included in this study).
2. Within-country differences: Job allocation – measured by job tasks, job characteristics, and firm characteristics – is indeed the most important factor of differences in training participation between less- and intermediate-educated workers in all countries, except Sweden. In other words, differences in job allocation by educational attainment contribute significantly to the training disadvantage of less-educated workers, above and beyond skills differentials and other worker

characteristics. The subset of job characteristics (including employment tenure in years, occupational status, and part-time employment) has the highest explanatory power in the majority of countries.

3. Between-country differences: Accounting for differences in job allocation and workers' skills at the individual level markedly reduces cross-national variation in less-educated workers' training disadvantage. Thus in contrast to the aforementioned within-country finding, skills differentials between less- and intermediate-educated workers are more important than job allocation for explaining between-country differences. Hence, on the one hand, single-country studies might underestimate the importance of workers' skills that we observe for explaining cross-national differences in training participation. On the other hand, only looking at between-country differences might underestimate the role of job characteristics.
4. Institutions matter: Our analyses suggest that educational and labor market institutions contribute to cross-national variation in less-educated workers' training disadvantage primarily via *moderating* the impact of individual-level predictors. Moderation by institutions is stronger for job allocation factors than worker characteristics.

Labor market institutions: High wage inequality increases the training disadvantage of less-educated employees, for example, because it is more profitable for companies to invest in further training for intermediate-educated employees. Union density has an ambiguous influence on the training disadvantage: In model specification only looking at job allocation factors, less-educated workers seem to benefit from higher trade union density by being allocated to "better" jobs, for example, skill-intensive jobs and/or jobs in training-active firms. However, when also including workers' characteristics, higher trade union density is associated with a larger training disadvantage of less-educated workers – for example, suggesting trade unions focus strategically more on skilled employees than less-educated workers in their commitment to further training. We do not find any influence of employment protection.

Educational institutions: The training disadvantage of less-educated workers is larger in countries with stratified secondary education and higher differences in the mean skills between less- and intermediate-educated adults, possibly because of higher skill transparency of educational degrees, which is consequential for job placement. Vocational orientation of upper secondary education does not seem to have a moderating impact on the training disadvantage.

The mutually reinforcing relationship between job allocation and training participation creates a vicious cycle for less-educated workers: They are more likely to be employed in workplaces that require fewer skills investments and provide less job-related learning opportunities, which in turn increases the risk of cementing their poor labor market prospects. This insight stresses the need for governments to take action. The findings of our analyses provide a good starting point for policy recommendations.

Policy recommendations

Policies designed to enhance less-educated workers' skills and labor market integration should not only focus on their training participation per se but also, and maybe foremost, on their workplace conditions and their inherent training barriers. In the following, we highlight six key areas of action and provide recommendations for policy-makers across EU-member states to help break the vicious cycle of path dependency between education and job placement, that is, to enhance less-educated workers' access to skills-enhancing jobs and networks as well as training. In a technologically ever-advancing world of work (see above), the implementation of such measures is all the more urgent.

I. Involve employers

Work placement (as shown in our analyses) and thus employers are important stakeholders for the adult education and training landscape. Accordingly, member states need to make sure that employers are prepared for changes in the world of work by providing guidance and financial incentives to integrate relevant training opportunities and make them broadly available to their workforce. Moreover, employers need to be held accountable to value certificates that are obtained through skill recognition and partial qualification, to grant education leave and financing, and to constantly communicate options of career guidance, skill validation and learning opportunities.

II. Regulate education leave and provide financial support and incentives

Time and financial constraints are important training barriers for less-educated workers because of low salaries and/or multiple jobs (OECD 2019, 17-20). Yet, they oftentimes disqualify for education leave and financing schemes because of their atypical employment relations (including part-time and/or fixed-term employment) and limited bargaining power. To overcome these structural barriers, member states need to introduce a comprehensive framework for education and training leave schemes, also for workers in atypical employment by law, through collective agreements or bilateral agreements with employers. Targeted financial incentives for less-educated adults are a means to this end as well but have to consider all costs of training, including direct course costs, indirect costs, and opportunity costs (e.g., foregone earnings or benefits).

III. Recognize existing skills

Being less-educated does not necessarily mean to be low-skilled. Basic skills levels vary considerably within the group of less-educated workers (Heisig and Solga 2015). In addition, workers possess occupation-specific skills that they have acquired in the course of their careers (OECD 2019, 13f.). A validated and certified inventory of the actual skills levels of less-educated workers is important to close skills gaps and to improve their job placement, which in turn provides a better learning environment (as our analyses show). Therefore, member states need to develop and adopt a

comprehensive legal framework for the assessment and validation of existing skills, which could also be a useful extension of the EU's *Upskilling Pathways* initiative. Advice and guidance services can help adults with low skills to navigate and prepare for the recognition process.

IV. Create interesting, relevant and validated learning opportunities

Tailor-made learning opportunities to update adults' skills and fill important deficits should be offered. Modular learning and partial qualifications for successfully completing individual modules should become a structural feature of the adult education and training landscape across Europe. Module designs need to consider how adults, and in particular the less-educated workers, learn best. They should be practical, problem-oriented and closely linked to the (work) context of the learner. Member states need to establish services that provide additional support where needed and systematise the connections between guidance, validation and partial qualification (see also V and VI).

V. Intensify outreach activities to activate potential learners

Awareness of learning needs and opportunities is low among the less-educated (OECD 2021, 157f.) – although differences in motivations to learn are generally small between less- and intermediate-educated workers, as our analyses show. Thus, the lack of interest (not learning motivation) is a major barrier for their training participation (OECD 2021, 157f.). Notably, this problem is partly inherent to their rather skills-distant working routines and relations. To increase awareness and encourage participation in adult learning, member states should finance outreach campaigns that approach less-educated adults actively and directly in their day-to-day environment, including their workplaces. Such campaigns should integrate services that promote the benefits of adult learning and provide high quality information as well as personalized advice and guidance for less-educated workers (see also VI).

VI. Offer individualized career advice and guidance

The landscape of adult education and training is diverse and hard to navigate for any individual, but especially for the less-educated, who lack the relevant network, including colleagues and employers, and/or skills (OECD 2019, 7f.). Therefore, member states need to set up career services both inside and outside of workplaces that are qualified to network and streamline current provision and to offer holistic and personalised guidance, including counselling and mentoring, that specifically tailor the needs and situation of less-educated adults. In that manner, services also take on the task of monitoring supply gaps and steering training choices towards skills in demand.

Although these proposed actions are relevant for all or most member states, the country differences in the importance of the different job allocation characteristics and workers' skills differentials for training participation, we found in our analyses, should be considered when designing country-

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specific policies in these and other fields of action. Moreover, in countries where the role of job allocation is particularly pronounced, policies should also promote more far-reaching restructuring processes with regard to labor market institutions. For countries with a high impact of skills differentials between educational groups, policies should also target on initial education in order to reduce skills inequality as early as possible.



1. Introduction

Research consistently shows that less-educated adults are severely disadvantaged in labor markets in terms of earnings, job security, and career development (e.g., Abrassart 2013; Gebel and Giesecke 2011; Heisig, Gesthuizen, and Solga 2019; Solga 2008; Tamborini and Kim 2017). Less-educated adults' labor market disadvantages might be amplified by their markedly lower participation in adult education and training (Bassini et al. 2005; OECD 2019a), with continuous training being considered essential for skills acquisition, maintenance, and enhancement (Cedefop 2015; Desjardins and Rubenson 2013). Moreover, previous research suggests that participation in continuous training has at least a safety-net function, because it prevents unemployment and increases employment stability (Dieckhoff 2007; Ebner and Ehlert 2018; Myers and de Broucker 2006; Richardson and van den Berg 2006). It is plausible to assume that the digital transformation of work will further amplify this safety-net function, especially for less-educated workers (Nedelkoska and Quintini 2018; OECD 2019b). Thus, although they might benefit most from adult training in terms of skills enhancement and employability, less-educated workers show the lowest participation rate in continuing training in all countries (e.g., OECD 2019b, 252ff; Cedefop 2020). A better understanding of why this is the case could therefore help reduce their labor market risks.

Our understanding of disparities in training participation between educational groups is still quite incomplete. In particular, we do not know the role of job placement (e.g., job tasks, work contracts, or economic sector) as compared to individual worker characteristics, such as their actual skills or motivation to learn. Moreover, satisfactory explanations for less-educated workers' disadvantage should also be able to account for the well-documented, yet not well-understood cross-country variation in their training disadvantage (Bassini et al. 2005; Cedefop 2015; OECD 2019a). The aim of this chapter, therefore, is to more closely examine the training disadvantage of less-educated workers within and between countries.

In doing so, we focus on participation in job-related non-formal training (hereafter job-related NFT) because it is the predominant form of adult education and training (Cedefop 2015; Desjardins and Ioannidou 2020). Job-related NFT refers to intentional training activities to improve job-related skills, organized by an education provider, and typically provided in the form of classroom instruction, lectures, theoretical and practical courses, seminars and workshops. It does not lead to recognized qualifications of national or sub-national education authorities, but it can be certified.¹¹ As job-related NFT activities are mostly fully or partly sponsored by employers (Cedefop 2015;

¹¹ In contrast to NFT, formal training leads to a recognized certificate such as a university degree or a vocational qualification, whereas informal training is also intentional but less organized, occurring in the workplace or the family, for example (Eurostat 2006). Examples of job-related NFT are type-writing courses or introductory courses on IT technologies.

Desjardins and Ioannidou 2020), Bills and Hodson (2007, 261) consider them a “job perk” and, in this respect, as an important aspect of labor market inequalities.

Employment as such is not sufficient for their equal integration into job-related NFT, because less-educated *employed* adults also participate less in job-related NFT than employees with higher levels of education (Cedefop 2015). Yet, as these NFT activities are job-related, less-educated workers’ training disadvantage might result from the kinds of jobs they hold. Previous research indeed shows that job characteristics (e.g., job tasks) strongly predict participation in job-related NFT, and perhaps even more so than worker characteristics such as age, education, or experience (see Chapter 2 of Deliverable 3.612 as well as Görlitz and Tamm 2016; Mohr, Troeltsch, and Gerhards 2016; Saar and Räis 2017; Schindler, Weiss, and Hubert 2011). However, this research often does not differentiate by educational group and is mainly confined to Germany.¹³ The German findings might not apply to other countries because of Germany’s rather unique firm-based vocational education and training system and its occupation-specific, highly credentialized labor market (Elbers, Bol, and DiPrete 2020; Protsch and Solga 2016; Shavit and Müller 2000a). Moreover, as existing studies do not account for workers’ skills, even though skills and job placements are strongly related (Heisig, Gesthuizen, and Solga 2019), the finding that job placement plays the most important role for training participation might be confounded by unobserved differences in workers’ actual skills.

Against this backdrop, we investigate the importance of job allocation for less-educated workers’ disadvantage in participating in job-related NFT. Our first research question is: To what extent is their training disadvantage explained by the simple fact that they carry out different jobs than better-educated workers in the 27 countries considered? Concerning cross-national variation, we then examine the extent to which cross-country differences in job allocation contribute to country differences in less-educated workers’ training disadvantage. In doing so, we also explore whether educational and labor market institutions moderate the disadvantage of less-educated workers by generating country differences in job allocation. Importantly, in contrast to previous research, our analyses include information on workers’ skills and motivation to learn. The group of less-educated workers is particularly interesting to closer examine of whether job allocation characteristics rather than worker characteristics are more important for educational disparities in training participation: Despite having the lowest mean levels of skills in all countries, the country variation in mean skills is largest for the less-educated group compared to upper secondary and tertiary education (OECD 2013).

¹² Also published as Ehlert (2020).

¹³ The study by Saar and Räis (2017) for five countries includes only reading at work as a direct measure of job tasks and otherwise indirectly proxies tasks with occupational groupings.

Hence, the role of skills for explaining cross-national variation in training participation should be most prominent for the less-educated group.

Our empirical analysis uses data from 38,320 adults in 27 countries, taken from the *Programme for the International Assessment of Adult Competencies* (PIAAC; OECD 2016). This cross-national survey provides high-quality and comparable data for job tasks (i.e., skills used at work) and adults' numeracy and literacy skills. The training disadvantage of less-educated workers is defined as the difference (gap) in the participation rate in job-related NFT between less-educated workers (who did not complete upper secondary education) and intermediate-educated workers (who hold an upper-secondary or non-tertiary post-secondary degree). This low-intermediate training gap is a more conservative measure of less-educated workers' training disadvantage compared to using all workers with more education (including tertiary-educated employees) as comparison groups.

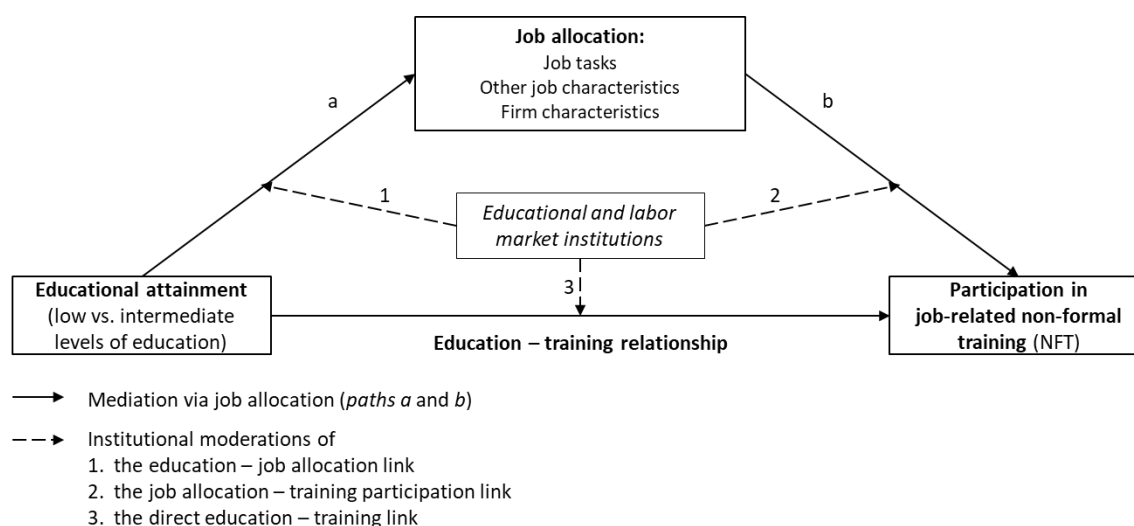
2. Theoretical considerations

Figure 1 presents our stylized theoretical model on the interplay between education, job allocation, and training participation, and how institutions might influence this interplay. In accordance with our research questions, we focus on the role of job allocation as an explanation for less-educated workers' training disadvantage (*paths a* and *b*) and on how educational and labor market institutions might generate country differences by moderating the role of job allocation (*paths 1* and *2*). At the end of this section, we also present some considerations on worker characteristics (such as skills and motivation to learn) for a subsequent empirical assessment of the relative importance of job allocation for job-related NFT participation.

Educational and labor market institutions might also directly impact the education-training relationship, independent of differences in job allocation (*path 3*). The relevance of this path should be rather small, however, as we considered *job-related* NFT. The potential importance of this path is indicated by the training gap remaining after accounting for the factors mentioned in Figure 1.¹⁴ As this direct moderation is beyond the scope of our research questions and, as our analyses show, small in relevance, we will not discuss this path.

¹⁴ An example of path 3 is that participation in NFT is required to keep one's eligibility to perform a certain occupation, regardless of whether one currently works in that occupation (e.g., certain types of medical occupations).

Figure 1: Stylized theoretical model on the role of job allocation for the education-training relationship



Analyses also include worker characteristics—workers’ skills and motivation to learn, and socio-demographics—to assess the relative importance of job allocation and to control for potential confounders of *paths a and b*.

Other job characteristics might be important as well. Less-educated workers are more often employed in fixed-term or part-time work and at less technologized workplaces¹⁵ (OECD 2019b), all of which have been found to be associated with lower participation in job-related NFT (Bassanini et al. 2005; Görlitz and Tamm 2016; Nedelkoska and Quintini 2018; Schindler, Weiss, and Hubert 2011). A common explanation for their relevance is that these job characteristics lower firms’ expected returns to training investments, for example, because workers on fixed-term contracts tend to leave firms earlier than their counterparts on permanent contracts. Similar returns-to-training investment explanations exist for firm characteristics, suggesting that less-educated workers’ training disadvantage is caused by their overrepresentation in smaller firms or less training-intensive economic sectors (Mohr, Troltsch, and Gerhards 2016; Schindler, Weiss, and Hubert 2011; Wotschack 2020).

These theoretical considerations suggest that, in all countries, less-educated workers’ disadvantageous job allocation in terms of job tasks, other job characteristics, and firm characteristics might lead to their lower participation rates in job-related NFT (*paths a and b* in Figure 1).

¹⁵ Technology and computer equipment of workplaces can be understood as tools that might influence job tasks. Correspondingly, many surveys collect only information on whether respondents use ICT tools at work but not on the tasks they perform with these tools.

Cross-national variation

We next turn to the country differences in less-educated workers' training disadvantage and provide theoretical considerations on why the strength of the mediating role of job allocation for the education-training relationship might vary across countries. Comparative research on training participation pays great attention to educational and labor market institutions (see e.g., Desjardins and Ioannidou 2020; Desjardins and Rubenson 2013; Martin and Rüber 2016; Roosmaa and Saar 2012; Saar, Ure, and Desjardins 2013; Vogtenhuber 2015). As a first channel, educational and labor market institutions might generate compositional differences in job allocation, in other words, differences in the strength of the association between educational attainment and job allocation (*path 1*: institutions as moderators of *path a*). Thus, if the job allocation of less- and intermediate-educated workers differs across countries, the low-intermediate training gap could vary across countries as well. A second channel is that these institutions moderate the strength of the association between job allocation and training participation, resulting in cross-country differences in the returns to job allocation characteristics (*path 2*: institutions as moderators of *path b*).

We now elaborate on this potential moderating role of educational and labor market institutions. In so doing, we consider individual institutional factors rather than institutional typologies, like the commonly used dichotomies between occupational vs. internal labor markets (Marsden 1990) or between coordinated vs. liberal market economies (Hall and Soskice 2001). As demonstrated by Gangl (2001), major limitations of using such typologies include the large variation within country clusters or problems detecting the relative importance of institutional factors for the observed cross-country differences.

Labor market institutions are widely considered in the training literature, however, not yet with respect to *educational disparities* in adult training participation—the focus of this chapter. Existing research primarily aims at explaining country variation in overall training participation (Acemoglu and Pischke 1999; Bassanini et al. 2005; Cutuli and Guetto 2013; O'Connell and Byrne 2012; Vogtenhuber 2015). Several institutions have been examined for job-related NFT: Trade union coverage is expected to affect training participation directly via bargaining for training agreements and indirectly via collective wage bargaining, resulting in wage compression—yet empirical evidence is mixed (Acemoglu and Pischke 1999; Bassanini et al. 2005). Research on wage compression indicates that employers' incentive to invest in training is larger when earnings differentials between skilled and low-skilled jobs are smaller, because they can keep a higher share of the returns to training (Acemoglu and Pischke 1999; Bassanini and Brunello 2003). High employment protection legislation is another relevant factor for job-related NFT participation: Under the condition of high employment protection, employers might more frequently invest in workers' training because of higher firing difficulties/costs. Moreover, both employers and employees might invest more in job-related NFT because, given the longer duration of job tenure, both have more time to collect the returns

(Acemoglu and Pischke 1999; Cutuli and Guetto 2013). This positive relationship between employment protection and training participation has also been found for less-educated workers (Doepke and Gaetani 2020).

In sum, these labor market institutions might generate cross-country differences in both less-educated workers' job allocation and eventual job-related NFT participation in the following ways: Less-educated workers might benefit from high employment protection legislation, collective training agreements, and firm-specific training activities, especially in larger firms and training-active sectors (Brunello 2001; Wotschack 2020). As a result, in countries with such institutional features, less-educated adults could be more likely to have jobs that demand more advanced skills (*path a*). This moderating impact of labor market institutions on the education-job allocation relationship (*path 1*) would generate compositional country differences in less-educated workers' job allocations, which in turn translate into cross-national variation in their training participation. Labor market institutions might also influence the strength of the job allocation-training relationship (*path b*): As discussed above, the impact of job allocation on training participation might differ by industrial relations such as level of wage compression, employment protection, or unions' training agreements. For example, unions might advance inclusive collective agreements that ensure access to NFT for workers in low-skilled jobs (Wotschack 2020).

Educational institutions are also widely considered in adult training research. Most obviously, education systems are markedly associated with skills differentials between less- and intermediate-educated adults (Heisig and Solga 2015) and the "skills transparency" of educational certificates. The latter is the extent to which formal qualifications provide information about the actual skills of individuals, for example, because of larger skills differentials between educational groups (Andersen and van de Werfhorst 2010; Heisig 2018; Heisig, Gesthuizen, and Solga 2019). Moreover, a stronger vocational orientation of upper secondary education is associated with acquiring more occupation-specific skills and a stronger linkage between education and occupational placement (Bol et al. 2019; Elbers, Bol, and DiPrete 2020).

Correspondingly, previous research shows that the occupational status gap between less- and intermediate-educated adults and the share of less-educated workers performing low-skilled jobs are larger in countries with stratified school systems, connected to higher skills transparency (Heisig, Gesthuizen, and Solga 2019; see also Andersen and van de Werfhorst 2010; Bol and van de Werfhorst 2013; Shavit and Müller 2000b). As a consequence, less-educated workers in these countries are more likely to be exposed to routine job tasks and lower requirements for skills maintenance/enhancement. The strength of vocational orientation in upper secondary education reinforces this boundary between skilled and low-skilled jobs: As employers can rely on occupationally trained workers for skilled jobs, less-educated workers (who lack completed vocational training) are more strongly sorted into low-skilled labor market segments and, vice versa,

intermediate-educated workers are more often employed in skilled-worker positions (Bol et al. 2019; Shavit and Müller 2000b). In sum, these education system characteristics are very likely to be associated with compositional country differences in the jobs that less- and intermediate-educated workers occupy (*path 1*: moderation of *path a*).

These differences in education systems might also influence *path b* (Figure 1). According to the Varieties of Capitalism approach, firms find different solutions to the coordination problem of securing a suitably skilled workforce (Hall and Soskice 2001). In systems that strongly rely on occupational skills, firms invest not only in initial vocational education and training but also in job-related NFT to ensure competitiveness with their high-skill equilibrium and to invest in employees' work effort. Thus, even when occupying the same job, workers in countries characterized by a high- vs. low-skill equilibrium might differ in their likelihood to participate in NFT. However, as this difference might affect especially skilled positions, participation in training might more strongly differ between less- and intermediate-educated workers in countries with a stronger vocational orientation in education.

Workers' skills and motivation to learn

Finally, as workers' (cognitive and non-cognitive) skills and motivation to learn are the most widely used explanations for differences in training participation, we briefly discuss them as alternative explanations for less-educated workers' training disadvantage. We know that less-educated workers have on average the lowest levels of skills among the workforce (Heisig and Solga 2015). Moreover, low(er) motivation to learn is an important predictor of their low level of educational attainment in the first place (e.g., Doll 2010; Heckman and Rubenstein 2001). Thus, based on the human capital account (Becker 1964), less-educated workers might not engage in training activities because they lack the necessary skills or training motivation (Acemoglu and Pischke 1999; Siebert 2006). This might also influence employers' training decisions, because inferior skills or lack of motivation make training investments more costly and lower the (expected) returns to training (Brunello 2001). As a result, less-educated workers' training disadvantage could be, at least partly, caused by differences in their skills and motivation.¹⁶

That being said, workers' skills and job allocation will likely be interrelated: Skills might influence workers' job placement, and job placement in turn might have feedback effects on their skills. With longitudinal data and repeated measurements of both competences and different job characteristics, these two pathways might be disentangled. The cross-sectional PIAAC data do not

¹⁶ Our cross-sectional data do not allow for estimating a causal effect of workers' skills on their training participation, as workers' skills might be affected by prior training participation. However, the usually shorter job-related NFT might considerably influence literacy and numeracy skills (the cognitive skills considered in our study) beyond initial education.

allow for doing this, but by accounting for differences in workers' actual skills and motivation to learn, our estimates for the mediating role of job allocation on the education-training relationship are, at least, less confounded by these workers' characteristics than in existing studies, which have not controlled for these worker characteristics.

How workers' skills impact on the education-training relationship might also vary between countries because of institutional differences. Labor market institutions might generate compositional differences in the actual skills of less- and intermediate-educated *employed* adults across countries. For example, high employment protection has been shown to exacerbate the insider-outsider divide with respect to less-educated workers (Biegert 2019), which in turn might be connected to a positive selection of *employed* less-educated adults with higher levels of cognitive skills (Kahn 2018). By generating such cross-national compositional differences in workers' skills, employment protection legislation might therefore moderate the education-training link.

In addition, strong vocational education and training systems might increase the low-intermediate training gap because intermediate-educated workers are better equipped with skills for continuous training participation and more professionally motivated to update their skills in these countries. Moreover, as stratified (tracked) upper secondary education systems increase the skills gap between less- and intermediate-educated workers (Heisig and Solga 2015), less-educated workers' skills might be important for training participation above and beyond actual job placement in countries with a larger skills gap.

Because of these considerations, it is necessary to account for workers' skills and learning motivation when examining the importance of job allocation for participation in job-related NFT to explain both the within-country training disadvantage of less-educated workers and the cross-country variation in the extent of this disadvantage.

Empirical expectations

Our theoretical considerations motivate the following expectations concerning our research questions:

Expectation 1: In all countries, differences in job allocation—job tasks, other job and firm characteristics—should be important predictors of the training disadvantage of less-educated workers, above and beyond worker characteristics such as skills, motivation to learn, and socio-demographics (see Figure 1, *paths a* and *b*).

Expectation 2: Accounting for differences in job allocation (and for worker characteristics) at the individual level markedly reduces cross-national variation in less-educated workers' training disadvantage (indirect assessment of institutional moderation of the role of job allocation).

Expectation 3: Educational and labor market institutions moderate the mediation of the education-training relationship via job allocation at the individual level (controlled for worker characteristics).

The aim of expectation 3 is explorative. We examine the overall moderating relevance of the educational and labor market institution considered—not distinguishing between how much these institutions contribute to cross-country compositional differences in job allocation (*path 1*) and how much to variations in the returns to job allocation (*path 2*). This analytical distinction might also be difficult to disentangle empirically not only because of our cross-sectional data but generally. These institutions might not affect *paths a* and *b* independently but as institutional solutions to broader-defined coordination problems, which include both job allocation and incentives to upgrade skills via training (see e.g., Hall and Soskice 2001).

3. Data and methods

Sample

We use the data from the first and second round of the *Programme for the International Assessment of Adult Competencies* (PIAAC), conducted in 2011/12 and 2014/15, respectively (OECD 2013, 2016). PIAAC provides internationally comparable and high-quality data on our variables of interest (see below). We use data from 27 of the 33 participating countries. We excluded Australia and Indonesia, because they do not provide public use files, Cyprus and Russia because of low data quality, and Singapore because of missing country-level variables. After conducting influence diagnostics (see Fox 1991), we further excluded the Slovak Republic, because it enormously affected the country-level regressions (for further discussion see Section 5). All analyses use the final survey weights as well as the replicate weights provided by PIAAC to correct the standard errors for the complex survey design (see OECD 2016).

We focus on the training participation of employed adults aged 25 to 54 (prime working age).¹⁷ We define less-educated workers' training disadvantage as the difference in the training participation rates of less-educated employees (who have not completed upper secondary education) and intermediate-educated employees (who have completed upper secondary

¹⁷ The age bounds increase cross-national comparability by reducing country differences due to age of labor market entry and retirement.

education). Tertiary-educated employees are excluded. We also exclude self-employed and family workers.¹⁸

A total of 38,863 cases meet these sample restrictions. 1,983 (5.1 %) of these cases have missing information on at least one of the variables included in the analyses (see below). We generally use multiple imputation via chained equations to deal with missing information, with 10 imputations obtained separately by country. However, we encountered persistent convergence problems in estimating the multinomial logistic regressions required to impute economic sector and foreign-birth/foreign-language status and therefore dropped the 543 cases with missing information on these variables. Our final sample consists of 38,320 cases.

Analytic strategy

Our analysis focuses on the training disadvantage of less-educated workers, estimated by the coefficient on an education indicator—less- vs. intermediate-educated workers—in country-specific linear probability models (LPM) of job-related NFT participation. In addition to the education indicator, the country-specific LPMs include varying combinations of six sets of worker and job allocation characteristics described below (see Table 1). Country-specific LPMs without further covariates (i.e., with only the education indicator) provide us with estimates of the *unadjusted* training disadvantage. The model with all covariates provides us with what we refer to as the *fully adjusted* training disadvantage. Besides, our analysis uses specifications that include some but not all of the six sets of covariates. We refer to the estimated training disadvantages from these intermediate specifications as “partially adjusted.”

Building on these country-specific LPMs, we proceed in three steps to answer our research questions. In the first step, we investigate to what extent the six different sets of covariates explain the disadvantage of less-educated relative to intermediate-educated workers *within countries*. We combine the LPMs with a Shapley decomposition approach to quantify the portion of the training disadvantage attributable to each of these factors. The change in the estimated training disadvantage from removing a set of predictors (e.g., job tasks) from the covariates included in our LPMs provides an estimate of how much differences in the respective set (like job tasks) contribute to training rate differences between less- and intermediate-educated workers. However, the magnitude of the change in the estimated disadvantage is sensitive to the order in which sets of covariates are removed from the list of predictors (i.e., it is path-dependent). With our Shapley decomposition approach, we address this path dependency by defining the contribution of a given

¹⁸ We additionally excluded 77 cases because of incomplete information on these sample-defining variables (i.e., age, highest educational degree, current employment status). So-called literacy-related non-respondents are also excluded.

set of predictors as the average marginal contribution of that set of predictors across all possible elimination sequences (Shorrocks 2013). With six sets of predictors, there are the factorial of 6 (= 720) possible elimination sequences.

In the second step of our analysis, we turn to *cross-national variation in the training disadvantage of less-educated workers* and to the question if it can be attributed to compositional differences with respect to the different sets of predictors. Quantifying the individual contributions of the six sets of predictors to cross-national variation in the training gap is subject to the same path dependency complications as the within-country analysis, so we again rely on a Shapley decomposition approach. That is, we define the contribution of a given set of covariates to cross-national variation in the training gap as the set's average marginal contribution across all 720 elimination sequences.

We also address that the country-specific estimates of the training disadvantage are based on finite samples and their cross-country variation therefore reflects both true variation (i.e., variation in the population training disadvantage) and sampling error. To isolate the former, we draw on τ^2 as our measure for the true between-country variation, estimated using a random-effects model that takes the country-specific estimates of the training disadvantage and their standard errors as inputs (see Viechtbauer 2010).

In the third and last step of our analysis, we explore *potential moderating effects of national institutional characteristics* on the training disadvantage of less-educated workers. We regress the estimated training disadvantages on various institutional variables in a series of country-level regressions. We thus utilize what is usually referred to as a two-step multilevel approach: the first-stage LPMs provide us with country-specific estimates of the quantity of interest (i.e., the coefficients on the education indicator), which are then our country-level dependent variables in a second-stage regression (see Heisig, Schaeffer, and Giesecke 2017; Lewis and Linzer 2005). The country-level regressions are estimated using Feasible Generalized Least Squared (FGLS) to account for the fact that the dependent variables are estimated with error and therefore heteroscedastic. We additionally use HC3 robust standard errors to adjust for any remaining heteroscedasticity.

In terms of the conceptual model in Figure 1 above, we are interested in the general question whether the moderating influence of the institutional features on the training disadvantage operates indirectly through job allocation (see Figure 1, *paths 1* and *2*) or whether it represents a more direct moderating effects of institutions (see Figure 1, *path 3*). To assess the importance of such mediation, we compare relationships between the institutional predictors and the training disadvantage before and after adjusting the latter for potential mediators in the country-specific LPMs. More specifically, we compare institutional effects on the training gap adjusted only for socio-demographics to institutional effects on the training gap adjusted for socio-demographics and each of the five additional sets individually as well as for the full set of covariates. If adding a specific set of covariates

(e.g., job tasks) to the country-specific LPMs leads to a substantial attenuation of an institutional effect (e.g., of unionization), we interpret this as support that the effect of the latter at least partly operates through the former.

We use a non-parametric (cases) bootstrap with 999 replications to assess the statistical significance of changes in institutional effects across different specifications of the level-1 regressions. Bootstrap samples are drawn by sampling with replacement from the 27 countries in our analysis. We calculate two-sided 95-percent confidence intervals using the percentile method and treat the change in the coefficient of an institutional variable as statistically significant if this interval does not include 0.

Variables of the individual-level analyses

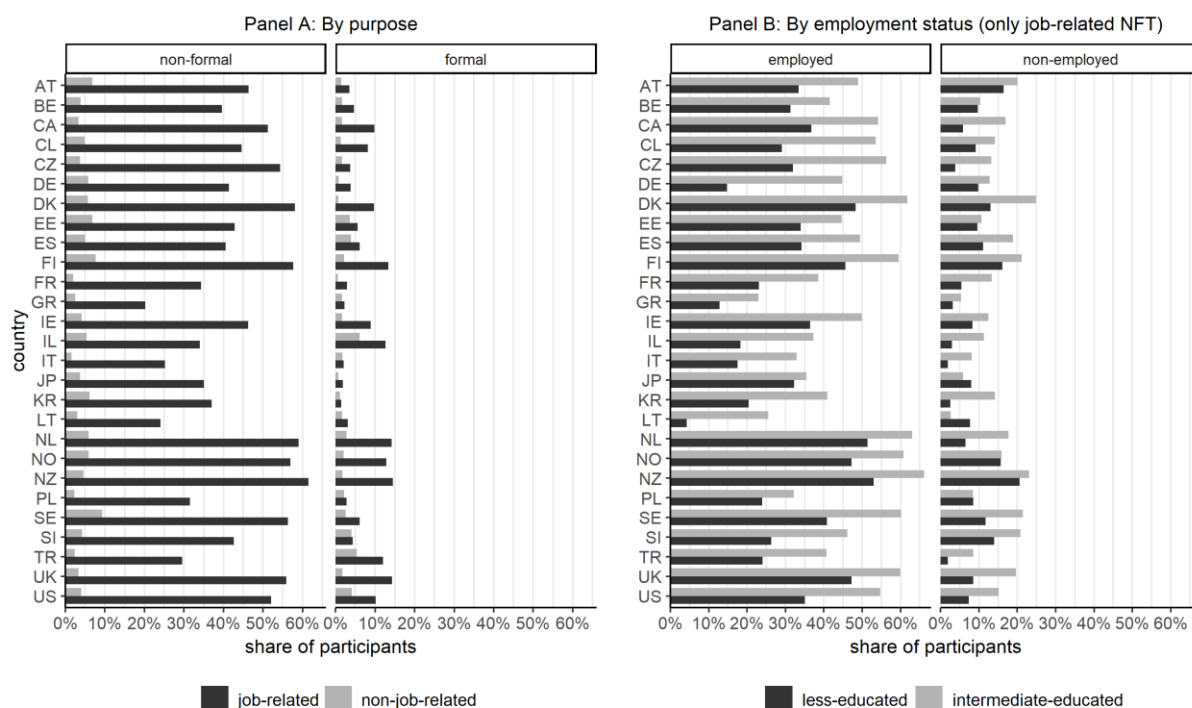
The *dependent variable* in the country-specific regressions is training participation, measured as attending job-related non-formal training (NFT) within the last 12 months prior to the interview. Figure 2 shows that this type of training is the dominant form of adult training participation for both less- and intermediate-educated workers.

We do not consider training intensity in terms of training hours because information on training hours is not available for all countries. Moreover, where available, our indicator of training participation (incidence) highly correlates with training hours (intensity) with Pearson correlations of 0.78 for less-educated and of 0.84 for intermediate-educated employees (see Appendix, Section A). Hence, additional analyses of training intensity would likely be redundant (see also Bassanini et al. 2005).¹⁹

Independent variables: Our central independent variable is educational attainment, more specifically a dummy variable of “being less-educated.” PIAAC provides internationally comparable information based on the 1997 revision of the International Standard Classification of Education (ISCED-97). We define less-educated workers as those with ISCED-97 levels 0 to 2 and intermediate-educated workers as those with ISCED-97 levels 3 and 4, serving as the reference category.

¹⁹ Moreover, the intensity variable is sensitive to the problem that training hours are reported only within the last 12-month reference period and thus underestimates the training intensity of all training episodes that started before the reference period (see Vogtenhuber 2015, 80). This is not an issue for our incidence indicator.

Figure 2: Training participation in adult education and training (in the last 12 months) of less- and intermediate-educated adults



Notes: Ordered by country code. Weighted.

Source: PIAAC, authors’ own calculations.

We operationalize job allocation with three subsets of variables: job tasks, other job characteristics, and firm characteristics. To measure *job tasks*, we conceptually follow Autor, Katz, and Kearney (2006) and distinguish between abstract, routine, and manual tasks. Empirically, we use the operationalization developed by de la Rica and Gortazar (2017) and integrate the adaptations by Ehlert (see Chapter 2 of Deliverable 3.6): We use principal-component factor analysis (PCF) on five items about complex reading and writing, problem-solving, and communication tasks to generate our indicator for abstract tasks, and PCF on four reverse-coded items about task discretion for our indicator for routine tasks (see Appendix, Section A, for items and factor loadings). Manual tasks are measured by two single-item indicators distinguishing between the frequency of working physically and of using hand and finger accuracy.

The subset *other job characteristics* is operationalized by dummy variables for computer use at work and part-time employment, and continuous variables for firm tenure (in years) and occupational status measured by the International Socio-Economic Index of Occupational Status (ISEI). The ISEI scores capture the relative position of occupations in a hierarchically stratified occupational system based on income and education (Ganzeboom and Treiman 1996). We had to assign ISEI scores based on one-digit 2008 International Standard Classification of Occupation (ISCO-

08) codes because more fine-grained categories are not available for all countries in our sample. We operationalize *firm characteristics* by measures of firm size (five categories), public vs. private firm ownership (dummy variable), and eight economic sector groups following the International Standard Industrial Classification of All Economic Activities (ISIC).

We define three subsets of worker characteristics. For *workers' skills*, we use measures for numeracy proficiency. As each respondent completed only a limited number of test items, PIAAC provides ten so-called plausible values that reflect the uncertainty about the individual competency estimates (OECD 2013). Following standard practice, we run all analyses that include the skills measures ten times, once per plausible value, and calculate final point estimates and standard errors according to the appropriate rules (Little and Rubin 2002). To assess workers' *motivation to learn*, we use PCF to construct an indicator based on four items that express intrinsic motivation for several learning behaviors (see Gorges et al. 2016; see Appendix, Section A, for items and factor loadings). Finally, we include several key *socio-demographic variables* as controls: gender, age (five-year groups), household status (indicator of living with a partner), household size (indicator of having children), and foreign-birth/foreign-language status (four categories capturing whether the respondent was born in the country of survey participation and whether the test language was their first language). Table 1 presents an overview of the six subsets of predictors (see Appendix, Section A, for descriptive statistics).

Variables of the country-level analyses

The *dependent variables* in the country-level FGLS regressions are the country-specific estimates of less-educated workers' training disadvantage, obtained by using country-specific regressions that adjust for six subsets of individual-level explanatory variables (see above).

The *independent variables* capture several institutional characteristics of education systems and labor markets. For education systems, we use the skills gap between less- and intermediate-educated adults as a more direct measure of skills transparency of educational degrees (Heisig and Solga 2015; Heisig 2018), the external differentiation index as a measure of tracking in secondary education, and the percentage of students attending vocational programs in upper secondary education as a measure of vocational orientation in upper secondary education (Bol and van de Werfhorst 2013). Labor market institutions are operationalized by using the OECD measures of employment protection legislation (EPL) on the dismissal of workers on regular contracts (with at least 12 months), union density rates, and the wage differential between workers at the 50th and the 10th percentiles (P50/P10) as an indicator of wage inequality (the reverse of wage compression). Descriptive statistics and a correlation matrix for the country-level variables are presented in Tables 2 and 3

Table 1: Overview of the subsets of individual-level predictors

Constructs	Variables
<i>Job allocation</i>	
Job tasks	Factor of abstract tasks (based on five items)
	Factor of routine tasks (based on four items)
	Single-item indicator for manual tasks
	Single-item indicator for manual accuracy tasks
Job characteristics	Part-time employment (yes/no)
	Firm tenure in years
	Respondent's occupational status (ISEI)
	Computer use at work (yes/no)
Firm characteristics	Firm size (five categories)
	Public (vs. private) firm ownership
	Economic sectors (eight ISIC groups)
<i>Worker characteristics</i>	
Workers' skills	Numeracy proficiency
Workers' motivation to learn	Factor of motivation to learn (based on four items)
Socio-demographics (controls)	Gender, age, household status, household size, and foreign-birth/foreign-language status

4. Results

Figure 3 shows the training disadvantage of less-educated workers relative to intermediate-educated workers in the 27 countries *before* and *after* adjustment for the worker, job, and firm characteristics listed in Table 1 (above). While the unadjusted training disadvantage is statistically significant and negative in almost all countries, its magnitude varies considerably across countries—ranging from -30 percentage points in Germany to only -3 percentage points in Japan.²⁰ This country variation decreases considerably once we account for all predictors: This fully adjusted training disadvantage is considerably lower in all countries and statistically insignificant in most countries. It ranges only from -13 percentage points in Lithuania to 5 percentage points in Japan.

²⁰ For training participation rates for less- and intermediate-educated workers by country see Figure 2 above.

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Table 2: Descriptive statistics of the country-level variables used

	Country code	Un-adjusted disadvantage	Fully adjusted disadvantage	Union density	Employment protection legislation	Wage inequality (P50/P10)	Skills gap	Index of external differentiation	Prevalence of vocational enrolment	% of less-educated adults	% non-employed among less-educated adults
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Austria	AT	-11.8	1.0	28.3	2.4	1.7	27.2	1.8	78.3	17.6	40.2
Belgium	BE	-9.1	-0.3	55.1	3.1	1.4	27.9	1.0	61.8	28.7	45.7
Canada	CA	-16.6	-6.3	29.8	1.5	1.9	46.4	-1.3	2.8	11.4	37.6
Chile	CL	-21.8	-5.6	15.3	1.8	1.6	40.5	0.3	37.0	38.6	35.3
Czech Rep.	CZ	-21.6	-11.7	15.4	2.8	1.9	30.6	1.6	79.2	7.7	46.2
Denmark	DK	-11.6	-4.9	67.8	2.3	1.4	27.9	-0.9	50.6	23.1	31.2
Estonia	EE	-12.9	1.7	7.0	2.1	2.0	31.1	Not avail.	31.0	11.0	34.7
Finland	FI	-11.0	-6.1	69.5	2.2	1.5	16.2	-0.9	57.1	16.3	37.4
France	FR	-13.8	-4.6	9.1	2.8	1.4	31.5	-0.5	49.6	28.4	36.1
Germany	DE	-24.8	-10.0	18.4	2.8	1.9	42.8	1.9	60.3	13.7	34.3
Greece	GR	-9.2	3.9	23.1	2.4	1.7	22.8	-0.5	33.9	31.7	35.1
Ireland	IE	-17.3	-8.3	32.7	2.0	2.0	37.6	-0.3	32.9	26.4	41.5
Israel	IL	-20.4	-7.8	22.8	2.2	2.0	39.6	-0.1	34.8	14.6	47.4
Italy	IT	-16.7	-6.2	35.8	3.0	1.4	33.5	0.2	61.7	44.0	43.9
Japan	JP	-5.5	5.0	18.0	2.1	1.6	23.5	-0.5	24.6	Not avail.	Not avail.
Korea	KR	-17.8	-3.7	9.8	2.2	2.0	28.2	0.1	28.6	18.5	32.9
Lithuania	LT	-22.9	-13.4	8.1	2.4	1.8	19.3	Not avail.	28.2	8.8	35.8
Netherlands	NL	-11.4	0.5	19.3	2.9	1.6	32.5	0.9	68.5	27.7	35.2
New Zealand	NZ	-12.7	-5.0	18.5	1.0	1.6	33.1	-0.4	24.3	25.9	25.2
Norway	NO	-14.1	-8.1	49.3	2.3	1.6	21.0	-1.0	60.2	18.1	28.4
Poland	PL	-8.2	2.2	17.0	2.4	2.0	27.2	-0.1	47.3	11.1	52.3
Slovenia	SI	-18.1	-3.1	26.4	2.4	1.7	35.8	0.1	64.1	14.3	42.6
Spain	ES	-15.3	-5.2	17.9	2.6	1.6	30.6	-1.0	40.6	46.0	29.0
Sweden	SE	-14.9	-11.5	68.3	2.5	1.3	28.6	-0.9	55.8	13.0	27.0
Turkey	TR	-16.4	-4.4	6.9	2.3	1.2	33.3	1.2	37.6	64.4	44.5
United Kingdom	UK	-12.7	-3.2	26.5	1.8	1.8	35.1	-1.0	36.6	23.2	37.1
United States	US	-12.7	-0.8	11.3	1.2	2.1	39.7	-1.3	0.0	10.7	39.0

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Mean	-14.9	-4.3	26.9	2.3	1.7	31.2	-0.1	44.0	22.9	37.5
Standard dev.	4.7	4.8	19.0	0.5	0.2	7.2	1.0	20.1	13.5	6.7

Notes: Alphabetical order. Training gap estimates are controlled for socio-demographics. For the country-level regressions all predictors were z-standardized to have a mean of 0 and a standard deviation of 1.

Sources: 1-2, 6: PIAAC (rounds 1 and 2), authors' calculations; 3-5, 9-10: OECD online database (<https://stats.oecd.org/>); 7: Educational Systems Database, Version 4 (Bol and Van de Werfhorst 2013); 8: OECD (2006: Table C2.5), UNESCO online database (<http://data.uis.unesco.org/>) and World Bank online database (<http://datatopics.worldbank.org/education>).

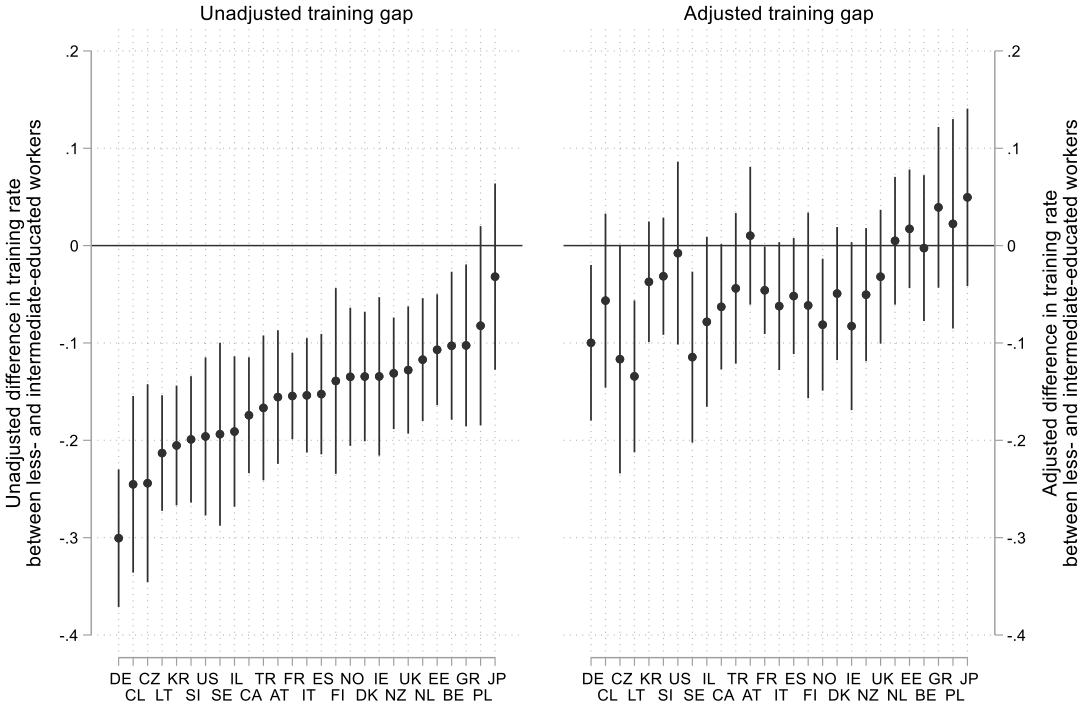
Table 3: Correlation matrix of country-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Unadjusted disadvantage	1									
(2) Fully adjusted disadvantage	0.783***	1								
(3) Union density	0.272	-0.193	1							
(4) Employment protection legislation	-0.081	-0.085	0.174	1						
(5) Wage inequality (P50/P10)	-0.224	0.070	-0.472*	-0.370	1					
(6) Skills gap	-0.448*	-0.140	-0.316	-0.285	0.336	1				
(7) Index of external differentiation	-0.341	-0.016	-0.281	0.524**	-0.046	0.101	1			
(8) Prevalence of vocational enrolment	-0.054	-0.131	0.352	0.754***	-0.399*	-0.295	0.606**	1		
(9) % of less-educated adults	0.082	0.152	-0.107	0.173	-0.590**	0.062	0.119	0.023	1	
(10) % non-employed among less-educated adults	-0.016	0.193	-0.182	0.268	0.246	0.157	0.403	0.172	-0.015	1

Notes: N=27. For pairwise correlations involving (7) N=25 because the index is not available for Estonia and Lithuania, for correlations involving (9) and (10) N=26 because the shares are not available for Japan. * p < 0.05, ** p < 0.01, *** p < 0.001.

Sources: See Table 2.

Figure 3: Training disadvantage of less-educated employees relative to intermediate-educated employees in 27 countries



Notes: Ordered by size of unadjusted training disadvantage. The adjusted training disadvantage accounts for differences in worker, job, and firm characteristics (see Table 1). For country abbreviations see Table 4 below.
 Source: PIAAC, authors’ own calculations.

Table 4 shows the country-specific Shapley decomposition results on the portion of less-educated workers’ training disadvantage that is attributable to compositional differences in job allocation and worker characteristics in percentage points (i.e., in absolute terms) and as the percentage of the unadjusted training disadvantage (i.e., in terms of “disadvantage explained” by the given set of predictors). The total explained part, which captures the combined contribution of the six sets of predictors, is equal to the difference between the unadjusted and the fully adjusted gaps in Figure 3. We use the Shapley approach by Shorrocks (2013) to decompose the total contribution into the average marginal contribution of the six subsets of characteristics across all possible elimination paths (see Section 3). Table 4 presents the sum of the respective subsets for job allocation and worker characteristics. Figure 4 displays the percentage points for each of the six subsets of predictors (see Appendix, Section B, for the percentage of the unadjusted training disadvantage). For

a better interpretation, we reversed the coding of the training disadvantage as dependent variable: Positive values mean that compositional differences with respect to the given set of predictors contribute to less-educated workers' training disadvantage, whereas negative values indicate that the given compositional differences reduce this training disadvantage (meaning that it would be even larger without these differences).

Table 4 shows that differences in job allocation characteristics contribute more to less-educated workers' training disadvantage than worker characteristics in all countries, except in Sweden. Among the job allocation indicators, job characteristics—that is, firm tenure in years, occupation, and part-time employment—have the largest impact on the training disadvantage of less-educated workers in most countries, while the contribution of jobs tasks is highest in three countries and that of firm characteristics in four countries (see Figure 4).

Figure 4 also shows that workers' skills account for a meaningful portion of the training disadvantage of less-educated employees in many countries, but with a considerably smaller proportion than the respective job allocation subset with the largest contribution in each country. Workers' skills are only more relevant in Canada than each of the three separate job allocation subsets. In eleven countries, workers' skills account for less than a tenth of the unadjusted gap, or their estimate is even close to zero. Motivation to learn is only marginally associated with the training disadvantage in all countries. The results for differences in the socio-demographic composition of less- and intermediate-educated workers are mixed: In some countries, they also play a minor role; in others, they are notably (but to a lesser extent than job allocation predictors) associated with the extent of the training disadvantage.

In sum, these results support our first expectation: Within-country differences in participation in job-related NFT between less- and intermediate-educated workers are largely driven by differences in job allocation—with the subset of job characteristics having the highest explanatory power in the vast majority of countries.

Table 4: Country-specific Shapley decompositions of less-educated workers' training disadvantage (reversed coded)

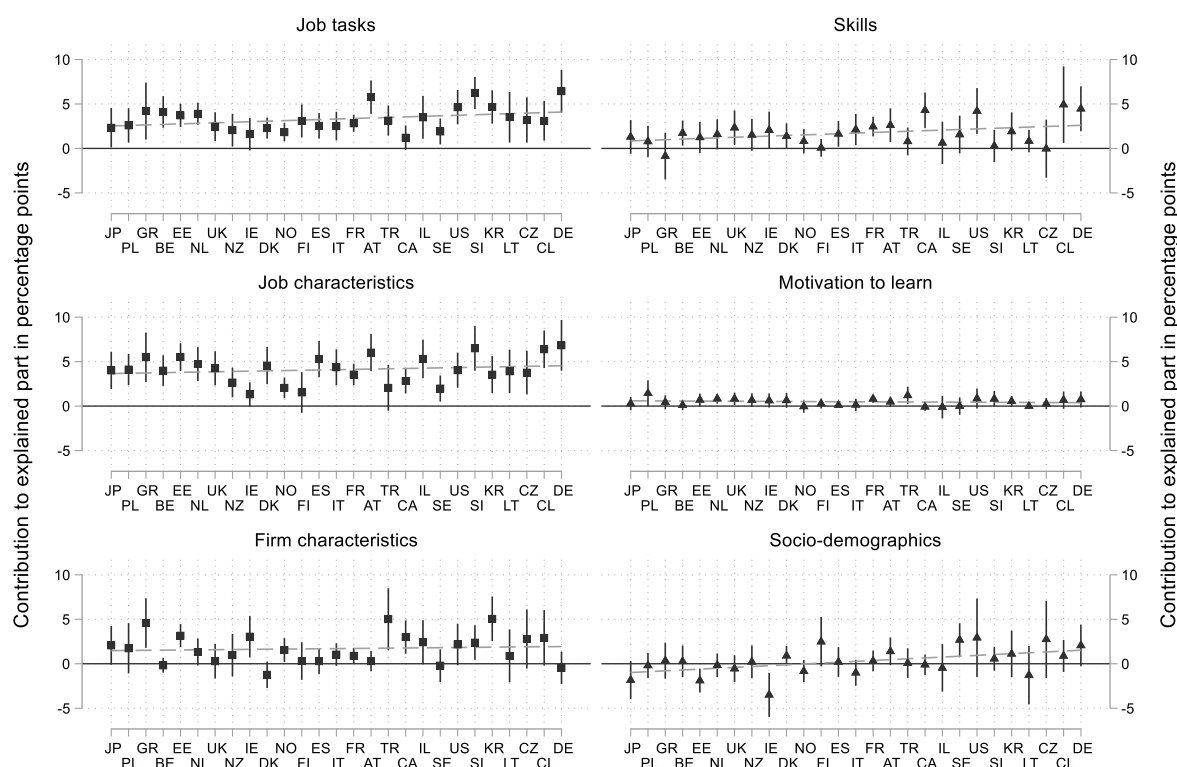
Country	Country code	Unadjusted training disadvantage	Total explained part of the training disadvantage		Explained part attributable to sets of predictors				
			% points	% points	% of unadj. disadvantage	(1) % points and (2) % of the unadjusted training disadvantage		(1) % points and (2) % of the unadjusted training disadvantage	
						Job allocation characteristics		Worker characteristics	
					(1)	(2)	(1)	(2)	
Austria	AT	15.6***	16.6***	106.6	11.7***	75.2	4.9***	31.3	
Belgium	BE	10.3**	10.0***	97.5	7.7***	74.9	2.3+	22.6	
Canada	CA	17.4***	11.1***	63.9	7.0***	40.2	4.1***	23.7	
Chile	CL	24.5***	18.9***	77.0	12.2***	49.9	6.6*	27.1	
Czech Rep.	CZ	24.4***	12.7***	52.2	9.6***	39.5	3.1	12.7	
Denmark	DK	13.4***	8.5***	63.4	5.3***	39.1	3.3**	24.3	
Estonia	EE	10.7***	12.4***	116.1	11.9***	111.1	0.5	5.0	
Finland	FI	13.9**	7.8***	55.8	4.8**	34.6	2.9*	21.2	
France	FR	15.4***	10.9***	70.3	7.2***	46.5	3.7***	23.8	
Germany	DE	30.1***	20.1***	66.8	12.1***	40.2	8.0***	26.6	
Greece	GR	10.3*	14.2***	138.3	14.1***	138.0	0.0	0.3	
Ireland	IE	13.4**	5.2*	38.4	5.9***	44.1	-0.8	-5.7	
Israel	IL	19.1***	11.3***	59.0	11.0***	57.6	0.3	1.4	
Italy	IT	15.4***	9.2***	59.6	7.7***	49.8	1.5	9.8	
Japan	JP	3.2	8.1***	255.5	8.3***	259.9	-0.1	-4.4	
Lithuania	LT	21.3***	7.9**	37.0	7.9***	37.0	-0.0	-0.0	
Netherlands	NL	11.7***	12.2***	104.2	9.7***	82.8	2.5+	21.5	
New Zealand	NZ	13.1***	8.1***	61.6	5.5**	41.6	2.6+	20.0	
Norway	NO	13.5***	5.4***	39.7	5.4***	39.7	-0.0	-0.0	
Poland	PL	8.2	10.5***	127.2	8.1***	98.2	2.4+	29.0	
Slovenia	SI	19.9***	16.8***	84.2	14.8***	74.3	2.0	9.9	
South Korea	KR	20.5***	16.8***	81.9	13.1***	63.7	3.7*	18.2	
Spain	ES	15.3***	10.1***	66.0	8.0***	52.7	2.0+	13.4	
Sweden	SE	19.4***	7.9***	40.9	3.4*	17.8	4.5**	23.1	
Turkey	TR	16.7***	12.3***	73.7	10.2***	61.3	2.1+	12.3	
United Kingdom	UK	12.8***	9.6***	75.0	6.7***	52.6	2.9*	22.4	
United States	US	19.6***	18.8***	96.0	10.5***	53.7	8.3**	42.3	

Notes: Alphabetical order. Positive values of the disadvantage indicate how much higher the training participation of intermediate-educated workers is compared to the less-educated group. Correspondingly, positive (negative) values of explained part indicate that compositional differences in job allocation or worker characteristics contribute to (reduce) within-country variation in the training disadvantage. Contributions of each set are estimated as the average contribution to the training disadvantage over all possible permutations of the different sets (Shapley decomposition). For subsets see Figure 4 and Appendix, Section B.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests).

Source: PIAAC, authors' own calculations.

Figure 4: Country-specific Shapley decompositions of less-educated workers' training disadvantage (reversed coded) for the six subsets of predictors (explained part in percentage points)



Notes: Ordered by size of unadjusted training disadvantage (see Figure 3). Horizontal lines indicate 95% confidence intervals. Dashed line: linear regression line. Shapley decomposition: contributions of each set are estimated as the average contribution to the training disadvantage over all possible permutations of the different sets (for variables see Table 1). For further information and % of the unadjusted training disadvantage see Appendix, Section B.

Source: PIAAC, authors’ own calculations.

These within-country results, however, do not yet allow us to make any statements about the contribution of job allocation (vs. worker characteristics) to the cross-national variation of the training disadvantage. A set of factors can play a crucial role in accounting for within-country differences in training participation while contributing very little to between-country variation—namely, when this crucial (absolute) within-country contribution does not vary, or only little, by the size of the training disadvantage. The dashed regression lines in Figure 4 indicate, for example, larger associations of the unadjusted training disadvantage (the ordering in Figure 4) with workers’ skills or socio-demographic characteristics than with all job allocation subsets.

Calculations of the between-country variance based on random-effects models (see Section 3) indicate that the “true” variance decreases from 13.3 for the unadjusted to 3.5 for the fully adjusted training gap (Table 5). This is a reduction of the total variance of 9.8 (or about 73.5 percent).

To assess the relative importance of job allocation for explaining country differences in the training disadvantage, we again use Shapley decompositions. Table 5 presents these averaged contributions of each subset in absolute terms (as percentage points squared) and in terms of “variance explained” by the given set of predictors (as percentage of the overall between-country variance in the unadjusted gap). The two most important factors for explaining the cross-national variance of the training disadvantage are country differences in workers’ skills and socio-demographics, reducing the between-country variance by 3.4 and 5.3 percentage points squared, respectively. This corresponds to reductions of 25.6 and 39.7 percent, relative to the baseline variance of 13.3 percentage points squared.

In contrast to the within-country analyses, job tasks, job characteristics, and firm characteristics are less important than workers’ skills. The contributions of the two subsets job characteristics and workers’ motivation to learn are even negative, but very small. If anything, their distribution appears to slightly attenuate—rather than contribute to—cross-national variation in the training disadvantage. Thus, in contradiction to our second expectation, job allocation characteristics contribute less to the explanation of cross-national variation than workers’ skills. As job allocation characteristics are so strong in explaining differences in the training disadvantage in all countries, they seem to be less predictive for between-country differences.

In a final step, we explore the role of educational and labor market institutions for the cross-national variation on less-educated workers’ training disadvantage. For each institutional factor, we estimated a sequence of regressions with different dependent variables (see Table 6): the unadjusted training disadvantage in model M1, different partly adjusted versions of the training disadvantage in specifications M2a to M2e (adjusted only for the mentioned subset), and the fully adjusted training disadvantage in model M3. As socio-demographic differences contribute markedly to between-country variation in the training disadvantage (see Table 5 above), we control for socio-demographic differences in all specifications, meaning the unadjusted training disadvantage is adjusted for socio-demographics as well. Given the small sample of only 27 countries, we entered the institutional explanatory variables one at a time.

	Variance of the training disadvantage	Explained part of the variance attributable to adjusting for given group of predictors	
		% points squared	% of unadjusted variance
Between-country variance of unadjusted training gap	13.3	---	----
<i>Adjusted for</i>			
Job allocation			
Job tasks		1.1	8.2
Job characteristics		-0.1	-0.7
Firm characteristics		0.6	4.3
Worker characteristics			
Workers' skills		3.4	25.6
Workers' motivation to learn		-0.5	-3.6
Socio-demographics (controls)		5.3	39.7
Between-country variance of fully adjusted training gap	3.5	----	73.5

Table 5: Shapley decomposition of cross-national variance in the (reversed coded) training disadvantage

Notes: True between-country variances estimated using random-effects models, estimated by restricted maximum likelihood. Positive (negative) values of explained part indicate that compositional differences with respect to the given set of predictors contribute to (reduce) between-country variation in the training disadvantage (reversed coded). Contributions of each set are estimated as the average incremental change in variance over all possible permutations of the different sets. Country-specific regressions for estimating the fully adjusted training gap are reported in the Appendix (Section C).

Source: PIAAC, authors' own calculations

Table 6 summarizes the results of altogether 48 separate country-level regressions. Again, we use a reversed coding for the training disadvantage to facilitate a more intuitive interpretation. Thus, positive estimates mean an increase in the training disadvantage and negative estimates a reduction. All six country-level predictors are z-standardized, so the coefficient estimates can be interpreted as the predicted change in the training disadvantage associated with a standard deviation increase in the respective institutional characteristic. We use bootstrapping to assess whether changes in effect sizes between the unadjusted model (M1) and the partly or fully adjusted models (M2a-2e, M3) are statistically significant (see Section 3). Coefficient estimates that differ significantly from M1 are underlined in Table 6.

Starting with the models M1, we see that none of the estimates reaches statistical significance at a 5 percent level; only trade union density is closer to it (with a significance level of 10 percent). Trade union density is associated with a smaller training disadvantage of less-educated workers of 1.3 percentage points for one standard deviation increase. This effect size is quite substantial: Given that the average unadjusted training disadvantage across the 27 countries is -14.9 percentage points, with a cross-country standard deviation of 4.7 percentage points (see Table 2 above), the estimate of 1.3 percentage points corresponds to 27.6 percent of the standard deviation. Similarly, only looking at the effect sizes (though estimated with high uncertainty), wage inequality (1.1 percentage points), skill transparency (1.8 percentage points), and external differentiation in secondary education (1.2 percentage points) are associated with a larger training disadvantage. In contrast, the effect sizes for high employment protection legislation and vocational orientation in upper secondary education are not only insignificant but also close to zero.

Turning to the M2a-e specifications for these four more substantial institutional characteristics, we see that the predictive power of union density and wage inequality decreases substantially when controlling for job allocation characteristics (specifications 2a to 2c) but does not change substantially when including workers' skills or motivation to learn (specifications 2d and 2e). These findings support our theoretical expectation that labor market institutions somewhat moderate workers' job allocation and its association with country differences in less-educated workers' training disadvantage. The estimates suggest that less-educated employees benefit from higher trade union density and less wage inequality in terms of job-related NFT participation by being allocated to "better" jobs, for example, skill-intensive jobs and/or jobs in training-active firms.

Table 6: Separate country-level regressions of the (reversed coded) training disadvantage of less-educated workers (controlled for socio-demographics)

	Unadjusted dis- advantage	Partially adjusted disadvantage					Fully adjusted dis- advantage
	M1	Job tasks M2a	Job char. M2b	Firm char. M2c	Workers' skills M2d	Workers' motivation to learn M2e	M3
Labor market institutions							
Union density	-0.013 ⁺ (0.006)	<u>-0.004</u> (0.008)	<u>-0.003</u> (0.009)	<u>-0.000</u> (0.006)	-0.009 (0.007)	<u>-0.011</u> (0.007)	<u>0.009</u> (0.008)
Employment protection legislation	0.003 (0.008)	-0.003 (0.008)	-0.004 (0.007)	0.007 (0.007)	0.004 (0.007)	0.002 (0.008)	0.002 (0.007)
Wage inequality (P50/P10)	0.011 (0.008)	0.005 (0.008)	0.003 (0.009)	<u>0.001</u> (0.007)	0.008 (0.008)	0.011 (0.008)	<u>-0.004</u> (0.008)
Educational institutions							
Skills transparency (skills gap btw. less- and intermediate-educated adults)	0.018 (0.014)	0.017 (0.012)	0.012 (0.013)	0.016 (0.014)	<u>0.005</u> (0.013)	0.017 (0.014)	<u>0.006</u> (0.012)
External differentiation in secondary education (tracking) ^{a)}	0.012 (0.012)	<u>-0.005</u> (0.012)	<u>-0.001</u> (0.012)	0.010 (0.012)	0.008 (0.010)	<u>0.009</u> (0.013)	<u>-0.005</u> (0.011)
Vocational orientation of upper secondary education	-0.001 (0.008)	-0.009 (0.010)	-0.007 (0.010)	<u>0.008</u> (0.008)	0.001 (0.009)	-0.002 (0.009)	0.002 (0.010)

Notes: N = 27 countries; ^{a)} N = 25 (w/o Estonia, Lithuania). Feasible Generalized Least Squares (FGLS) estimates, based on 10 imputations/plausible values. All country-level variables are z-standardized (mean of 0, standard deviation of 1). Robust HC3 standard errors in parentheses. ⁺p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed tests). Underlined coefficient estimates differ significantly from coefficients in M1. Country-specific regressions for estimating the fully adjusted training gap are reported in the Appendix (Section C).

Source: PIAAC, authors' own calculations.

Concerning educational institutions, the considerable reductions in the effect sizes suggest a moderating role of external differentiation via job allocation (M2a and M2b) and of skills transparency via workers' skills (M2d). Moreover, the strong explanatory role of workers' skills for between-country differences in the training disadvantage (as presented in Table 5 above) is not moderated by labor market but educational institutions.

Model M3 shows that all remaining associations between labor market institutions and the *fully* adjusted training disadvantage are insignificant and small, and the estimates for the four institutional features with substantial associations in M1 differ significantly from the M1 estimates. Interestingly, in model M3 the association for union density turns positive, meaning that union density increases the training disadvantage when accounting for the several predictors. One possible explanation is that, beyond job allocation, trade unions focus strategically more on skilled employees than less-educated workers in their commitment to further training (Wotschack 2020).

In sum, the findings from this explorative country-level regression analyses support our third expectation that educational and labor market institutions—that is, union density, wage inequality, and external differentiation—are associated with country differences in job-related NFT participation rates of less- and intermediate-educated workers by moderating their job allocation. For the role of workers' skills, only the extent of countries' skills transparency of educational certificates appears to be a moderating institutional feature.

5. Discussion

To assess the robustness of our findings, we conducted a series of sensitivity analyses (partly presented in the Appendix, otherwise available upon request from the authors). Overall, these additional analyses indicate that our results are quite robust and, most likely, conservatively estimated. We reran each step of our analysis using literacy instead of numeracy proficiency. Results were very similar to the main analysis.

Section D (Appendix) reports the findings of influence diagnostics examining the impact of individual country cases on the country-level regression results presented in Table 6 (above). This analysis revealed that the Slovak Republic has an enormous impact on the regression results and was therefore excluded from our analysis.

We excluded workers who had worked in their current jobs for less than 12 months, so that—given the cross-sectional nature of the data—the time frame for job allocation characteristics

and training incidence match (see Appendix, Section E). The individual-level results are similar to the results presented in Section 4. For the between-country analyses, we see some important changes: First, both the unadjusted and the fully adjusted training disadvantage are considerably larger than in the analyses presented above. Second, cross-national variation in the training disadvantage increases considerably—mainly attributable to differences in job allocation: The joined contribution of job tasks and other job characteristics to the explanation of the between-country variance is larger (not smaller as in the main sample) than the contribution of workers’ skills. Third, the influence of educational and labor market institutions on the training disadvantage increases—again, mostly by moderating workers’ job allocation. Thus, the exclusion of mobile workers from the analysis increases (rather than reduces) both the training disadvantage of less-educated workers and the role of job allocation. Put differently, job mobility of less-educated workers (within the last 12 months) seems to be associated with higher participation in job-related NFT participation as well as higher skills.

Finally, we address concerns that our results presented in Table 6 might be confounded by cross-national differences in aggregated factors related to selection into employment of less-educated adults and substantial correlations with some of our institutional measures. We included the share of less-educated adults as a control variable in our country-level regression as higher shares could decrease their risk of being stigmatized and hence increase their likelihood of employment (Gesthuizen, Solga, and Künster 2011; Solga 2002) and because of its notable correlation with wage inequality (Pearson’s r of -0.590 , see Table 3 above). As expected, higher shares are associated with a smaller training disadvantage of less-educated workers via both job allocation and workers’ skills. Secondly, we controlled for the share of non-employed adults in the less-educated group as a selectivity indicator and because of its notable correlation with external differentiation (0.403). Higher shares are associated with an increase in the training disadvantage via job placement. Both indicators do not, however, change the results of our main analysis.

Among the limitations of our study is that we cannot make any causal claims given our cross-sectional data. We are unable to disentangle interdependencies between the observed variables both at the individual and the country level. However, in contrast to existing studies on training participation, our analyses include high-quality individual-level measures of workers’ skills; and we apply the Shapley decomposition technique to account for the sequence of introducing the predictors into the estimation models. In so doing, we account at least partially for any potential confounding of workers’ skills on the role of job allocation for the education-training relationship.

Moreover, the sample size of less-educated workers is small, generally resulting in larger standard errors; yet we were still able to identify statistically significant effects. Our sample of *employed* workers is not randomly selected, for example, in terms of participation in job-related NFT (see Figure 2 above) or skills (see Appendix, Section A). This kind of selectivity would suggest, however, that the effects of the predictors are conservative.

6. Conclusions

A better understanding of the relationship between educational attainment and participation in adult training is of high interest both theoretically and policy-wise. Theoretically, this relationship concerns the question of whether differences in job characteristics (and work environments) or attainment-related worker characteristics, such as workers' skills and motivation to learn, are the main driver of inequality in workers' training participation, which in turn results in labor market inequalities. As discussed in the article, several studies, mostly for single countries and predominantly for Germany, find that job allocation is more important than worker characteristics for training participation. However, this research often does not differentiate between educational groups and does not include measures of workers' actual skills, with the latter being a potential confounder of the estimates for job characteristics. Policy-wise, a better understanding of within- and between-country differences in this education-training relationship is important as it opens different "doors" for reducing inequality in training participation.

Against this background, we examined the education-training relationship for less-educated workers compared to intermediate-educated workers using the recent PIAAC data. We study job-related non-formal training (NFT) because this type of adult training is both the most dominant type of adult training in advanced economies and most closely related to the job allocation vs. worker characteristics question.

Our main findings are: First, in all countries, differences in job allocation by educational attainment contribute significantly to the training disadvantage of less-educated workers, above and beyond skills differentials and other worker characteristics. Job tasks, job characteristics, and firm characteristics are indeed the most important predictors of differences in training participation between less- and intermediate-educated workers in all 27 countries, except Sweden. The subset of job characteristics (including employment tenure in years, occupation, and part-time employment) has the highest explanatory power in the majority of countries. Second, accounting for differences in

job allocation and workers' skills at the individual level markedly reduces cross-national variation in less-educated workers' training disadvantage. In contrast to the within-country finding, skills differentials between less- and intermediate-educated workers are more important than job allocation for explaining between-country differences. Hence, on the one hand, single-country studies might underestimate the importance of workers' skills that we observe for explaining cross-national differences in training participation. On the other hand, only looking at between-country differences might underestimate the role of job characteristics. Third, the educational and labor market institutions considered in this study appear to contribute to cross-national variation in less-educated workers' training disadvantage primarily via moderating the individual-level mediation via job allocation and, to a lesser extent, via worker characteristics. For limitations of our study, see the discussion in Section 5.

The mutually reinforcing relationship between job allocation and training participation, found in our study, creates a vicious cycle for less-educated workers: They are more likely to be exposed to work situations that require fewer skills investments and provide less job-related learning opportunities, which in turn increases the risk of cementing their poor labor market prospects. Thus, policies designed to enhance less-educated workers' skills and labor market integration should not only focus on their training participation per se but also, and maybe foremost, on their workplace conditions, including access to skill-enhancing jobs and job-related NFT. However, country differences in the importance of the different job allocation characteristics should be considered when designing country-specific policies in this respect. The same applies to country differences in the importance of workers' skills differentials. Thus, for countries with a high impact of skills differentials, policies should also target on initial education in order to reduce skills inequality between educational groups as early as possible.

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Appendix

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- Section E. Country-level results with sample restriction to at least one year job tenure with the employer at time of interview



Section A. Descriptive statistics of the variables used

Table A1: Descriptive statistics of the individual-level variables used

Country	Country code	%					Mean							
		Training participation	Less-educated (ISCED 0-2)	Intermed.-educated (ISCED 3-4)	Computer use at work	Part-time	Numeracy score	Learning motivation	Abstract tasks	Routine tasks	Manual-physical tasks	Manual-accuracy tasks	Firm tenure	ISEI score
Austria	AT	46.3	16.9	83.1	70.4	26.3	273.8	0.1	0.0	-0.5	3.4	4.1	10.0	40.6
Belgium	BE	39.6	18.4	81.6	59.3	21.5	271.2	-0.4	-0.1	-0.2	3.5	4.0	11.3	36.8
Canada	CA	51.2	17.2	82.8	66.0	15.6	251.4	0.3	0.2	-0.0	3.5	4.4	8.1	40.9
Chile*	CL	44.6	36.6	63.4	32.9	14.6	197.9	0.4	-0.2	0.4	3.6	4.5	5.5	29.4
Czech Rep.	CZ	54.4	8.1	91.9	58.0	4.3	271.2	-0.0	0.1	-0.1	3.5	4.0	8.2	36.8
Denmark	DK	58.1	27.4	72.6	74.3	15.5	273.8	0.3	0.0	-0.5	3.6	4.3	7.2	38.5
Estonia	EE	42.8	17.5	82.5	50.6	7.5	265.9	-0.2	-0.2	-0.1	3.7	4.4	6.3	35.7
Finland	FI	57.6	13.8	86.2	75.8	11.6	280.1	0.4	0.3	-0.6	3.3	3.9	9.0	34.8
France	FR	34.3	27.4	72.6	55.0	16.3	243.9	0.2	-0.2	0.3	3.4	3.7	10.8	36.1
Germany	DE	41.4	11.4	88.6	61.7	30.6	265.9	-0.0	0.0	-0.4	3.6	4.3	9.8	35.6
Greece*	GR	20.2	27.2	72.8	41.9	20.2	248.1	-0.0	-0.3	0.7	3.7	4.0	8.7	33.3
Ireland	IE	46.2	27.4	72.6	57.4	34.3	248.0	0.1	0.1	0.3	3.6	4.4	8.8	36.8

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Israel	IL	34.1	17.1	82.9	53.2	21.0	238.2	0.0	-0.1	-0.1	3.2	3.9	6.5	41.0
Italy	IT	25.2	49.6	50.4	45.5	19.3	251.5	0.2	-0.3	0.4	3.4	3.9	11.1	35.2
Japan	JP	35.0	14.2	85.8	70.3	19.0	283.2	-0.9	-0.0	-0.5	2.9	2.9	11.0	36.2
Lithuania*	KR	24.1	6.9	93.1	30.5	7.5	259.4	-0.5	-0.6	0.7	4.0	4.4	7.3	32.8
Netherlands	LT	59.0	34.8	65.2	77.6	36.6	275.2	-0.4	0.0	-0.0	3.4	3.8	9.6	42.3
New Zealand*	NL	61.4	35.7	64.3	65.9	23.8	260.4	0.3	0.5	-0.2	3.8	4.6	7.4	40.8
Norway	NZ	56.9	28.4	71.6	80.4	22.4	271.1	0.2	0.2	-0.4	3.6	3.4	8.1	37.8
Poland	NO	31.5	8.3	91.7	36.4	6.7	252.9	-0.0	-0.3	0.2	4.1	4.6	8.8	33.6
Slovenia	SK	42.6	18.0	82.0	55.1	5.7	252.7	-0.1	-0.2	0.4	3.9	4.6	11.6	36.0
South Korea	SI	37.0	19.3	80.7	50.1	15.2	250.3	-1.1	-0.1	0.4	3.7	2.6	5.1	32.3
Spain	ES	40.6	58.2	41.8	42.5	17.7	244.2	0.2	-0.3	0.2	3.6	3.7	8.8	32.9
Sweden	SE	56.3	19.7	80.3	81.3	14.3	275.2	0.3	0.2	-0.5	3.4	3.8	8.8	38.9
Turkey*	TR	29.6	66.6	33.4	28.5	5.9	224.1	-0.2	-0.5	0.2	4.2	4.0	6.5	34.1
United Kingdom	UK	55.9	32.2	67.8	68.9	25.7	257.5	0.1	0.3	0.0	3.4	4.3	8.3	37.2
United States	US	52.0	13.5	86.5	65.5	14.4	242.5	0.4	0.3	-0.0	3.9	4.7	7.4	37.9
Mean		43.6	24.9	75.1	57.6	17.5	256.6	-0.0	-0.0	-0.0	3.6	4.0	8.5	36.5
Standard dev.		11.8	14.8	14.8	15.4	8.6	18.6	0.4	0.3	0.4	0.3	0.5	1.8	3.1

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Table continues on next page.

Table A1: Descriptive statistics of the individual-level variables used (continued)

Country	Firm size (in %)					Sector (in %)								Public Sector (in %)	N
	1-10 employees	11-50	51-250	251-1000	1000+	Agri-culture	Mining	Manu-facturing	Electricity/Water supply	Construc-tion	Commerce	Transport	Services		
Austria	26.7	31.2	20.4	14.6	7.1	1.0	0.3	19.1	1.2	7.7	17.1	6.0	47.5	21.9	1,730
Belgium	20.7	28.5	29.5	13.2	8.1	0.6	0.2	24.9	1.8	8.4	11.9	10.3	41.8	24.0	1,219
Canada	24.8	32.2	24.9	12.1	6.0	1.5	2.6	15.1	1.6	11.1	19.0	6.5	42.7	19.4	4,976
Chile*	38.5	27.6	20.7	9.2	3.9	9.8	3.9	18.0	1.0	8.5	15.7	6.8	36.2	11.7	1,135
Czech Rep.	30.8	30.4	22.2	11.7	5.0	2.0	1.6	37.9	3.4	6.3	12.4	7.3	29.0	20.1	1,523
Denmark	23.9	35.8	24.9	10.7	4.7	1.4	0.1	20.4	2.3	10.9	14.1	7.6	43.0	26.5	1,335
Estonia	33.3	36.9	19.5	7.3	3.0	5.0	1.2	28.4	1.3	11.5	14.9	8.3	29.4	16.9	1,761
Finland	32.3	35.0	21.2	8.5	3.0	1.9	0.5	20.2	1.3	10.5	15.3	10.3	40.0	25.1	1,006
France	29.9	29.5	21.3	12.7	6.6	1.5	0.2	18.0	1.7	9.9	14.0	7.9	46.7	21.7	1,743
Germany	28.9	25.4	22.9	14.9	7.9	0.9	0.4	25.5	2.0	7.0	16.3	6.8	41.1	14.1	1,737
Greece*	48.8	30.1	13.6	4.6	3.0	2.4	0.0	13.0	5.3	4.9	17.4	6.4	50.7	26.0	751
Ireland	35.0	34.2	17.2	9.7	4.0	1.9	0.4	15.2	1.8	6.0	17.0	5.4	52.3	21.8	1,089
Israel	39.4	28.9	16.8	8.1	6.8	0.6	0.1	13.7	1.0	9.3	16.3	5.4	53.5	23.4	870
Italy	38.4	26.8	18.7	8.3	7.8	4.2	0.1	26.1	2.6	8.0	12.6	6.9	39.4	17.6	1,392
Japan	26.4	32.4	25.5	10.7	4.9	1.5	0.1	27.6	2.4	6.1	16.3	8.3	37.7	8.5	980
Lithuania*	24.0	33.4	27.2	12.7	2.7	6.2	0.3	27.5	1.6	10.9	16.7	8.9	28.0	20.1	1,186
Netherlands	22.8	32.1	26.0	11.5	7.6	0.7	0.1	17.6	0.5	7.3	15.7	6.2	51.9	21.4	1,358

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New Zealand*	33.3	32.5	23.1	7.6	3.4	6.8	0.9	17.5	1.5	10.9	15.6	6.5	40.2	16.6	1,121
Norway	25.2	36.3	20.7	9.9	7.9	1.0	2.1	11.0	1.0	12.1	20.4	7.5	44.9	27.5	1,120
Poland	28.8	30.5	22.9	11.1	6.8	2.1	2.0	29.9	2.6	13.7	18.0	7.5	24.3	21.8	1,335
Slovenia	25.1	25.7	25.6	14.3	9.2	1.5	0.6	35.9	2.2	8.1	12.3	7.3	32.2	22.5	1,429
South Korea	42.7	30.0	15.2	8.0	4.2	0.6	0.4	30.3	0.6	10.1	16.7	4.7	36.7	8.5	1,173
Spain	43.6	29.8	16.0	7.4	3.2	5.5	0.7	13.2	1.0	9.4	15.9	7.6	46.8	13.8	1,230
Sweden	25.6	32.3	23.6	11.4	7.1	1.0	0.2	17.0	1.7	8.5	14.1	8.2	49.3	28.5	1,084
Turkey*	38.2	26.3	18.4	10.8	6.3	2.4	1.1	27.9	1.4	9.3	14.0	6.0	37.9	13.8	867
United Kingdom	20.7	28.7	25.0	16.4	9.3	0.2	0.1	14.0	3.3	6.0	15.3	8.6	52.5	24.4	1,782
United States	22.3	30.5	24.2	14.1	8.9	1.1	0.9	16.1	1.4	8.8	13.4	6.7	51.6	16.4	1,388
Mean	30.7	30.9	21.7	10.8	5.9	2.4	0.8	21.5	1.8	8.9	15.5	7.3	41.7	19.8	
Standard dev.	7.6	3.2	3.9	2.8	2.1	2.3	0.9	7.3	1.0	2.1	2.1	1.4	8.3	5.5	

Notes: Alphabetical order. * Second PIAAC round. Weighted. Values are averages across 10 imputations/plausible values. ISEI=International Socio-Economic Index of Occupational Status; ISCED=International Standard Classification of Education. Socio-demographics are not presented, but available upon request.

Source: PIAAC, authors' own calculations.

Table A2: Individual-level skills statistics by country and employment status, separately for less- and intermediate-educated adults

Country	Country code	% non-employed		Mean numeracy score				Mean literacy score			
		ISCED 0-2	ISCED 3-4	ISCED 0-2		ISCED 3-4		ISCED 0-2		ISCED 3-4	
				Employed	Non-employed	Employed	Non-employed	Employed	Non-employed	Employed	Non-employed
Austria	AT	29.8	13.3	239.8	231.5	280.7	266.9	243.0	232.4	273.3	262.7
Belgium	BE	32.7	15.2	244.7	218.3	277.2	261.1	240.4	215.7	271.2	258.6
Canada	CA	44.7	23.2	213.0	194.6	259.3	238.4	222.4	211.2	269.6	255.7
Chile*	CL	41.3	28.5	168.2	142.6	215.0	194.5	187.2	167.0	227.5	213.8
Czech Rep.	CZ	45.1	22.7	238.2	224.6	274.0	265.4	245.1	232.2	272.1	265.7
Denmark	DK	36.0	19.4	252.4	222.7	281.9	268.5	247.6	220.9	271.4	263.4
Estonia	EE	36.4	20.5	243.2	225.3	270.7	255.1	248.8	237.8	271.8	262.2
Finland	FI	37.1	22.0	262.6	231.3	282.8	262.1	265.2	240.3	288.7	272.8
France	FR	36.0	19.9	214.8	194.8	254.8	241.7	230.4	219.7	261.4	258.0
Germany	DE	43.5	17.0	220.5	211.7	271.8	251.6	220.7	215.4	267.6	256.5
Greece*	GR	68.1	52.9	228.4	229.8	255.5	249.9	225.9	242.9	254.4	255.8
Ireland	IE	61.1	39.0	228.5	207.9	255.3	248.5	238.7	224.6	267.9	261.7
Israel	IL	55.2	30.7	200.4	192.2	246.1	229.6	210.3	202.4	249.7	239.0
Italy	IT	41.4	25.1	233.5	216.0	269.3	255.9	233.9	230.6	265.8	257.3
Japan	JP	24.9	17.7	261.2	244.2	286.9	276.5	279.9	267.9	295.6	293.6
Lithuania*	LT	59.1	31.5	242.7	231.6	260.6	243.7	244.5	245.4	260.1	252.7
Netherlands	NL	23.8	14.1	254.0	215.2	286.5	269.4	257.3	227.4	291.0	277.9



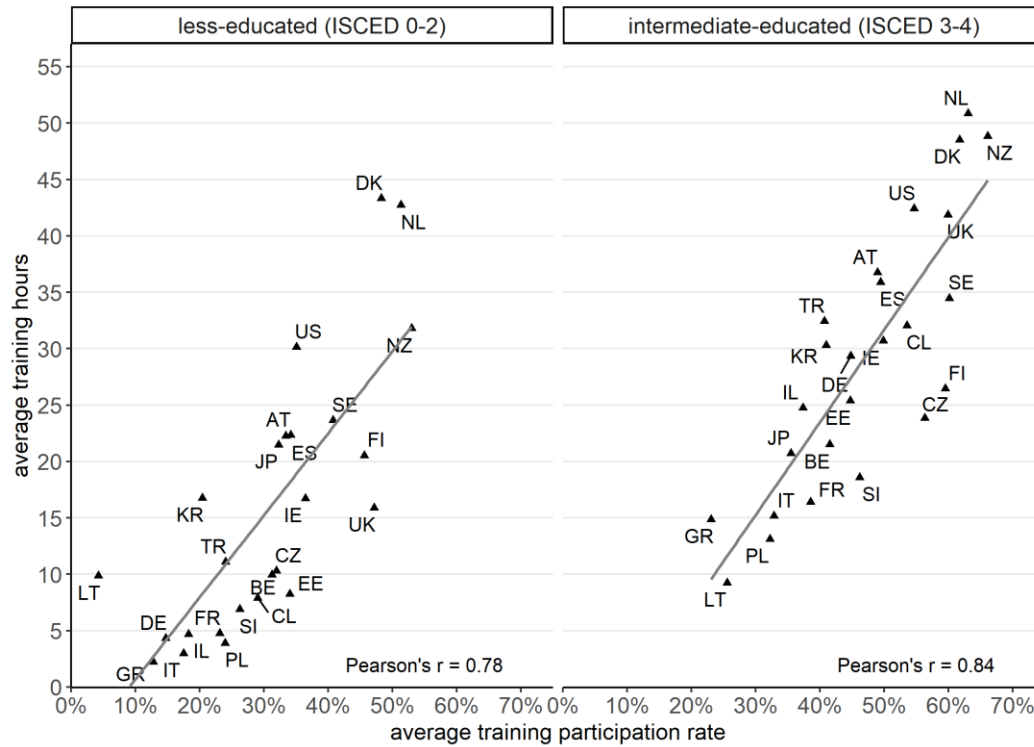
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New Zealand*	NZ	37.2	24.9	240.7	215.2	271.3	249.3	253.9	236.8	279.4	269.9
Norway	NO	26.9	14.9	254.0	222.3	277.9	262.0	259.1	237.7	276.5	265.8
Poland	PL	58.1	33.5	225.9	211.8	255.4	244.7	233.2	226.9	258.1	254.9
Slovenia	SI	46.0	23.1	218.7	199.8	260.2	257.0	223.6	216.0	254.6	257.6
South Korea	KR	35.8	29.3	221.7	208.9	257.1	258.4	234.4	225.7	265.2	268.9
Spain	ES	49.2	32.6	233.2	212.2	259.5	250.3	238.2	222.5	261.5	258.3
Sweden	SE	33.0	14.4	245.5	205.7	282.5	252.5	248.8	214.8	283.1	258.4
Turkey*	TR	69.4	50.1	213.6	192.2	245.1	241.5	220.5	209.9	244.6	244.9
United Kingdom	UK	50.5	28.3	234.6	204.2	268.3	239.4	246.2	228.3	278.5	260.9
United States	US	58.8	40.3	194.5	190.1	250.0	228.1	205.4	212.5	266.0	249.3
Mean		43.7	26.1	230.7	211.0	265.0	250.4	237.2	224.6	267.7	259.1
Standard dev.		12.8	10.4	21.3	19.7	16.0	16.4	19.4	17.9	14.5	13.8

Notes: Alphabetical order. * Second PIAAC round. Weighted. Values are averages across 10 plausible values.

Source: PIAAC, authors' own calculations.

Figure A1: Correlation between average training incidence and average training hours per employee by educational attainment



Notes: N = 25 (w/o Canada, Norway). Lines are linear fits estimated using linear least squares.

Source: PIAAC, authors' own calculations.

Table A3: Factor loadings for the principal-component factor analyses (PCF)

Abstract tasks¹	Factor
Read diagrams, maps or schematics (G_Q01h)	0.589
Write reports (G_Q02c)	0.610
Face complex problems (F_Q05b)	0.671
Persuading/influencing people (F_Q04a)	0.747
Negotiating with people (F_Q04b)	0.753
Routine tasks²	
Choose/change sequence of tasks (D_Q11a)	0.850
Choose/change how to do the work (D_Q11b)	0.859
Choose/change speed/rate of work (D_Q11c)	0.809
Choose/change working hours (D_Q11d)	0.623
Motivation to learn³	
Like learning new things (I_Q04d)	0.791
Like to get to the bottom of difficult things (I_Q04j)	0.861
Like to figure out how different ideas fit together (I_Q04l)	0.852
Look for additional information to make things clearer (I_Q04m)	0.815

Notes: N = 27. Multiple imputation estimates (10 imputations). Survey weights applied. Item scales: ¹ 1 (Never) to 5 (Every day); ² 1 (Every day) to 5 (Never); ³ 1 (Not at all) to 5 (To a very high extent). Original item numbers in parentheses.

Source: PIAAC, authors' own calculations.

Section B. Detailed results for country-specific Shapley-decompositions of the training gap

Table B1: Country-specific Shapley decompositions of less-educated workers' training disadvantage (reversed coded) for the six subsets of predictors

Country	Explained part attributable to sets of predictors											
	(1) percentage points and (2) % of the unadjusted training disadvantage											
	Job allocation subsets						Worker characteristics					
	Job tasks		Job characteristics		Firm characteristics		Skills		Motivation to learn		Socio-demographics	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Austria	5.8***	37.1	6.0***	38.7	0.3	1.9	2.6**	16.8	0.5+	3.1	1.4+	8.9
Belgium	4.1***	39.9	4.0***	38.8	-0.2	-1.8	1.7*	16.8	0.1	1.1	0.3	2.7
Canada	1.2+	6.9	2.8***	16.2	3.0**	17.2	4.3***	24.7	-0.1	-0.5	-0.1	-0.6
Chile	3.1**	12.7	6.4***	26.1	2.9+	11.9	4.9*	20.1	0.7	2.7	0.9	3.6
Czech Rep.	3.2*	13.1	3.8**	15.4	2.8	11.4	-0.0	-0.1	0.3	1.1	2.7	11.2
Denmark	2.3***	17.0	4.6***	33.9	-1.2	-9.2	1.4+	10.2	0.6	4.8	0.9	6.7
Estonia	3.7***	34.7	5.5***	51.5	3.2***	29.5	1.2	11.6	0.7+	6.5	-1.9**	-17.7
Finland	3.1**	22.2	1.5	11.1	0.3	2.2	0.1	0.5	0.3	2.0	2.5+	17.8
France	2.8***	18.3	3.6***	23.0	0.9*	5.8	2.5***	15.9	0.8***	5.3	0.3	2.0
Germany	6.4***	21.4	6.8***	22.7	-0.5	-1.5	4.5***	14.8	0.7	2.5	2.1+	6.8
Greece	4.2*	41.0	5.5***	53.6	4.6**	44.6	-0.9	-8.4	0.4	4.2	0.3	3.4
Ireland	1.6+	12.0	1.3+	9.9	3.1*	22.7	2.1+	15.3	0.6	4.6	-3.5**	-26.0
Israel	3.5**	18.3	5.3***	27.8	2.4+	12.7	0.6	3.3	-0.1	-0.6	-0.5	-2.5
Italy	2.5**	16.3	4.4***	28.4	1.0	6.8	2.1*	13.8	0.1	0.9	-1.0	-6.6
Japan	2.3*	73.1	4.0***	125.7	2.1+	64.8	1.3	40.6	0.3	8.9	-1.8+	-57.6
Lithuania	3.5*	16.5	3.9**	18.4	0.9	4.2	0.8	3.9	0.0	0.0	-1.3	-6.0
Netherlands	3.9***	33.3	4.7***	40.3	1.3+	11.3	1.6+	13.6	0.8**	7.1	-0.2	-1.4
New Zealand	2.1*	15.7	2.7**	20.2	1.0	7.4	1.5+	11.6	0.7+	5.1	0.2	1.6
Norway	1.8***	13.6	2.1***	15.3	1.5*	11.4	0.8	6.0	-0.0	-0.3	-0.8	-6.2
Poland	2.6**	31.5	4.1***	50.0	1.7	21.1	0.8	9.5	1.4+	17.4	-0.2	-2.4
Slovenia	6.2***	31.3	6.5***	32.6	2.4*	12.0	0.3	1.4	0.8+	4.1	0.6	2.8
South Korea	4.7***	22.7	3.5***	17.3	5.1***	24.6	1.9+	9.3	0.5+	2.6	1.1	5.4
Spain	2.5***	16.7	5.3***	34.7	0.3	1.9	1.6*	10.7	0.1	0.7	0.2	1.3
Sweden	1.9*	9.9	2.0**	10.2	-0.2	-1.1	1.6	8.1	0.0	-0.0	2.7**	13.8
Turkey	3.1***	18.8	2.1	12.3	5.0**	30.1	0.8	4.8	1.2*	7.2	0.1	0.5
United Kingdom	2.4**	19.1	4.3***	33.3	0.3	2.2	2.3*	18.3	0.8*	6.4	-0.5	-4.3
United States	4.6***	23.7	4.0***	20.6	2.2+	11.1	4.2**	21.4	0.9	4.4	2.9	14.9

Notes: Alphabetical order. Positive values of the disadvantage indicate how much higher the training participation of intermediate-educated workers is compared to the less-educated group. Correspondingly, positive (negative) values of explained part indicate that compositional differences with respect to the given set of predictors contribute to (reduce) within-country variation in the training disadvantage. Contributions of each set are estimated as the average contribution to the training disadvantage over all possible permutations of the different sets (Shapley decomposition). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$ (two-tailed tests).

Source: PIAAC, authors' own calculations.

Section C. First-step regressions for estimating the fully adjusted training gap

Table C1: Country-specific regressions of training participation on individual-level predictors

	AT	BE	CA	CL	CZ	DE	DK	EE	ES
Education (highest degree)									
Low (ISCED 0-2) (ref.: intermed. (ISCED 3-4))	0.01 (0.04)	0.00 (0.04)	-0.06+ (0.03)	-0.06 (0.04)	-0.12+ (0.06)	-0.10* (0.04)	-0.05 (0.03)	0.02 (0.03)	-0.05+ (0.03)
Job tasks									
Abstract tasks	0.12*** (0.02)	0.08*** (0.02)	0.08*** (0.01)	0.07* (0.03)	0.06* (0.02)	0.12*** (0.02)	0.05* (0.02)	0.04** (0.01)	0.05* (0.02)
Routine tasks	0.01 (0.01)	-0.03+ (0.02)	0.01 (0.01)	-0.01 (0.02)	-0.01 (0.02)	-0.02 (0.02)	0.01 (0.02)	0.00 (0.01)	-0.02 (0.01)
Manual-physical tasks	0.01 (0.02)	0.01 (0.01)	0.02 (0.01)	0.00 (0.02)	0.03 (0.02)	0.00 (0.02)	0.01 (0.01)	0.00 (0.01)	0.01 (0.02)
Manual-accuracy tasks	-0.01 (0.01)	-0.01 (0.01)	0.04** (0.01)	0.04 (0.03)	-0.02 (0.02)	0.01 (0.01)	0.01 (0.02)	0.02 (0.02)	0.01 (0.01)
Job characteristics									
Computer use at work (ref.: non-user)	0.18*** (0.03)	0.08* (0.04)	0.09* (0.04)	0.16** (0.04)	0.04 (0.04)	0.06+ (0.03)	0.16** (0.05)	0.14*** (0.03)	0.05 (0.03)
Part-time (<=30hrs) (ref.: full-time (>30hrs))	-0.07* (0.03)	-0.07 (0.04)	-0.05 (0.03)	0.08* (0.03)	-0.09 (0.06)	-0.10** (0.04)	-0.10** (0.03)	-0.10** (0.04)	-0.08* (0.04)
Firm tenure in years	-0.01 (0.01)	-0.01 (0.01)	-0.02+ (0.01)	-0.04 (0.02)	0.00 (0.02)	0.01 (0.01)	0.01 (0.02)	0.01 (0.02)	-0.01 (0.02)
Occupational status (ISEI)	0.01 (0.02)	0.05* (0.02)	0.01 (0.01)	0.00 (0.03)	0.06* (0.03)	0.03+ (0.02)	0.04* (0.02)	0.04* (0.02)	0.07*** (0.02)
Firm characteristics									
Firm size (ref.: 1 to 10 employees)									
11 to 50	0.02 (0.03)	0.01 (0.04)	0.09* (0.03)	0.08+ (0.04)	0.10* (0.04)	0.02 (0.03)	0.04 (0.04)	0.04 (0.03)	0.10** (0.04)
51 to 250	0.10** (0.04)	0.02 (0.04)	0.14*** (0.03)	0.14* (0.05)	0.12* (0.05)	0.13*** (0.04)	0.03 (0.05)	0.11*** (0.03)	0.18** (0.05)
251 to 1000	0.04 (0.04)	0.04 (0.05)	0.15*** (0.04)	0.25** (0.07)	0.22** (0.07)	0.18*** (0.05)	0.08 (0.06)	0.16** (0.05)	0.24*** (0.07)
More than 1000	0.07 (0.06)	-0.03 (0.05)	0.21*** (0.05)	0.14 (0.09)	0.19+ (0.11)	0.24*** (0.05)	0.11 (0.08)	0.16+ (0.08)	0.24** (0.09)
Public sector (ref.: private)	0.09* (0.03)	0.00 (0.03)	0.10*** (0.03)	0.07 (0.06)	-0.01 (0.05)	0.09* (0.04)	0.12** (0.04)	0.12*** (0.04)	0.05 (0.04)
Economic sector (ref.: Agriculture)									
Mining	-0.13 (0.30)	0.04 (0.34)	0.45*** (0.08)	0.12 (0.15)	0.21 (0.21)	0.35 (0.23)	0.03 (0.80)	-0.30** (0.10)	-0.08 (0.14)
Manufacturing	0.12 (0.10)	0.06 (0.14)	0.15* (0.07)	-0.05 (0.05)	-0.14 (0.18)	0.07 (0.10)	0.09 (0.11)	0.00 (0.05)	0.00 (0.07)
Electricity/Water supply	0.23 (0.16)	0.20 (0.17)	0.39*** (0.09)	-0.16 (0.22)	0.22 (0.18)	0.28* (0.12)	0.05 (0.15)	-0.11 (0.13)	0.22 (0.13)
Construction	0.00 (0.11)	0.10 (0.14)	0.20** (0.07)	-0.11 (0.07)	-0.16 (0.16)	-0.08 (0.10)	-0.02 (0.12)	0.00 (0.06)	0.17* (0.07)
Commerce	0.10 (0.10)	0.06 (0.14)	0.12+ (0.06)	-0.02 (0.05)	-0.02 (0.19)	0.12 (0.10)	-0.02 (0.12)	0.09+ (0.05)	0.02 (0.07)
Transport	0.12 (0.12)	0.09 (0.15)	0.26*** (0.07)	-0.03 (0.07)	0.10 (0.18)	0.18 (0.11)	0.14 (0.12)	0.15** (0.06)	0.16* (0.08)
Services	0.11 (0.11)	0.18 (0.14)	0.21*** (0.06)	-0.07 (0.05)	-0.03 (0.18)	0.17+ (0.10)	0.12 (0.11)	0.08 (0.05)	0.08 (0.06)
Worker characteristics									
Skills (Numeracy score)	0.01 (0.02)	0.00 (0.02)	0.04* (0.01)	0.03 (0.03)	-0.03 (0.03)	0.02 (0.02)	0.00 (0.02)	0.00 (0.02)	0.03 (0.02)
Motivation to learn	0.02 (0.02)	0.02 (0.01)	0.01 (0.01)	0.03 (0.02)	0.01 (0.02)	0.02 (0.02)	0.06** (0.02)	0.04* (0.02)	0.00 (0.02)
Constant	0.14 (0.10)	0.08 (0.13)	0.12 (0.08)	0.24* (0.08)	0.41+ (0.21)	0.16 (0.12)	0.30** (0.11)	0.25*** (0.06)	0.21** (0.08)
N	1730	1219	4976	1135	1523	1737	1335	1761	1230
R2	0.17	0.14	0.16	0.24	0.14	0.26	0.17	0.16	0.16

Table continues on next page (ordered by country code).

Table C1: Country-specific regressions of training participation on individual-level predictors (continued)

	FI	FR	GR	IE	IL	IT	JP	KR	LT
Education (highest degree)									
Low (ISCED 0-2) (ref.: intermed. (ISCED 3-4))	-0.06 (0.05)	-0.05* (0.02)	0.04 (0.04)	-0.08+ (0.04)	-0.08+ (0.04)	-0.06+ (0.03)	0.05 (0.05)	-0.04 (0.03)	-0.13*** (0.04)
Job tasks									
Abstract tasks	0.09*** (0.02)	0.07*** (0.01)	0.07** (0.02)	0.05** (0.02)	0.10*** (0.02)	0.06** (0.02)	0.14*** (0.02)	0.09*** (0.02)	0.08** (0.03)
Routine tasks	0.00 (0.02)	-0.01 (0.01)	-0.03+ (0.02)	0.02 (0.02)	-0.02 (0.02)	0.00 (0.02)	0.01 (0.02)	-0.02+ (0.01)	-0.02 (0.01)
Manual-physical tasks	0.00 (0.02)	-0.01 (0.01)	0.00 (0.02)	0.02 (0.02)	0.04* (0.02)	0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Manual-accuracy tasks	0.02 (0.02)	0.02* (0.01)	0.00 (0.02)	0.01 (0.02)	0.01 (0.02)	0.00 (0.01)	0.02 (0.01)	0.00 (0.01)	0.01 (0.02)
Job characteristics									
Computer use at work (ref.: non-user)	0.15** (0.05)	0.08** (0.03)	0.08+ (0.04)	0.00 (0.04)	0.10* (0.04)	0.03 (0.03)	0.11** (0.03)	0.10** (0.03)	0.08+ (0.05)
Part-time (<=30hrs) (ref.: full-time (>30hrs))	-0.10* (0.05)	0.03 (0.03)	-0.08* (0.03)	-0.05 (0.04)	-0.02 (0.04)	0.05 (0.04)	0.01 (0.03)	-0.04 (0.04)	-0.07 (0.04)
Firm tenure in years	0.01 (0.01)	0.00 (0.01)	-0.02 (0.02)	0.00 (0.02)	0.01 (0.02)	0.01 (0.02)	0.00 (0.02)	0.05* (0.02)	0.00 (0.02)
Occupational status (ISEI)	0.03 (0.02)	0.03* (0.01)	0.04 (0.03)	0.02 (0.02)	0.03+ (0.02)	0.05** (0.02)	0.03+ (0.02)	-0.02 (0.02)	0.08*** (0.02)
Firm characteristics									
Firm size (ref.: 1 to 10 employees)									
11 to 50	0.08* (0.03)	0.05* (0.03)	0.12** (0.04)	0.15*** (0.04)	0.02 (0.04)	0.03 (0.03)	0.06+ (0.03)	0.16*** (0.03)	0.02 (0.03)
51 to 250	0.21*** (0.04)	0.09** (0.03)	0.16* (0.06)	0.13** (0.05)	0.10 (0.06)	0.12** (0.04)	0.10* (0.04)	0.29*** (0.04)	0.09* (0.04)
251 to 1000	0.22*** (0.06)	0.08+ (0.04)	0.17 (0.12)	0.19** (0.06)	0.17* (0.08)	0.10* (0.05)	0.09+ (0.05)	0.19** (0.06)	0.11* (0.05)
More than 1000	0.23** (0.08)	0.18*** (0.05)	0.15 (0.11)	0.32*** (0.07)	0.26** (0.09)	0.09+ (0.05)	0.10 (0.08)	0.36*** (0.07)	-0.01 (0.07)
Public sector (ref.: private)	0.05 (0.04)	0.08* (0.03)	-0.06 (0.05)	0.10* (0.05)	0.10+ (0.05)	0.06 (0.05)	-0.07 (0.06)	0.20*** (0.06)	0.07 (0.05)
Economic sector (ref.: Agriculture)									
Mining	0.03 (0.18)	-0.11 (0.24)	0.00 (0.00)	0.45*** (0.12)	-0.54*** (0.14)	-0.16 (0.10)	-0.24+ (0.12)	0.59** (0.18)	-0.15* (0.06)
Manufacturing	-0.04 (0.12)	-0.09 (0.08)	0.06 (0.05)	0.23*** (0.06)	-0.26* (0.12)	0.04 (0.05)	-0.04 (0.11)	0.07 (0.08)	-0.03 (0.05)
Electricity/Water supply	0.33* (0.14)	0.09 (0.11)	0.12 (0.09)	0.21 (0.13)	-0.03 (0.19)	0.20+ (0.11)	0.00 (0.15)	-0.10 (0.10)	-0.11 (0.09)
Construction	0.04 (0.12)	-0.19* (0.08)	-0.08 (0.06)	0.26** (0.09)	-0.29* (0.13)	0.09 (0.07)	-0.13 (0.11)	0.07 (0.08)	-0.09+ (0.05)
Commerce	0.09 (0.12)	-0.10 (0.07)	0.10+ (0.06)	0.22** (0.07)	-0.39** (0.13)	0.02 (0.06)	0.00 (0.11)	0.18* (0.09)	0.02 (0.05)
Transport	0.16 (0.11)	-0.01 (0.08)	0.17+ (0.09)	0.30** (0.11)	-0.31* (0.14)	0.05 (0.06)	-0.05 (0.11)	0.29** (0.10)	0.13+ (0.07)
Services	0.11 (0.11)	-0.06 (0.07)	0.12* (0.05)	0.29*** (0.07)	-0.30* (0.12)	0.04 (0.05)	0.09 (0.12)	0.20* (0.08)	0.09 (0.06)
Worker characteristics									
Skills (Numeracy score)	-0.02 (0.02)	0.02+ (0.01)	-0.03 (0.02)	0.03 (0.02)	0.00 (0.02)	0.03 (0.02)	0.01 (0.02)	0.02 (0.02)	0.00 (0.02)
Motivation to learn	0.03 (0.02)	0.02+ (0.01)	0.02 (0.02)	0.03 (0.02)	-0.02 (0.02)	-0.01 (0.01)	0.01 (0.02)	-0.01 (0.01)	-0.01 (0.01)
Constant	0.24+ (0.14)	0.26** (0.08)	-0.03 (0.08)	0.07 (0.08)	0.57*** (0.13)	0.23** (0.07)	0.17 (0.12)	0.07 (0.09)	0.18* (0.08)
N	1006	1743	751	1089	870	1392	980	1173	1186
R2	0.17	0.14	0.17	0.16	0.17	0.11	0.18	0.24	0.21

Table continues on next page (ordered by country code).

	NL	NO	NZ	PL	SE	SI	TR	UK	US
Education (highest degree)									
Low (ISCED 0-2) (ref.: intermed. (ISCED 3-4))	0.00 (0.03)	-0.08* (0.03)	-0.05 (0.03)	0.02 (0.05)	-0.11* (0.04)	-0.03 (0.03)	-0.04 (0.04)	-0.03 (0.03)	-0.01 (0.05)
Job tasks									
Abstract tasks	0.08***	0.04+	0.11***	0.09***	0.07**	0.07***	0.12***	0.05*	0.08***

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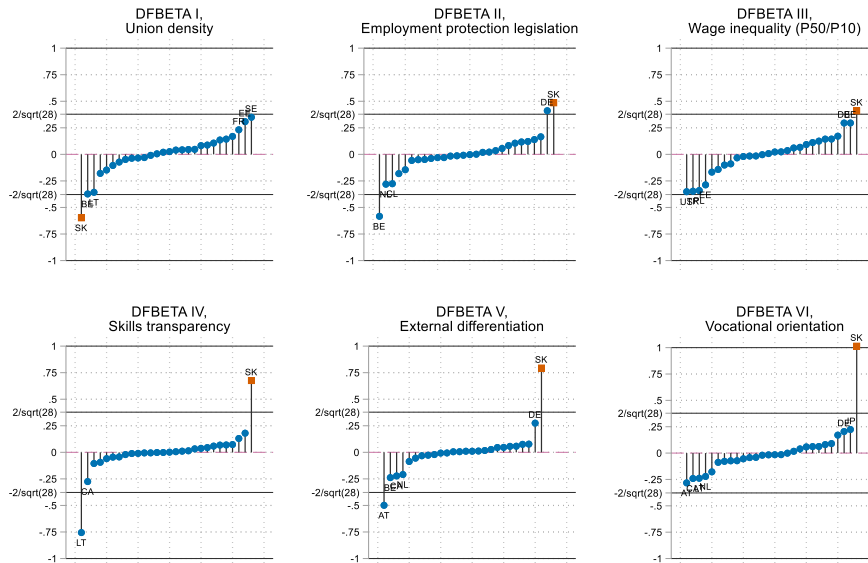
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Routine tasks	0.02	0.00	0.05*	0.00	0.00	-0.03*	0.02	0.02	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Manual-physical tasks	0.04***	0.00	0.00	0.02	0.02	-0.03*	-0.01	0.03+	-0.04*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Manual-accuracy tasks	0.00	0.01	-0.02	0.03	-0.02	0.05**	0.00	-0.02	0.02
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Job characteristics									
Computer use at work (ref.: non-user)	0.13***	0.14***	0.09*	0.14**	0.10*	0.08**	0.03	0.17***	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)
Part-time (<=30hrs) (ref.: full-time (>30hrs))	-0.08*	-0.05	-0.04	0.05	-0.07	-0.16**	-0.08	-0.08+	-0.08*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)	(0.04)	(0.04)
Firm tenure in years	0.02	0.00	-0.01	-0.01	0.01	0.00	0.04*	-0.01	-0.05**
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Occupational status (ISEI)	0.03*	0.03	0.01	0.02	0.04+	0.03	0.00	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Firm characteristics									
Firm size (ref.: 1 to 10 employees)									
11 to 50	0.11**	0.08*	0.09*	0.07*	0.10*	0.08*	0.10**	0.20***	0.05
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.04)
51 to 250	0.10*	0.11*	0.13*	0.22***	0.13**	0.14***	0.17**	0.26***	0.11*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)
251 to 1000	0.10*	0.10+	0.18**	0.31***	0.17**	0.13**	0.29***	0.29***	0.14*
	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.04)	(0.06)	(0.05)	(0.06)
More than 1000	0.12*	0.08	0.13	0.28***	0.34***	0.12*	0.44***	0.25***	0.22**
	(0.06)	(0.07)	(0.09)	(0.07)	(0.05)	(0.05)	(0.07)	(0.06)	(0.07)
Public sector (ref.: private)	0.05	0.07+	0.06	0.04	0.11**	0.11**	-0.07	0.03	0.10**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Economic sector (ref.: Agriculture)									
Mining	0.35+	0.15	-0.13	0.19	-0.28	-0.31*	0.21	-0.05	0.60***
	(0.20)	(0.14)	(0.24)	(0.13)	(0.28)	(0.15)	(0.13)	(0.28)	(0.13)
Manufacturing	-0.16	-0.11	-0.13	0.05	-0.12	-0.07	0.14*	-0.45+	0.11
	(0.18)	(0.13)	(0.08)	(0.06)	(0.12)	(0.09)	(0.06)	(0.25)	(0.12)
Electricity/Water supply	0.08	0.21	0.06	0.05	-0.01	-0.08	0.28+	-0.20	0.32*
	(0.21)	(0.17)	(0.12)	(0.10)	(0.17)	(0.15)	(0.15)	(0.25)	(0.13)
Construction	0.02	-0.11	0.20*	0.06	-0.06	-0.11	0.08	-0.20	0.25*
	(0.19)	(0.13)	(0.09)	(0.07)	(0.12)	(0.10)	(0.08)	(0.24)	(0.12)
Commerce	-0.06	-0.09	-0.06	0.09	-0.13	0.04	0.00	-0.36	0.20+
	(0.18)	(0.12)	(0.08)	(0.06)	(0.11)	(0.09)	(0.07)	(0.24)	(0.11)
Transport	-0.14	-0.11	-0.07	0.04	-0.15	0.07	-0.05	-0.36	0.09
	(0.18)	(0.13)	(0.09)	(0.07)	(0.12)	(0.10)	(0.08)	(0.25)	(0.13)
Services	0.05	-0.06	-0.04	0.11+	-0.08	0.00	0.08	-0.28	0.23*
	(0.18)	(0.13)	(0.08)	(0.06)	(0.11)	(0.09)	(0.07)	(0.24)	(0.11)
Worker characteristics									
Skills (Numeracy score)	0.01	0.01	0.02	0.00	0.00	-0.02	0.00	0.03	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Motivation to learn	0.03+	0.06**	0.03	0.01	0.06**	0.04*	0.02	0.02	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Constant	0.38*	0.46**	0.47***	0.02	0.51***	0.29**	0.21*	0.50*	0.17
	(0.18)	(0.14)	(0.08)	(0.06)	(0.13)	(0.10)	(0.08)	(0.23)	(0.14)
N	1358	1120	1121	1335	1084	1429	867	1782	1388
R2	0.17	0.11	0.16	0.17	0.17	0.16	0.22	0.18	0.16

Notes: Controlled for socio-demographics. Multiple imputation estimates (10 imputations/plausible values). Survey weights applied. Standard errors in parentheses. Metric variables are z-standardized. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$ (two-tailed tests). ISCED = International Standard Classification of Education. ISEI = International Socio-Economic Index of Occupational Status. Ref. = Reference category.

Source: PIAAC, authors' own calculations.

Section D. Outlier Analysis

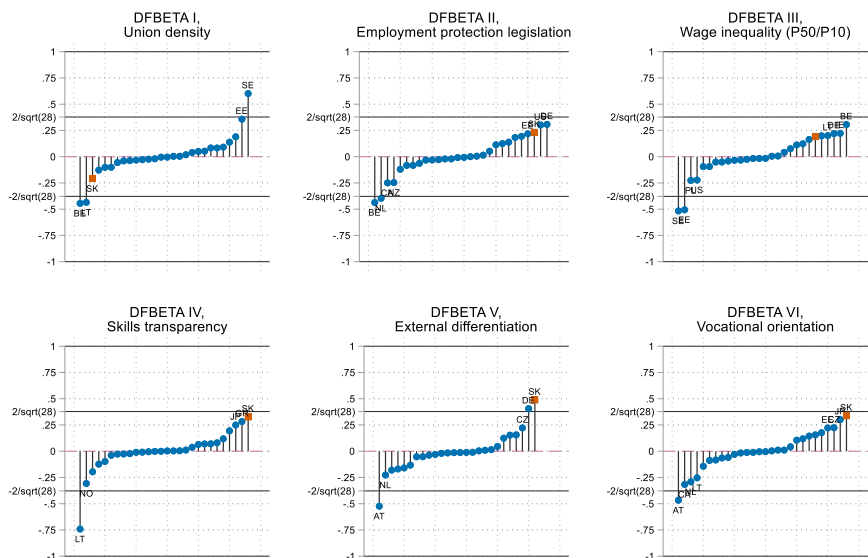
Figure D1: Delete-1 influence statistics for 28 country sample (M1)



Notes: “Delete-1” statistics for country-level regressions on the unadjusted training diadvantage (see Table 3, model M1, in the main article). Positive (negative) DFBETA values indicate that the respective country case draws the institutional estimate upward (downward), which is toward an increase (decrease) in the training disadvantage of less-educated employees (reversed coded). The solid lines indicate common cut-off values for DFBETA.

Source: PIAAC, authors' own calculations.

Figure D2: Delete-1 influence statistics for 28 country sample (M3)



Notes: “Delete-1” statistics for country-level regressions on the fully adjusted training diadvantage (see Table 3, model M3, in the main article). For interpretation see Figure D1.

Source: PIAAC, authors' own calculations.

Section E: Country-level results with sample restriction to at least one year job tenure with the employer at time of interview

Table E1: Shapley decomposition of between-country variation in the (reversed coded) training gap

		Change in variance attributable to adjusting for given group of predictors	
		In percentage points	In % of unadjusted variance
Cross-country variance of unadjusted training gap	20.5	---	---
<i>Job allocation</i>			
Job tasks		3.7	18.2
Job characteristics		3.0	14.4
Firm characteristics		-0.1	-0.4
<i>Worker characteristics</i>			
Workers' skills		3.9	19.0
Workers' motivation to learn		-0.9	-4.6
Socio-demographics (control var.)		4.3	20.8
Cross-country variance of fully adjusted training gap	6.7	---	67.4

Notes: True between-country variances estimated using random-effects models, estimated by restricted maximum likelihood. Positive (negative) values of explained part indicate that compositional differences with respect to the given set of predictors contribute to (reduce) between-country variation in the training disadvantage (reversed coded). Contributions of each set are estimated as the average incremental change in variance over all possible permutations of the different sets.

Source: PIAAC, authors' own calculations.

Table E2: Separate country-level regressions of the (reversed coded) training disadvantage of less-educated workers (controlled for socio-demographics)

	Unadjusted dis-advantage	Partially adjusted disadvantage					Fully adjusted dis- advantage
		Job tasks	Job character- istics	Firm character- istics	Workers' skills	Workers' motivation to learn	
	M1	M2a	M2b	M2c	M2d	M2e	M3
Labor market institutions							
Union density	-0.010	-0.004	-0.002	<u>-0.000</u>	-0.007	-0.008	<u>0.006</u>
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)
Employment protection legislation	0.008	<u>-0.000</u>	0.002	0.013	0.008	0.007	0.006
	(0.010)	(0.010)	(0.008)	(0.010)	(0.009)	(0.010)	(0.009)
Wage inequality (P50/P10)	0.017 ⁺	0.013	0.007	<u>0.008</u>	0.014	0.017	<u>0.004</u>
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Educational institutions							
Skills transparency (skills gap btw. less- and intermediate-educated adults)	0.021	0.019	0.011	0.019	<u>0.008</u>	0.020	<u>0.007</u>
	(0.016)	(0.014)	(0.015)	(0.017)	(0.015)	(0.017)	(0.016)
External differentiation in secondary education (tracking) ^{a)}	0.018	<u>0.002</u>	0.007	0.018	0.012	0.016	<u>0.004</u>
	(0.015)	(0.014)	(0.014)	(0.017)	(0.013)	(0.016)	(0.014)
Vocational orientation of upper secondary education	0.007	<u>-0.004</u>	0.002	<u>0.016</u>	0.007	0.006	0.008
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)

Notes: N = 27 countries; ^{a)} N = 25 (w/o Estonia, Lithuania). Feasible Generalized Least Squares (FGLS) estimates, based on 10 imputations/plausible values. All country-level variables are z-standardized (mean of 0, standard deviation of 1). Robust HC3 standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$ (two-tailed tests). Underlined coefficient estimates differ significantly from coefficients in M1.

Source: PIAAC, authors' own calculations.

Chapter 4: The causes of labor market careers without further training – Does training beget training over the life course in Germany and the UK?

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Extended summary

In this extended summary, we embed our analyses into the larger Technequality framework, outline our main findings, and derive policy implications.

Considering the findings from WP1, continuous participation in job-related training can be expected to become an increasingly crucial feature of integration into technology-driven labor markets. Preceding chapters from Deliverable 3.6 addressed different questions with regard to participation barriers in job-related training.

Previous chapters illustrated how workers in jobs with the highest risk of automation (Chapter 2) and less-educated employees (Chapter 3) have the lowest training participation rates in all the studied countries. Both chapters conclude that job placement processes separate workers into more and less training-intensive positions, leading to training (dis-)advantages.

It might further be the case that early (dis-)advantages widen over the course of time, leading to an even more substantive polarization of labor market opportunities. This chapter investigates the causes of the accumulation of training experiences. Processes of non-formal training accumulation may occur via two paths: (1) (Rather) Time constant factors like individual, job, and company characteristics that influence the probability of individual training participation at all time points (for further detail see chapters 2 and 3), and (2) previous training experiences, which might foster further participation. This chapter aims to separate the first from the second path: Is training participation mainly driven by time constant factors or does *training beget training*? We aim to examine individual training participation dynamics after job placement: Does participation in further training encourage further participation? Do such processes differ by educational level?

Analogous to chapters 2 and 3, we contribute to answering the following two questions from task 3.5 of the grant proposal: *What are the consequences of a lack of learning competencies? And how do education and labor market institutions shape opportunities for skill acquisition “against the odds”?* We complement the findings of previous chapters by integrating a *dynamic perspective*, focusing on in-depth analyses using longitudinal data from Germany (NEPS) and the UK (UKHLS – Understanding Society). This chapter further aims to analyze how processes of (non-)accumulation of training experiences are moderated by two contrasting educational and labor market systems. The findings of this analysis in turn provide the basis for assessing and developing targeted interventions



that ensure continuing participation in further training for all workers. This chapter could especially contribute to policy by providing an understanding of which spheres of intervention might be most promising in promoting continuing training participation for all.

In our analyses, we attempt to discover if there is training inherent cumulative advantage. This would be the case if training participation in one year would increase the probability of training participation in the following year (true state dependence). We therefore need to disentangle the impact of previous further training participation from time-constant factors that influence training participation at all time points.

Main findings

1. Training begets training in Germany and the UK, but even after controlling for individual, job, and workplace characteristics, unobserved time constant factors (like executed tasks, personality, firm cultures etc.) remain more important than training participation during the previous year.
2. Within-country differences: in both countries, high- and medium-educated workers benefit most (and to a similar extent) from previous participation in training. Only low-educated workers seem to be less affected (UK) or even unaffected (Germany) by previous participation in training. Time-constant factors, in contrast, seem to affect all workers in both countries.
3. Between-country differences: Accounting for individual, job and firm characteristics, we find that previous participation in training has a stronger effect on later training participation in the UK than in Germany. As mentioned above, we find that less-educated workers have the lowest extent of training inherent cumulative advantage within both countries. We also find the highest between-country differences for less-educated workers, although we cannot judge whether the differences are statistically significant due to low case numbers in Germany. We assume that between-country differences are based on differences in skill-formation systems. General skills, more strongly emphasized in the UK system, might foster cognitive connectivity to a larger number of different training courses.

This insight demonstrates the need for governments to take action. The findings of our analyses provide a good starting point for policy recommendations.

Policy recommendations

Our analyses shed light on the role of both structural and individual factors in the accumulation of training experiences. Interventions designed to increase the short-term training participation of adults do not necessarily need to have long-lasting effects; Although we find that previous training participation has a causal effect on later training participation, these effects seem to be rather small compared to the effect of (rather) time-constant factors (e.g., job and workplace characteristics). Hence, (as already outlined in Chapter 3), we conclude that policies aimed at increasing job-related

training participation for all groups of workers should not exclusively focus on their training participation per se, but also, and perhaps most importantly, on their workplace conditions and their inherent training barriers.

In the following section, we recommend (based on scientific evidence from Chapter 4) for encouraging the accumulation of training experience all workers.

I. Involve employers

Due to the importance of work placements, employers are important stakeholders for the adult education and training landscape. Governments and employers are therefore responsible for guaranteeing access to further training courses for all workers, regardless of their working position and contract type. This means that a widening of access to workplace training will become an important task for the future. Economic barriers need to be overcome, especially for workers with a lower socio-economic status. Member states could sanction job-related in-company inequalities in access to training opportunities while simultaneously rewarding company-related programs of inclusion of all workers into holistic training concepts.

II. Foundational education (metalearning)

Participation in job-related non-formal training is associated with different types of costs. Individuals' self-perceived capability to learn can act as a barrier to participating in lifelong learning. The individual's capacity to learn is, therefore, an essential skill for workers to adapt to new skill-needs and (successfully) participate in job-related training courses. The foundation for metalearning is built in early schooling. Accordingly, the development of cognitive and meta-cognitive skills, like learning to learn, might become more and more important for young people to adapt to changing workplaces throughout their lives. A positive foundation in metacognitive skills might help to more easily trigger continuous training participation while also reducing participation barriers caused by learning inhibitions. A re-orientation towards these types of skills might help workers enter training loops instead of disrupting their learning pathways because they feel unable to cope with learning requirements.

III. Universal access to lifelong learning opportunities

Lifelong learning opportunities are unequally distributed. Member states therefore need to establish the vision and norm of lifelong learning societies and economies, and develop self-understandings into learning societies that do not view education as a simple economic transaction without acknowledging its public and private value (UNESCO 2020: 8). Thus, the access to lifelong learning should further not be restricted to the working population. Establishing lifelong learning as a common good should become one of the important goals of future societies. This would also mean that universities and schools

should change their self-understanding into lifelong learning institutions without restricted access to training courses.

IV. Systematic planning

The adult-education and training landscape is diverse and hard to navigate for any individual but especially so for the less-educated, who lack the relevant networks, including colleagues and employers, and/or skills (OECD 2019, 7f.). Therefore, a culture of lifelong learning should also integrate modular training-course structures within companies and provide orientation on useful follow-up courses that might connect to previous courses. Member states could thereby make it easier for all workers to accumulate training experiences. Skill adaption should not be based on isolated one-off participation but should be embedded in a plan for different groups of workers. But not only companies should be responsible for planning learning steps. The learners themselves should be integrated into planning and choice of courses out off a modular training structure, based on their strengths, weaknesses, and interests.

V. Diversify learning provision

The accumulation of job-related training experiences might be especially challenging for parents of young children, who might reject job-related training courses due to family obligations (Cedefop 2015). Thus, a diversification of training opportunities might help to balance work, childcare obligations, and learning. Online training courses, for instance, may have a modular structure that enable flexible timing of learning processes, addressing the barrier of time constraints.

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1. Introduction

Times of technological innovation require constant adaptation to workplace and occupational skill requirements. Many policy analysts and scholars expect that foundational education will become increasingly insufficient and that the importance of lifelong learning in ensuring individuals' lifelong employability will grow (e.g., Cedefop, 2015; Kilpi-Jakonen et al. 2014; OECD, 2019). Some postulate that education has already turned into a “lifelong process” (Blossfeld et al. 2011). Moreover, the pace of current technological developments suggests that workers need to continuously engage in training over their careers to stay up to date. Workers who spend a long time without training might face skill obsolescence and labor market marginalization (e.g., deGrip, 2006).

While there is already a large literature on training participation from a cross-sectional perspective, we know little about the dynamics of training participation over workers' careers. In particular, we lack knowledge of why some people train continuously over their careers while others rarely or never do so. In this paper, we aim to shed light on this important issue by analyzing whether previous training participation has a causal effect on future participation in two distinct labor market regimes: Germany and the UK. Our paper aims to uncover the microlevel mechanisms of further training dynamics and investigate whether there are institutional influences.

Training dynamics over the life course are characterized by a “two-fold path-dependency” (Offerhaus, 2014: 81) that hinges on both initial education and previous further training experience. The first path has its roots in educational attainment and consequent positioning in the labor market. There is a broad consensus regarding the influence of previous educational attainment (e.g., Kramer & Tamm, 2018; Chapter 3, D3.6), workplace characteristics, and task profiles on training participation probability (e.g., Görlitz & Tamm, 2016; Schindler, Weiss, & Hubert, 2011). In particular, workers in jobs with the highest automation risk have the lowest training participation rates (Nedelkoska & Quintini 2018; Chapter 2, D3.6). Thus, one explanation for differences in training dynamics is that some workers are channeled into jobs with higher continuous training demands and opportunities, generating unequal access to training (Blossfeld et al. 2020: 5).

The second path generating further training dynamics within careers relates to previous participation, as it facilitates and motivates further participation over the career. In this path, training may be caused by the individual's training history itself and not (only) by job demands. Thus, training advantages accumulate over a career because of previous participation, constituting an example of “cumulative advantage” (DiPrete & Eirich, 2006; Offerhaus, 2014: 79). If cumulative advantage does play a major role in path dependency, this may have unclear impacts on social inequality. On one hand, training participation gaps might increase over time between those who have early advantages and those who have early disadvantages, amplifying existing skill gaps (see also discussion in Blossfeld et al. 2020 or Turek and Henkens 2021). On the other hand, cumulative advantage would



also mean that single training events among long-term non-participants might trigger continuous training participation. In this case, it might be beneficial to implement short- and medium-term programs to promote persistent nonlearners' participation in training.

The role of further training in skill attainment over careers likely differs between countries, depending on their educational systems and labor market context. One of the main tasks for further training is skill adaptation, which is needed when previously attained skills no longer match the requirements of the individual job. There are different potential causes of skill mismatches, and it is likely that the causes, degree, and timing of mismatching vary with educational and labor market settings (e.g., Blossfeld et al., 2020).

The most important crossnational differences in explanations of why further training is needed relate to the interplay between the educational system and the labor market. Several typologies have been developed to describe the different training rationales found across different national labor markets, as well as the institutional settings that shape employers' and employees' incentives to invest in different forms of labor training and education. One common typology distinguishes between occupational labor markets (OLM) and internal labor markets (ILM) (Gangl, 2003; Marsden, 1986, 1990). In OLMs, individuals enter the labor market with occupation-specific skills and only require further training to adapt to changes in skill needs. In ILMs, by contrast, more individuals enter the labor market with rather general skills and immediately require further training to learn job-specific skills. Thus, they require further training both at the beginning of a job and later in response to changes in skill requirements. These differences are likely to not only affect the level of life-long learning, but also its potential to promote or counter processes of cumulative disadvantage.

Based on these considerations, we argue that the two processes that generate path dependence in training over the course of a career are influenced by institutions. Previous research has shown that educational systems and labor market institutions are related to participation in further training. Countries with a stratified school system, where students are selected into different tracks early on, have been shown to have lower participation in further training (Brunello, 2001; Vogtenhuber, 2015). This is presumably due to the vocational tracks in such stratified systems, which teach occupation-specific skills and hence tend to be common in OLMs. In comprehensive school systems, which focus more on general skills (and are therefore often connected to ILMs), further training participation is higher. Yet, these arguments are mainly concerned with path dependence in further training participation due to initial education and training. In this paper, we examine whether this also applies to cumulative advantage due to previous further training participation.



Only a few studies have tried to disentangle the effect of previous training participation from the influence of initial education and training. This is also due to the methodological difficulties that arise in separating the two processes that generate path dependence. The raw correlation between previous training and current training contains both mechanisms. Offerhaus (2014) presents descriptive evidence suggesting that in Germany, training is more prevalent among those who have trained earlier. However, she does not analyze the mechanisms behind this. The same pattern shows up in an analysis of training trajectories among older workers in several European countries by Turek and Henkens (2021). They also compared the extent of path dependency between countries and found lower path dependency in countries with higher expenditure on education and in countries with a more developed knowledge economy. They concluded that these countries avoid the accumulation of training (and hence inequality) by providing training opportunities for all workers. However, they do not distinguish between the reasons for path dependency. Therefore, they cannot analyze and determine which of the mechanisms that drive path dependency are affected by the macroconditions. Sousounis and Bladen-Howell (2010) showed that previous training has a sizeable effect on further training participation in the United Kingdom. Their advanced methodology also enables a causal interpretation of the effect, indicating that previous training indeed influences current training outside of other possible mechanisms.

In this study, we investigate path dependence in further training and its causes in Germany and the United Kingdom. Our research questions are: What are the individual-level mechanisms of path dependence in training participation, and how do institutions influence these processes? We go beyond the previous literature by both disentangling the reasons for the accumulation of training opportunities over careers and attempting to relate them to institutional differences. We analyze data from Germany, which features OLMs, and the United Kingdom, where ILMs are predominant. We apply dynamic random effects probit models to separate path dependence due to time-constant factors such as initial schooling from path dependence due to previous further training participation.

2. Theoretical framework

In this section, we develop theoretical arguments and hypotheses about the dynamics of training participation over a career. In addition to existing explanations that rely on the worker's structural position and career paths and other individual specific factors such as personality traits, we aim to especially consider the dimension of cumulative dynamics due to previous training participation. Furthermore, we develop hypotheses about institutional influences on these dynamics.

Chains of further training participation over time can be caused by two broad types of mechanisms. First, they may be the consequence of individual and job-specific stable risk/success factors that are also related to training participation in any given year. Second, they may be caused



by previous training participation. This distinction mirrors Heckman's (1981) two explanations for "state dependence" (the recurrence of events or states within individuals over time). He described the first group of mechanisms as "spurious state dependence" because the current state (training participation at time t) is not caused by the previous state (participation at time $t-1$); both are caused by other observed and unobserved factors. Only the second group has "true state dependence", as the states at the two points in time are directly causally linked. Figure 1 summarizes these ideas. In the sociological literature, both processes are often called "cumulative advantage." To distinguish between them, DiPrete and Eirich (2006) call processes of true state dependence "strict cumulative advantage."

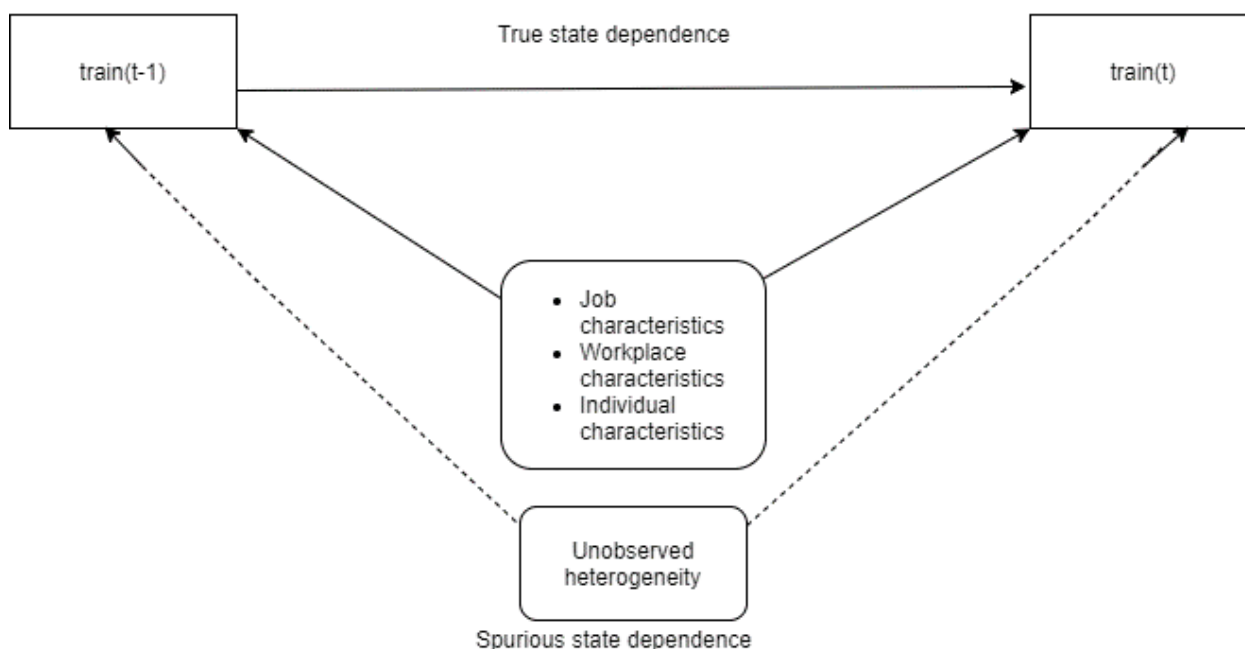
Cunha and Heckman (2007) provide a theoretical justification of why education may follow true state dependence over the life course. Their assumed "technology of skill formation" is based on two key features: (1) Skills produced at one stage augment the skills attained at later stages; they describe this effect as "self-productivity" (Cunha & Heckman, 2007: 35). Skills might be self-reinforcing and cross-fertilizing. The latter means that skills in one area can foster skills in another area. (2) Skills produced at one stage may raise the productivity of investment at subsequent stages. Cunha and Heckman describe skill investments as synergistic, as skill investments at different ages may bolster each other. They name this feature "dynamic complementarity" in skill formation; "early investment should be followed up by later investment for the early investment to be productive" (Cunha & Heckman, 2007: 35). Dynamic complementarity together with self-productivity produces multiplier effects—the mechanisms through which "skills beget skills" and "abilities beget abilities" (Cunha & Heckman, 2007: 35). Therefore, previous educational investment should promote subsequent educational investment, creating cumulative advantages.

Cunha and Heckman's ideas are focused on children's education, but their theoretical arguments can be fruitfully extended to further training. According to the assumed mechanisms, participation in one training course may set off chains of further training participation because of "cross-fertilization." For example, a language course may enable someone to attend another course about something else in that language. Dynamic complementarity, on the other hand, implies that a basic computer course would make it possible to attend a course on a specific computer program. In both situations, further training investments are more productive because they can build on previously acquired skills. Therefore, from a human capital theory perspective, both employers and employees have greater incentives to invest in training if another relevant spell of training has previously taken place.

Cunha and Heckman's technology of skill formation (like other variants of human capital theory) assumes that the growth in productivity from educational investments is always visible and

can thus be used when making decisions. However, in practice, this may not be the case. Instead, employers presumably use signals of productivity to make decisions, as formulated in signaling theory (Spence, 1973). Employers finance most job-related further training and consequently have a considerable say in who takes courses (Wotschack and Solga 2014; CEDEFOP, 2015). From the perspective of transaction cost theories (Coase 1937; Williamson 1985), operational activities and thus also investments in continuing education are always associated with costs. Assuming rational, efficiency-oriented companies, employers should invest primarily in those people from whom they expect the greatest benefit. If employers believe or have experiences suggesting that skills learned at one stage make later skill acquisition easier, companies should invest more often in those who have previous training experience. Clearly, skills and productivity may not be observable for companies, but training participation is. Therefore, companies may use earlier training participation as a signal for trainability and productivity, presuming that workers who trained earlier will incur lower training costs and gain greater benefits.

Fig. 1: Directed Acyclic Graph of True State Dependence in Training Participation



Similarly, employees themselves may not be directly aware of the potential payoffs of further training. Therefore, we add perspectives about individual motivation to our theoretical considerations. The expectancy-value theory (Eccles, 2005) outlines mechanisms that explain why previous training participation increases the motivation to train in the future. It argues that the determinants for educational choices are mainly based on the individual's expectations of success

and the value that the individual attaches to the different options that appear to be available. Furthermore, it includes a circular perspective, meaning that expectancy and value have an influence on educational choices, and educational choices have an impact on expectancies and values related to future choices (Eccles, 2005). If training participation at time point 1 influences the expectancy of success and value assigned to a training course at time point 2, then this dynamic could help to explain why earlier training might lead to later training and thereby trigger cumulative advantages. By applying Eccles' expectancy-value theory to adult education, we follow the approach and suggestion of Gorges and Kandler (2012) and Gorges (2015). We argue that, besides school experience, previous non-formal training experiences and participants' impressions of them might also influence expectations of success and the value of non-formal training participation (Gorges, 2015). Based on these considerations from both the employer and the employee perspective, we expect to find:

H1 *Participation in job-related non-formal training in one year increases the probability of training participation in the following year (in both countries under study)*

Research shows that skill levels are strongly associated with educational attainment (Heisig & Solga, 2015), and according to the technology of skill formation, skills beget skills. Therefore, we argue that higher education increases success expectancy and reduces costs with regard to future training decisions. Furthermore, Gorges (2015) highlights the importance of autobiographical memories and socio-cultural influences in the decision to participate in a training course. Educational biographies have a strong influence on social capital and networks (Jusri & Kleinert, 2018). The networks of highly educated people are likely to assign higher values to adult education. Such education-oriented social networks may then also promote individuals' own interests in different topics, and enjoyment of learning processes. Furthermore, such networks may have a good overview of the field of further training opportunities, reducing the costs of finding an appropriate training course. At the same time, memories of school could influence success expectancy. Positive memories of school, for example, could have an influence on adult learning motivation (Gorges & Kandler, 2012). Moreover, in knowledge-intensive jobs, the demand for firm-specific capital—often acquired through non-formal further training—is very high (Acemoglu, 1997). Highly educated people are likely to start from an advantageous position. In other words, training in the previous year falls on a more fertile soil. Therefore, it can be argued that highly educated people are likely to exhibit the highest amount of true state dependence, and hence “strict cumulative advantage”, in non-formal work-related training. Based on these arguments, we formulate the following hypothesis.

H2 *People with higher education levels exhibit a stronger effect of previous training participation on future training participation (in both countries)*



Institutional Context

We now turn to the question of how these individual-level mechanisms are moderated by institutional environments, and how these different environments may result in path dependencies being more pronounced in one context than in another.

A well-known dichotomy used in the political economy literature to describe different skill formation rationales distinguishes between “general” and “specific” skill regimes (Estevez-Abe et al. 2001). Specific skill regimes, found in occupational labor markets (OLMs), are characterized by high levels of occupational specificity and highly developed and standardized vocational training systems. General skill regimes, found in internal labor markets (ILMs), are more strongly focused on the development of general skills, with vocational training at career entry being much less developed and standardized. Marsden (1990: 415) describes OLMs as contexts “in which workers have access to jobs of a particular type in many firms, this access usually being based upon the holding of a recognized diploma or qualification, or on the recognition of the worker’s peers.” For this reason, occupations in OLMs need to be clearly defined, with standardized qualifications as well as standardized entry requirements. In OLMs, (vocational) educational diplomas signal that the employee is in possession of occupation-specific skills that are in demand in the labor market (Arum & Shavit, 1995). For a long time, young people in the German system have been predominantly channeled into the labor market within the traditional dual system, which strongly connects education and training with occupations (Shavit & Müller, 1998). The high level of standardization results in a high level of skill transferability, allowing German employees to move between companies within the same sector during their career. The German educational system provides labor market entrants with occupation-specific skills, enabling them to be productive from an early career stage and resulting in early skill matches. Due to strong skill standardization and an equivalent standardization of job vacancies, even semi-skilled and skilled positions can be filled by external workers (Marsden, 1990: 415f.).

In ILMs, employers generally aim to fill vacancies at higher levels in the organization “from among its existing employees” (Marsden, 1990: 415). Boundaries in entry requirements are rather broadly defined and entry is often limited to lower skilled positions from which employees work their way up by gaining experience and participating in training (Marsden, 1990: 416). The UK is considered to have a rather general education system that provides people with more general skills. For this reason, educational certificates may predominantly be used as a signal for trainability (Arrow, 1973). In the UK, job-specific skills are mainly developed after the transition into the labor market, in the context of enterprise-related training (Wolbers, 2003: 134) and experience. Therefore, job and skill matches are achieved later than in OLM countries. Since qualifications provided by the educational system in ILM countries are not occupationally standardized—or at least are



standardized to a much lower extent than in OLMs, occupational skill transparency of vocational qualifications is low, resulting in rather few skill matches at the beginning of a career. Employees entering the labor market have to start in unskilled job positions and work their way up by gaining experience and participating in training (Marsden, 1990: 416).

Enterprises usually train their current workforce in response to new skill needs within the company. We argue that an employee in an ILM can be seen as a “broad craftsman” (Rözer & van de Werfhorst, 2020) who possesses general skills upon entry to the labor market, but attains firm-specific occupational skills by gaining experience and participating in training. Importantly, the difference between ILM and OLM contexts is not only that skill matching occurs later in ILMs than in OLMs, but also that occupational outcomes and attainment are much more “amenable to career contingencies and discretionary employer behaviour” (Gangl 2003:110) in the former, whereas in the latter they are mainly determined by educational and vocational certificates. This is likely to result in increasing variance of occupational attainment within skill groups over time in ILM contexts (ibid: 111).

Since we assume that OLMs lead to early job and skill matches while ILMs achieve job and skill matches during later career stages, we expect that non-formal training might serve different functions within both systems. In regard to the expectancy value theory, we do not see many arguments for country differences relating to intrinsic interest value and attainment value. We therefore focus on utility value and costs assigned to participation in a job-related non-formal training course. Given that labor market entrants in OLMs already have occupation-specific skills, the main benefit of non-formal training may lie in a skill-adaptation function to address selective skill gaps. Here, non-formal training is less likely to be an instrument for career progression than for skill adaptation to remain employable over the life course, as shown by Ebner and Ehlert (2018). The employee or specialized craftsman (Rözer & van de Werfhorst, 2020) in Germany has expertise in their rather standardized occupational context and might hence benefit less from the cross-fertilizing aspect of skill development. With an early skill match due to the “frontloading” of the occupational skill formation process, the need for non-formal training may be lower in Germany. Due to the early occupational skill match, there could be a ceiling effect, with few additional utility benefits arising due to additional training spells. In sum, we predict this will reduce the utility value assigned to further courses. In OLMs, skill adaptation difficulties—if the skills needed are rather unrelated to the standardized occupation specific task profile—are a likely consequence.

Hanushek et al. (2017) argue that there are trade-off effects in vocational education that enable easy school-to-work transitions while also leading to lower adaptability to technological change. The logic of the German skill system would suggest that employers and employees gain little



utility from engaging in more substantial further training—or at least less utility than the UK skill system. However, the German labor market context actually represents a setting with incentives for such training, even if it is unrelated to the standardized occupation-specific task profile. The German labor market can be described as a coordinated production regime (Hall and Soskice, 2001) with high levels of employment protection. The high employment protection means that employees can safely invest time and effort into further training even if the skills acquired have a strong firm-specific component (Estevez-Abe et al. 2001). More importantly, the high level of employment protection means that it can be less costly for employers to invest in the substantial skill upgrading and/or skill conversion of their workforce than to fire them and hire a new worker with the relevant skills from the external labor market (Dieckhoff 2013: 94). We expect this to be especially relevant in terms of cumulative advantage and disadvantage in further training participation, as employment protection has the potential to counter these dynamics.

By contrast, in the UK (as an example of an ILM), non-formal training participation is likely to be a central aspect of occupational skill formation and (vertical) job matching within a company. As a result, transitions into the labor market may be more likely to occur in steps and to be turbulent and problematic in the UK (Brzinsky-Fay, 2007; Scherer, 2001). In order to achieve job matching, labor market entrants need to acquire firm-specific (occupational) skills through extensive non-formal training and employment experience. Here, the general skills obtained in the educational system serve as the foundation for further learning and on-the-job training (Hanushek et al., 2017). The skill-formation function of non-formal training in the UK may be important for employers in making their workforce productive and for employees in their career development. Therefore, unlike in the OLM context, an early “ceiling effect” of occupation-specific skills may be less likely to arise. As a result, high utility values might be assigned to a higher number of different training courses (with a large diversity of content) in the UK. Besides the self-reinforcing effects of the “technology of skill-formation,” UK employees, with their rather general skill profiles, are likely to also benefit from the cross-fertilizing aspect of skills. This would explain why workers in ILMs have less difficulties to adapt to technological and structural changes in the economy (Hanushek et al., 2017). This flexibility might also lead to a higher expectation of success in unfamiliar training contents in ILM countries, and consequently lower costs in terms of cognitive effort.

In the UK, it is also likely that employers (in the case of occupational skill needs at the company level) might prefer to train their current workforce rather than hire from the external market, as the current workforce has already accumulated firm-specific skills which a new employee would need to develop. Therefore, employers might only fill positions with the external workforce if it is not possible to train their current workforce. This would lead to a higher utility value of further training in the UK.



Moreover, while the skill system of the UK labor market would suggest a high utility of training for both employers and employees, lower employment protection might reduce the utility value assigned to further training. If firing is easy, and -based occupational skills have little value to other companies, employees' personal training benefits may be somewhat precarious and individuals could be less willing to invest in training (Estevez-Abe et al., 2001). Given that most non-formal training is paid for by the employer, the effect of employment protection on companies training rationales is even more crucial. The UK constitutes a liberal market economy (Hall and Soskice, 2001) with low levels of employment protection, so employers' further training decisions are mostly driven by productivity considerations. While workers with strong productivity signals are most likely to receive training, low employment protection may render it more cost effective to replace those employees signalling low productivity or trainability with external workers. There is, thus, no strong institutional impediment to cumulative advantages in training.

With Hypothesis 1, we expect to find that training begets training in both countries (Hypothesis 1). However, we expect that there are more training course contents that are beneficial to employees in the UK. Therefore, in the UK, employers might offer more training to employees for occupational skill formation, especially during early career phases and when entering new jobs. In Germany, however, training participation might only be important for skill adaptation. Overall participation in training should therefore be higher in the UK. But where do we expect to find higher levels of state dependence? Acquiring skills that are not part of a specific occupational skills profile might be easier for UK employees, as they should benefit more from the cross-fertilizing aspect of skill formation because of their more heterogeneous skill profile. Crucially, this might also lead to a higher success expectancy for courses which do not directly relate to the occupation. Moreover, we expect that productivity and trainability signals are probably of even higher relevance to employers' training decisions in the low employment protection context of the UK. Also, as discussed above, occupational attainment and career progression in the UK (as an ILM) generally hinge more heavily on employer discretion and career contingencies, resulting in greater variance of attainment over time, even within skill groups. These are reasons to expect that cumulative advantage and disadvantage in further training would be more frequently promoted in the UK labor market than in Germany:

H3 *In the UK, participation in non-formal training in one year increases the probability of training participation in the following year to a higher extent than in Germany.*

We expect that in both countries, cumulative advantages are largest for highly educated people (hypothesis 2). However, regarding differences between countries, we expect to find the largest variance between Germany and the UK for the group of low- and medium-educated people.



While it is true that the differences in vocational orientation are found between the countries' vocational education and training (VET) systems and their higher education (HE) systems (Leuze 2011), these (institutional) differences are much more pronounced for VET (as discussed in detail earlier in this paper). Moreover, the demand for firm-specific human capital is higher in knowledge-intensive jobs (e.g., Acemoglu 1997). Thus, even in the context of the more vocationally oriented German HE system, higher-educated labor market entrants will have repeated spells of further training to acquire the relevant firm-specific skills—similar to higher-educated labor market entrants in the UK. We thus expect country variance in terms of cumulative advantage in further training to be most pronounced in the group of low and medium educated people, who are most affected by the VET systems and work in less knowledge-intensive jobs. Against this backdrop, we expect to find:

H4 *The differences between countries in the effect of previous training participation on later training participation is highest for less and medium educated people.*

3. Data and Method

We use two longitudinal datasets to test our hypotheses. For the UK, we use the UK Household Longitudinal Study *UKHLS* (Understanding Society) which includes members of approximately 40,000 households in the United Kingdom (University of Essex 2020; Institute for Social and Economic Research 2020). We employ data from 2009 (wave 2) to 2018 (wave 10). We select employment spells without missing data on important covariates, especially interview date and socio-demographic and job characteristics. To ensure comparability with the German data set, we use the *UKHLS* variable indicating whether training has taken place since the previous interview, and information on the training purpose. The *UKHLS* provides detailed information for up to three training spells between interviews. We only looked at non-formal training and disregarded formal training spells (training for the purposes of leisure and hobbies were also excluded. Youth training schemes, key skills, and basic skills training were categorized as non-formal). Hence, if one of the three spells is a non-formal training course, the respondents were assigned the value of 1, otherwise they were assigned 0.

For Germany, we use the starting cohort 6 (SUF 12.0.0) of the National Educational Panel Study (NEPS) (Allmendinger et al. 2011; Blossfeld et al. 2011). NEPS collects detailed information on educational trajectories, competencies, and returns to education over the life course of people born between 1944 and 1986. We use waves 2 to 10 which contain detailed information on non-formal training participation. Respondents are asked whether they have participated in training courses since the last interview. Detailed information is collected for two randomly chosen courses. We again focus on job-related training courses and assign the value of 1 if at least one of the two courses was job-related and non-formal.



Since hypotheses refer to (dependent) employees, we exclude all respondents who are not employed or are self-employed. For both datasets, we restrict our sample to continuously employed prime-age workers, aged 25–55. The theoretical concept of true state dependence (or path dependency) is quite straightforward. Methodologically, however, there are some challenges. The main question is how to address the initial condition and endogenous covariate problem and how to deal with unobserved heterogeneity. To solve these issues, we used *dynamic random-effects probit models* proposed by Rabe-Hesketh and Skrondal (2013), applying the Stata ado *xtpdyn* developed by Grotti and Cutuli (2018). Dynamic random-effects probit models are mainly used to calculate outcome inertia caused by previous states of a binary outcome variable. The independent variable is the lagged outcome variable; in our case, previous training participation, $y_{(it-1)}$. To measure true state dependence, we need to estimate the effect of $y_{(it-1)}$ on $y_{(it)}$ while controlling for unobserved heterogeneity. One problem we face is the initial condition problem, which refers to the possibility that there might be a correlation between $y_{(i0)}$ and relevant unobserved factors. With a multilevel random intercept model approach (which can be an equivalent to RE panel models), this would mean that the initial response at the start of the observation period would be affected by the random intercept and presample responses, leading to endogeneity and hence an inconsistent estimation (Skrondal & Rabe-Hesketh, 2014). We therefore conditioned on the response at $y_{(i0)}$, as proposed by Wooldridge (2005) and Rabe-Hesketh & Skrondal (2013).

A second challenge to address is the problem of endogenous covariates. Beside the strict exogeneity assumption with respect to u_{it} , consistent estimation of RE panel models require exogeneity with respect to c_i . This means that we assume no correlation between c_i and x_{it} at any time $E(c_i | x_{it})=0$, which can be considered a very strong assumption. If the exogeneity assumption with respect to c_i did not hold, we would face the problem of between-subject confounding. Wooldridge (2005) suggested the inclusion of values of time-varying confounders at each period (except the initial period). This approach requires balanced data sets. A more common and parsimonious approach is based on the inclusion of within-means of time varying confounders for unbalanced data, although no justification for this approach has been given in the literature (Rabe-Hesketh & Skrondal, 2013). Further, research has shown that this parsimonious approach can cause severe bias in the case of short panels (Akay, 2012; Rabe-Hesketh & Skrondal, 2013), since the conditional distribution of the unobserved effects depends more on the value of the first period than on the values of the other periods (Rabe-Hesketh & Skrondal, 2013). Therefore, we additionally modeled unobserved heterogeneity by including within-unit averages of the independent time-varying variables (Biewen, 2009; Stewart, 2007; Rabe-Hesketh & Skrondal, 2013) and the initial values of the explanatory variables (Rabe-Hesketh & Skrondal, 2013). Summing up, we tried to measure true state dependence in the following way:



$$y_{it}^* = \gamma Z_{it} + \rho y_{it-1} + c_i + u_{it}$$

y_{it}^* expresses the chance of participating in non-formal training for unit i ($i = 1, \dots, N$) at time t as a function of a set of time-varying explanatory variables, Z_{it} , that are considered strictly exogenous, conditional on the unit-specific unobserved effect c_i . Based on Rabe-Hesketh and Skrondal (2013), c_i can be written as follows:

$$c_i = a_0 + a_1 y_{i0} + \bar{Z}_i a_2 + Z_{i0} a_3 + a_i$$

y_{i0} and Z_{i0} stand for the initial value of the response variable and the time-varying explanatory variables. \bar{Z}_i symbolizes the within-unit averages of the explanatory variables, based on all periods. a_i stands for the unit-specific time-constant error term. If c_i captures unobserved heterogeneity, then ρy_{it-1} can be interpreted as true state dependence.

In our models, we controlled for gender, educational level (high, medium, and low), cohabitation and marital status, the number of children under the age of 6 years, part-time working contract (coded 0/1), changes of occupation between waves (coded 0/1), company size (number of employees: operationalizations can be seen in tables A1 and A2), and occupation fixed effects. We distinguish the three levels of education for Germany by using the International Standard Classification of Education (ISCED97): low (ISCED 0–2), intermediate (ISCED 3–4), and high (ISCED 5–6). The UKHLS does not provide an educational variable based on ISCED but on an own classification. For making the educational levels in the UK comparable to those we build for Germany, we define people with less than an upper secondary degree as low educated, workers who attained at least an upper secondary degree but less than a tertiary degree as medium educated and people with some kind of tertiary degree as high educated. Our British classification thus resembles our German classification based on ISCED. As explained above, we additionally controlled for the initial training condition, the initial condition of the time-varying confounder, and their within time means, with the intent to control for unobserved heterogeneity.

We are aware that our models are based on strong assumptions. Although we tried to control for unobserved time-constant factors, it is likely that a residual confounding bias remains. Skrondal and Rabe-Hesketh (2014) argue that dynamic random effect probit models should be referred to as working models that aim to be “almost consistent,” meaning that the estimator is sufficiently close to the parameters of interest for practical purposes. While controlling for the initial training condition is essential for taking unobserved heterogeneity into account, it can also be problematic. The previously mentioned benefits come at the cost of potentially causing an endogenous selection bias like most lagged dependent variable models (Morgan & Winship, 2015: 111). Figure A1 (in the appendix) is an attempt to illustrate why the initial condition might be a



collider if both our exogeneity assumptions do not hold and there is residual confounding via a_i and u_{it} . Both error terms might be parents of the initial training condition, thereby opening the following backdoor path: $\text{train}(t-1) \leftarrow a_i \rightarrow \text{train}(t) \leftarrow u_{it} \rightarrow \text{train}(t)$ (see upper part of Figure A1). While the association between a_i and training participation should be constant over time, we assume that the relationship between u_{it} and $\text{train}(t)$ is stronger the closer the measure time point of u_{it} is to t . Thus, we expected that the endogenous selection bias shown above would weaken the longer individuals are observed in our analysis sample (see lower part of Figure A1).

We give a short overview of both country samples. Table A1 (in the appendix) shows the descriptive information for Germany. Our German sample consists of 4,545 individuals with 28,945 person-years. The job-related training participation rate is 35%. The sample is almost equally divided between men and women and has an average age of 45 years. Over half of the sample is highly educated, 46% are medium-educated, and the share of less-educated people is rather low. 35% of our person-years work part time, and only 5% work on a fixed-term working contract. The proportion of person-years after a job change is 6%. The greatest share of person-years is spent working as professionals, technicians, and associate professionals. Descriptive information for the UK is presented in Table A2. Our UK sample consists of 11,730 individuals with 75,753 person-years. The average person-years per person is comparable to our German sample. The training participation rate is 30%; this is slightly lower than in our German sample. The average age is 42 years. The sample consists of slightly more women than men. Most individuals attained a medium educational credential (40%), followed by those with higher educational credentials (38%) and less-educated respondents (22%). The proportion of person-years in part-time work is 29%. As in Germany, most people work in large or medium-size companies. The share of person-years after changes of occupation is 7%.

We additionally give an overview in Table 1 of descriptive transition rates in job-related non-formal training within both countries. In Germany, workers who trained during the previous year have a probability of 52% of training in the following year. Accordingly, the exit probability (training participation during $t-1$ and no training participation at timepoint t) is 48%. Workers who did not train at $t-1$ have a likelihood of 23% of training the following year (entry probability). Persistence in non-participation is rather high; the probability of not participating in a training course is 77% if the individual did not train during the previous year.

In the UK, workers who trained at $t-1$ have a probability of training at timepoint t of 51%. The exit probability, therefore, is 49%. The entry probability is 20%. Workers in the UK who did not train during $t-1$ have an 80% probability of not participating at timepoint t . In both countries we find strong inertia in training participation; those who trained before, continue to train, and those who



did not participate before, continue to not participate. Next, we aim to disentangle the reasons for training participation inertia.

Table 1: Descriptive transition rates in job-related non-formal training

	Training participation t	No training participation t	Total
Germany			
Train. Part. $T-1$	51.55	48.45	100
No train. Part. $T-1$	23.48	76.52	100
	33.41	66.59	100
United Kingdom			
Train. Part. $T-1$	50.86	49.14	100
No train. Part. $T-1$	20.04	79.96	100
	29.39	70.61	100

Source: NEPS and UKHLS, authors' calculations.

4. Results

Figure 2 shows our findings when testing hypotheses H1 and H3, based on our full dynamic random effects probit models (see table A3 and A4 in the appendix). It shows that in both countries, we find a causal, substantive, and statistically significant effect of previous training participation on later training participation, suggesting processes of training-inherent cumulative advantage. H1 can therefore be confirmed. Having trained during the previous year increases training participation probability, *ceteris paribus*, by about 12 percentage points in the UK and by about 7 percentage points in Germany. Hence, true state dependence in training participation is higher in the UK than in Germany, confirming H3.

As outlined in the previous sections, we argue that even after controlling for relevant confounders, there might still be unobserved time-constant factors that influence training participation at all time points, which in turn might cause spurious state dependence. Although our research focuses on true state dependence, we additionally report the results of the coefficient of the initial training condition. This aims to control for stable risk and success factors (unobserved heterogeneity) that might influence training participation at all time points beyond the observed control variables. Although it is unclear which unobserved factors may be captured by the initial condition, we assume that it might (among other factors) capture company-specific (training) cultures and executed tasks within individual jobs, known to be important determinants of training participation. Unobserved heterogeneity captured by our initial training condition variable seems to have a stronger influence on training participation than training in the previous year ($t-1$) (see figure



2). Having trained in the year before the first interview of our observation period increases training participation by 18 percentage points in Germany and 15 percentage points in the UK. Thus, unobserved factors (like personality traits, company (training) cultures, and executed tasks within individual jobs) might be important drivers for training participation in both countries.

Figure 3 illustrates our findings testing hypothesis 2 and 4. For hypothesis 2 (predicting a stronger effect of previous training participation on future training participation for higher educated workers), we find mixed evidence. We expected to find the highest degree of true state dependence for higher educated workers. Indeed, we found differences in *strict cumulative advantage* via educational levels. In the UK, previous training participation increases the training participation probability by, *ceteris paribus*, 14 percentage points (pp.) for higher educated workers (8 pp. for Germany), 13 pp. for medium educated workers (7 pp. for Germany), and 8 pp. for less-educated workers (-0.1 pp. for Germany). Our results, therefore, suggest higher true state dependence in job-related non-formal training for highly educated employees than for less educated ones, according to our expectations. Contrary to our expectations, medium-educated workers seem to benefit from previous training participation to the same extent as higher-educated employees. We therefore need to reject hypothesis 2, although we find differences in effect by educational level.

Fig. 2 True State Dependence in Job-related Training Participation in Germany and the UK.

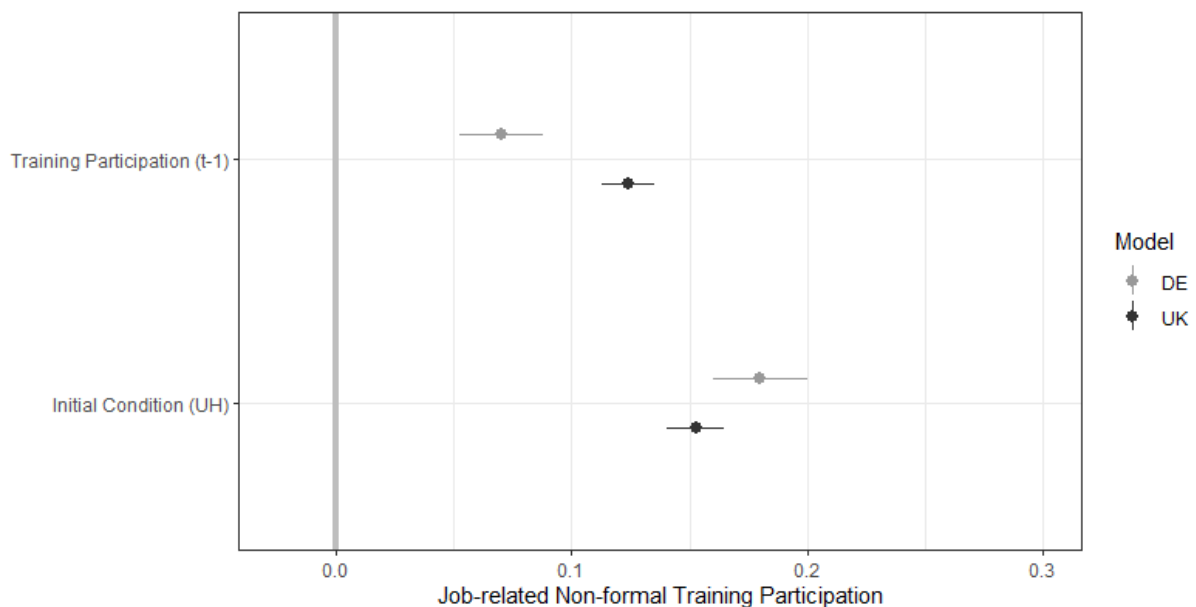
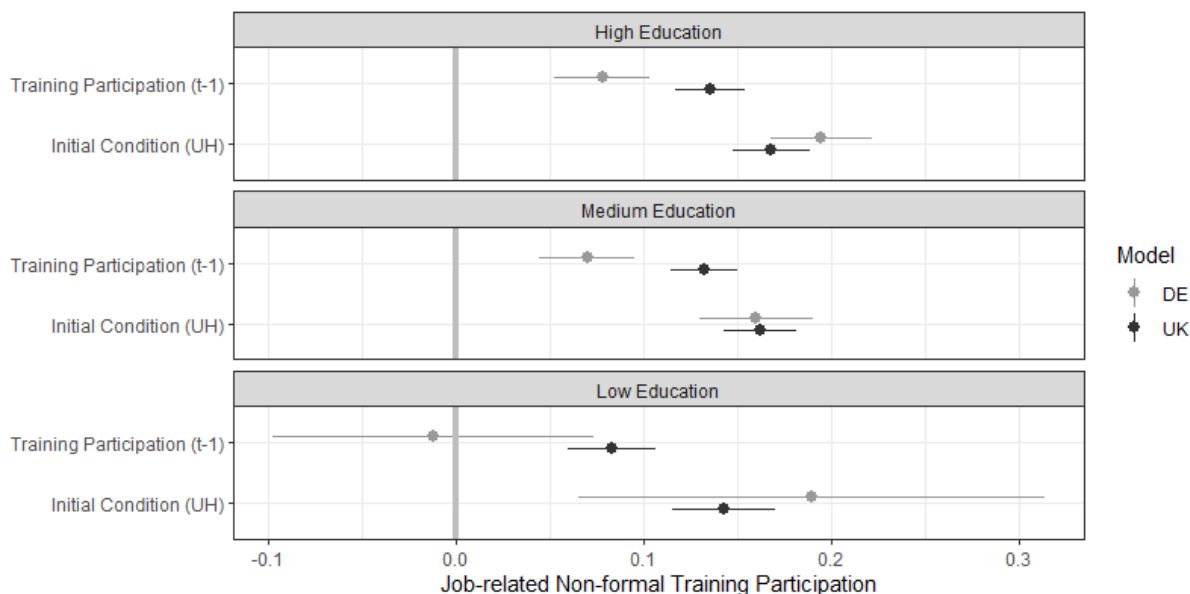


Fig. 3 True State Dependence of Job-related Training by Educational Groups in Germany and the UK



Our results also imply that country differences are substantially higher for the group of less-educated workers, although the differences are not statistically significant as indicated by the confidence intervals. Country differences in true state dependence in further training are smaller for high- and medium-educated workers. We therefore cannot confirm Hypothesis 4, which stated that the largest difference between the countries would be between medium- and less- educated workers due to the dual German training system.

Interestingly, we find smaller country differences regarding the importance of unobserved factors, captured by the initial training condition. Having trained in the first observation year increases training probability in the UK by about 17 pp. (20 pp. for Germany) for high-educated workers, 16 pp. for medium-educated (14 pp. for Germany) and 16 pp. for less-educated employees (19 pp. for Germany). Unobserved factors seem to be important for all educational levels in both countries.

5 Discussion and conclusions

Research on job-related training presents evidence for cumulative advantages. Some workers are channeled into jobs with higher continuous training demands and opportunities, generating unequal access to training (Blossfeld et al. 2020: 5). Accordingly, previous educational attainment (e.g., Kramer & Tamm, 2018), workplace characteristics, and task profiles (e.g., Görlitz & Tamm, 2016;

Schindler, Weiss, & Hubert, 2011) are important determinants of training participation. Due to recent transformations of the labor market, especially concerning the pace of technological change, the importance of continuous participation in job-related training is expected to rise. Yet, path dependency in training participation might foster a polarization of labor market chances and unemployment risks.

The question, however, is why we find cumulative advantages—whether they are only caused by stable factors like educational attainment (leading to the allocation of workers into certain jobs) or if there is “strict cumulative advantage” (DiPrete & Eirich, 2006). The latter is a causal effect of previous training participation on later training participation—training begets training. In this case, training-inherent cumulative advantages might be a means to counterbalance increasing unemployment risks for those who find themselves in disadvantaged positions on the labor market. We used the concept of true state dependence as an indicator for strict cumulative advantage. Our theoretical arguments were based on the technology of skill formation (Cunha & Heckman, 2007) and the expectancy-value-theory (Eccles, 2005). We were also interested in whether training-inherent processes of cumulative advantage might depend on institutional settings, especially with regard to educational and labor market systems. We used Germany and the UK for our comparison, two countries in which there are very different relationships between the education system and the labor market (Gangl, 2003; Marsden, 1986, 1990), and differing skill (Estevez-Abe et al. 2001) and production regimes (Hall and Soskice, 2001). We used dynamic random effects probit models to disentangle true state dependence from spurious state dependence (caused by unobserved factors that might influence training participation at all time points). Indeed, we found indications of training-inherent processes of cumulative advantage in both countries. In line with our expectations, we found true state dependence in job-related training to be higher in the UK than in Germany.

Regarding educational differences, we found different amounts of training-inherent cumulative advantage in both countries. We expected to find a threshold that is evident below the high-educated level; below this, we speculated, true state dependence might be lower. Instead, we found that only low-educated people seem to benefit less from previous training participation. We therefore conclude that we indeed find educational differences, but the threshold after which true state dependence becomes weaker is lower than expected. The group of low-educated individuals is also the group for which we found the highest differences between countries in training-inherent cumulative advantage. Interestingly, our results suggest that the effect of unobserved heterogeneity associated with the initial training condition ranges between 15 and 20 percentage points for all educational levels in both countries. Assuming that unobserved heterogeneity is mainly based on company cultures, job characteristics, and the concrete tasks executed within individual jobs, we find



that such structural factors remain important for all groups. With regard to training-inherent cumulative advantage, we find much more variation within and between countries.

Regarding social inequalities, our results show that previous training participation might trigger continuous participation in both countries. While all educational groups in the UK might benefit from previous training participation, our results indicate that low-educated people in Germany have a double disadvantage. They are the workers who, due to path-dependency, enter disadvantaged positions in the labor market with the highest unemployment risks, and at the same time, this is the only group which does not seem to benefit from previous training participation.

We therefore conclude that, especially in Germany, policy should focus on companies, supporting their provision of job-related training to all workers (independent of their job positions), as structural aspects seem to be the main driver of (non)participation in job-related training. In the UK, our results are rather mixed. Unobserved time-constant factors and previous training participation experiences seem to be more similar in their importance in the UK than in Germany. This holds for all educational groups. As a result, we argue that for low-educated people in the UK, another beneficial option besides easing access to training opportunities within companies would be to provide single short-term training courses that might trigger continuous training participation.



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Appendix

Table A1. Descriptive statistics: Germany

	Mean
Job-related Training Participation	.35
Female	.5
Age	45.03
High Education	.51
Medium Education	.46
Low Education	.03
Cohabiting	.11
Married	.52
Number of Children	.15
Part-time Work	.35
Fixed-Term contract	.05
Company size: Max. 19 employees	.24
Company size: Min. 20 Max 199 employees	.38
Company size: Min. 200 employees	.38
Change of occupation	.06
Managers	.06
Professionals	.27
Technicians and associate professionals	.26
Clerical Support workers	.14
Service and sales workers	.09
Skilled agricultural, forestry and fishery workers	.01
Craft and related trades workers	.1
Plant and machine operators, and assemblers	.03
Elementary occupations	.05
Number of persons	4545
Number of person-years	28945
Mean person-years per person	6.89

Source: NEPS SC6 SUF 12.0.0, authors' calculations. Note: Statistics shown are mean values for unweighted data



Table A2. Descriptive statistics: United Kingdom

	Mean
Job-related Training Participation	.30
Female	.54
Age	42.09
High Education	.38
Medium Education	.4
Low Education	.22
Cohabiting	.78
Married	.63
Number of Children (under 6 years)	.22
Part-time Work	.29
Fixed-Term contract	.03
Company size: Max. 24 employees	.27
Company size: Min. 25 Max 199 employees	.37
Company size: Min. 200 employees	.37
Change of occupation	.07
occ1	.18
occ2	.17
occ3	.19
occ4	.13
occ5	.06
occ6	.09
occ7	.05
occ8	.05
occ9	.08
Number of persons	11730
Number of person-years	75753
Mean person-years per person	6.81

Source: Source: UKHLS, authors' calculations. Note: Statistics shown are mean values for unweighted data



Table A3. Dynamic Random Effects Probit Models: Average Marginal Effects Germany

	Coeff. (Std.Err)
Training Participation (t-1)	0.07*** (0.01)
High Education	0.04*** (0.01)
Low Education	-0.02 (0.03)
Female	0.05*** (0.01)
Number of children (under 6)	-0.01 (0.01)
Married	0.01 (0.02)
Cohabiting	0.01 (0.02)
Change of Occupation	0.08*** (0.01)
Firmsize: Min 20 Max 199 employees	0.01 (0.03)
Firmsize: Min 200 employees	0.07* (0.03)
Fixed-term contract	0.03 (0.03)
Part-time Work	-0.05*** (0.02)
Age	0.00 (0.00)
Occupation Fixed Effects	YES
Initial Conditions	
Training Participation	0.18*** (0.01)
Number of children (under 6)	0.02 (0.01)
Cohabiting	-0.03 (0.02)
Married	0.01 (0.02)
Firmsize: Min 20 Max 199 employees	0.00 (0.03)
Min 200 employees	0.05 (0.04)
Fixed-term contract	0.02 (0.03)
Part-time Work	0.05** (0.02)
Occupation Fixed Effects	YES
Individual Means	
Cohabiting	0.02 (0.04)
Married	-0.01 (0.04)
Company Size: Min 20 Max 199 employees	0.02 (0.05)
Company Size: Min 200 employees	-0.08 (0.05)
Fixed-term contract	-0.07 (0.05)
Part-time Work	-0.03



	(0.03)
Number of Children	-0.01
	(0.02)
Change of Occupation	-0.09*
	(0.05)
Occupation Fixed Effects	YES

Source: NEPS SC6 SUF 12.0.0, authors' calculations.

Table A4. Dynamic Random Effects Probit Models: Average Marginal Effects United Kingdom

	Coeff. (Std.Err)
Training Participation (t-1)	0.12*** (0.01)
High Education	0.01+ (0.01)
Low Education	-0.04*** (0.01)
Female	0.01+ (0.01)
Number of children (under 6)	0.00 (0.01)
Married	-0.03** (0.01)
Cohabiting	0.02 (0.01)
Change of Occupation	0.06*** (0.01)
Company Size: Min 25 Max 199 employees	0.01 (0.01)
Company Size: Min 200 employees	0.02 (0.01)
Fixed-term contract	-0.02 (0.01)
Part-time Work	0.01 (0.01)
Age	0.00 (0.00)
Occupation Fixed Effects	YES
Initial Conditions	
Training Participation	0.15*** (0.01)
Number of children (under 6)	0.01 (0.01)
Cohabiting	0.01 (0.01)
Married	0.00 (0.01)
Company Size: Min 25 Max 199 employees	-0.04* (0.02)
Company Size: Min 200 employees	-0.02 (0.01)
Fixed-term contract	0.01 (0.01)
Part-time Work	0.01 (0.01)
Occupation Fixed Effects	YES
Individual Means	
Cohabiting	-0.02 (0.02)
Married	0.03 (0.02)

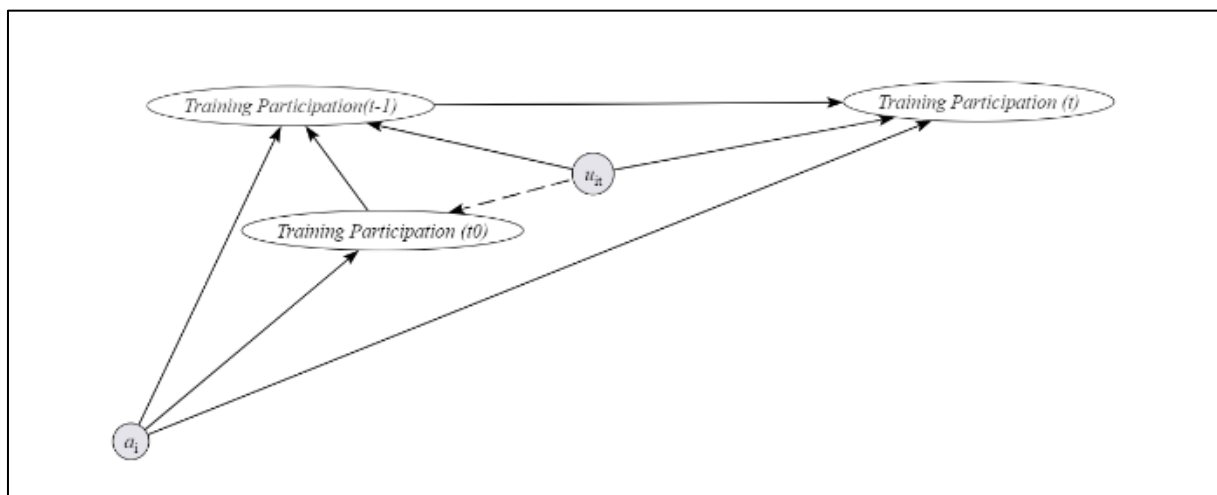
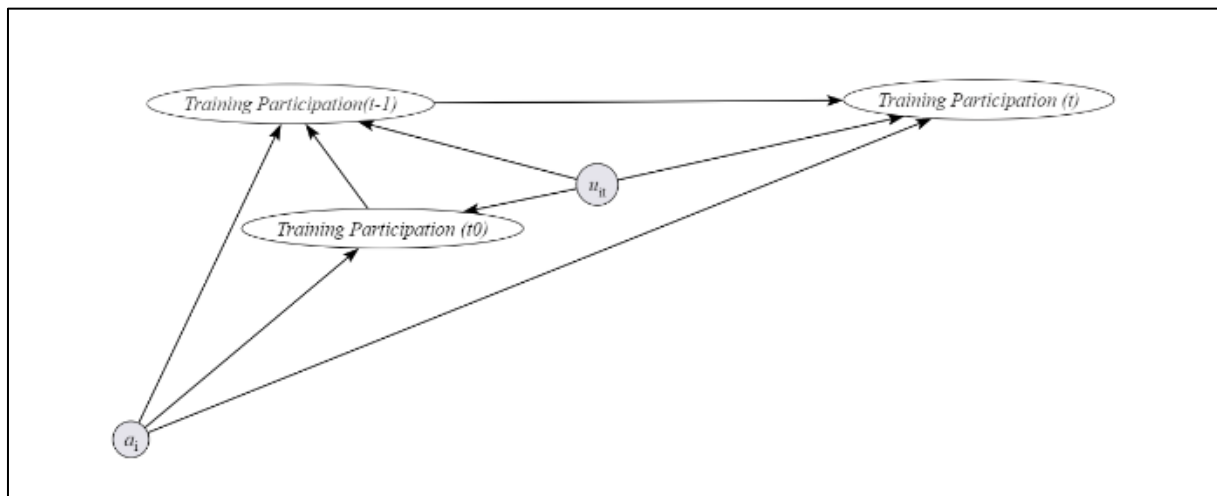


TECHNEQUALITY Deliverable D3.6

Company Size: Min 25 Max 199 employees	0.03+ (0.02)
Company Size: Min 200 employees	0.05* (0.02)
Fixed-term contract	-0.01 (0.03)
Part-time Work	-0.05** (0.02)
Number of Children	-0.02* (0.01)
Change of Occupation	0.05* (0.02)
Occupation Fixed-Effects	YES

Source: UKHLS, authors' calculations.

Figure A1. DAG Initial Condition



Chapter 5: Consequences of labor market careers without further training - Further training and job mobility in Germany and the United Kingdom

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Extended summary:

Politicians and pundits regularly point to the importance of investments in education and training for individuals and the society at large (Commission of the European Communities 2000; OECD 2012; UIL 2016). Given the recent pace of technological change, training even becomes more important because it may help workers adapting to new tasks or even transition from declining to emerging occupations. Yet so far, we lack knowledge about the actual influence of training participation for transitions from declining to emerging jobs. Also, we do not know which role country specific institution play for this. We aim to close these research gaps by answering two research questions: First, does the impact of non-formal further training on job mobility vary between occupations that are at different risk of substitution through technology? Second, does the institutional setup moderate the impact of training on job mobility? To study these questions, we compare use high-quality panel data from countries with a distinct institutional setup: NEPS data from Germany as a prime example of a system geared towards occupation-specific skills and UHLS data from the United Kingdom where the focus is more on general skills.

The core findings of our analysis suggest that job-related training prevents unemployment for employees in both Germany and the UK. The protection through training participation in the UK is even larger than in Germany. Nevertheless, compared to the observed transition rates to non-employment in both countries, the protection is not particularly strong. As a consequence, workers who do not participate in training face somewhat higher employment instability in both countries. We do not find that job-related training is associated with increased within- or between-firm mobility, or occupation changes in both countries. The results show that employees who participated in non-formal or short-formal job-related further training rather stay on their current jobs. While this could be expected on the German labor market, where turnover is low and the prerequisites to change occupations are high, it is somewhat surprising to also find this for the UK. Apparently short training courses in both countries are mainly used to improve skills on the current job. This finding is in line with a firm-centered perspective on further training. In both countries, firms pay for most of the courses. Consequently, it would be inefficient for firms to move workers to different tasks after training them for their current tasks. Also, this finding suggests that training workers after they moved to new positions is common in both Germany and the UK.



Our analyses that consider the occupational risk of substitution by automation found hardly any differences. We assumed that the effects of training would be more pronounced among vulnerable workers because they are more likely to use training for career stabilization and job-to-job mobility. Also, we expected to find more pronounced differences between the UK and Germany among workers with a high substitution risk. The assumption behind it was that a high-turnover labor market and an education system with a focus on general skills, as in the UK, would enhance the role of short training courses for job-to-job mobility. Yet, the results do not confirm these assumptions.

1. Introduction

Politicians and pundits regularly point to the importance of investments in education and training for individuals and the society at large (Commission of the European Communities 2000; OECD 2012; UIL 2016). Given the recent pace of technological change, training has become even more important because it may help workers adapt to new tasks or even transition from declining to emerging occupations. Thus, further training may protect workers from unemployment due to technological change. Moreover, it may help workers to reap the benefits brought by digitization, enabling them to move to new and better-paid jobs. On the other hand, if workers do not regularly train for a long period during their careers, they may face the risk of downward mobility because their skills become outdated.

However, recent research casts some doubt on the effectiveness of training in cushioning the negative effects of technological change on workers. First, it is well known that workers in jobs that are at risk of being substituted by machines participate in training less often (See Deliverable 3.6, Chapter 2²¹; Nedelkoska and Quintini 2018). Second, even if workers do participate, training is unlikely to lead to career advancement (Ehlert 2017). However, some evidence suggests that training leads to job stability and protects against unemployment (Ebner and Ehlert 2018; Parent 1999). Furthermore, research shows that the returns to training vary cross-nationally (Dieckhoff, Jungblut, and O’Connell 2007; Vogtenhuber 2015). This is presumably due to different educational systems, labor market regimes, and adult learning policies (Saar, Ure, and Desjardins 2013). Thus, it is plausible that the institutional setup moderates whether training is helpful for workers at risk of being replaced by automation.

Institutional characteristics may be especially important when thinking about how further training may help workers transitioning from declining to emerging occupations in times of technological change. Job mobility within a country is influenced by educational and labor market

²¹ Also published as Ehlert (2020)



institutions (Allmendinger and Hinz 1998; DiPrete et al. 1997). One very basic distinction is between occupational labor markets (OLM) and internal labor markets (ILM) (Marsden 1990). In countries where OLMs predominate, workers learn occupation-specific skills in initial schooling and tend to remain in their occupation over their career. In countries where ILMs are common, educational institutions teach general skills, workers learn occupation-specific skills on the job, and may change occupations within the same firm. When occupations become automated, workers with occupation-specific skills face the problem of obsolescent skills while workers with general skills remain employable (Hanushek et al. 2017). Thus, countries with a focus on general skills may find that their workers can more readily transition to new occupations following further training.

To the best of our knowledge, no study has explicitly analyzed the role of further training on the job mobility of workers at risk of being replaced by automation. Previous research showed that workers in Germany jobs with high automation risk are more likely to lose their jobs or to change occupations (Nedelkoska 2013). Furthermore, such workers often change to less well-paid jobs, presumably because of skill mismatches (Nedelkoska, Neffke, and Wiederhold 2015). This points to the importance of further training to cushion the transitions by providing new skills. Yet, we lack knowledge about the actual influence of training participation when workers aim to transition from declining to emerging jobs. Further, we do not know which role country specific institution play for this. We aim to close these research gaps by answering two research questions: First, does the impact of non-formal further training on job mobility vary between occupations that have different risks of substitution through technology? Second, does the institutional setup moderate the impact of training on job mobility? To study these questions, we compare two distinct setups: we use Germany as an example of a system geared towards occupation-specific skills and the United Kingdom as an example of a system geared toward general skills.

For our analysis, we need to look more closely at the definition of the term “further training”. Further training can encompass a range of very different educational activities in adulthood. The spectrum ranges from formal education to non-formal courses to self-directed informal training. We define these as follows: formal continuing education, includes university courses or certifications; non-formal courses include, training such as learning new equipment or language courses; and self-directed informal learning includes conference attendance or reading trade journals (Eurostat 2016). Since informal training is difficult to measure empirically, most research focuses on formal and non-formal further training (but see: Rüber and Bol 2017). The structured learning environments of formal and non-formal courses also correspond better to the everyday understanding of further training. Studies show that non-formal further training is much more widespread than formal continuing education (Cedefop 2015). Especially in Germany, participation in formal further education courses is very rare. This is partly because formal courses in Germany are usually very long



(one year or longer) and require attending a formal institution. In the UK, participation formal further education is more widespread. This is mainly because more short courses are recognized within the national qualification framework and therefore count as formal than in other European countries (Hefler and Markowitsch 2013). In this paper, we focus on short further training courses because they are more policy-relevant for the problems we address. They are more accessible for workers without reducing their working hours or requiring that workers go on leave. Therefore, we analyze non-formal courses in Germany, whereas in the UK, we look at both non-formal and short formal courses.

2. Theoretical Considerations

Job mobility is a subset of social mobility. Pitirim Sorokin (1927:133) defined social mobility as “...any transition of an individual or social object or value - anything that has been created or modified by human activity - from one social position to another”. We follow this basic understanding of social mobility and analyze the impact of further training on the change of social positions among employed adults. The social positions we consider are defined by the labor market. Thus, we study job mobility on the labor market.

Transitions from the labor market to unemployment or inactivity constitute the most basic form of job mobility where further training may play a role. These transitions are likely to have a large impact on an individual’s social position. Unemployment and retirement may lead to long-lasting income reductions (Ehlert 2016; Heisig 2015). Among women, employment interruptions due to childbirth also leave severe scars in earnings trajectories (Gangl and Ziefle 2009). Moreover, adults with prolonged non-employment spells may suffer from skill obsolescence and this may hinder future re-employment (de Grip 2006). Further training may help workers to stay employed or to move to new jobs, a point we will elaborate below.

Furthermore, we focus on job-to-job mobility that involves changes in skill sets to evaluate the impact of further training. A first important distinction for job-to-job mobility is that between firm-internal and firm-external labor markets (Doeringer and Piore 1971). In internal labor markets (ILM), workers change jobs, tasks, and occupations within firms. Here, workers need new occupational skills but can continue to use their acquired firm-specific skills. Next to the firm, occupations also structure job mobility. On occupational labor markets (OLM), workers move between firms but remain in their occupation (Althausser and Kalleberg 1981). This is possible because the set of tasks is similar across firms so that workers can apply their occupational skills in many firms. However, they usually need to learn firm-specific skills. Finally, some workers are on secondary labor markets (SLAM), which are constrained neither by firm nor by occupation (Althausser and Kalleberg 1981). Here, workers must learn both new occupational and firm-specific skills. This



type of mobility is often associated with low-quality and precarious jobs for which only basic skills are needed and where turnover is high. Therefore, such a labor market is labeled “secondary” compared to the “primary” labor market consisting of ILM and OLM, which offers better working conditions and more security. Yet, when occupations and industries decline because of digitalization, this type of job mobility may be a chance for vulnerable workers to enter growing occupations. Thus, the label “secondary” may not be appropriate.

Following these considerations, we distinguish between the following types of job mobility:

1. Within-firm mobility (ILM)
2. Between-firm mobility within an occupation (OLM)
3. Between-firm and occupational mobility (SLAM)
4. Transition to unemployment and inactivity

Following human capital theory (Becker 1975), investments in (continuing) education lead to an increase in individual productivity because workers enhance their skills. Participation in further training should therefore generally enable workers to keep pace with technical and social changes at the workplace or simply to refresh knowledge. Thus, further training could fulfill the function of a safety net for employed persons and prevent job losses. Also, it could equip workers with new skills for new jobs. This should be especially relevant for workers in occupations that are likely to be replaced by automation in the future. They are at higher risk of job loss but if they learn new skills they may be able to keep their jobs or move to a new job. According to these considerations, further training should lead to lower chances of unemployment and higher chances of job changes, especially among vulnerable workers.

Hypothesis 1: Short further training courses reduce the probability of transitions into non-employment especially in jobs with a high risk of substitution by automation.

Hypothesis 2a: Short further training courses increase the probability of transitions into new jobs, especially when the current job has a high risk of substitution by automation.

However, considering firms’ personnel policies and transaction costs leads us to a refine of Hypothesis 2a. Firms pay for most of the short training courses in both countries (Cedefop 2015). From the perspective of transaction cost theories (Coase 1937; Williamson 1985), it is important to consider the cost of investment in continuing education. Assuming rational, efficiency-oriented companies, they should invest primarily in those people from whom they expect the greatest benefit and whom they would like to employ for a longer period of time. Companies have a strong incentive to promote training with a company-specific focus, for example to enable employees to adapt to

company changes of a technical or organizational nature. Thus, employees are also likely to acquire (company-) specific human capital in particular. Following this reasoning, transitions to new jobs after training should mainly occur within the firm. Here, we also expect that this is more relevant for workers in declining occupations because they presumably use training more often to gain new skills for new jobs.

Hypothesis 2b: Short further training courses increase the probability of transitions into new jobs within the firm, especially when the current job has a high risk of substitution by automation.

The job competition model by Thurow (1975) however reverses the temporal order of training and mobility compared to the previous considerations: It posits that firms first promote workers and then train them on their new job. This would make it even less likely for firms to lay off workers who participated in training. Instead they try to keep those workers in their current positions because they just trained to do new tasks. If this is that case, training should mainly lead to job stability. From this perspective, selection into the new job occurs before training. Therefore, we should not find differences between workers based on automation probability because they are potentially already on the new less affected jobs when they receive the training.

Hypothesis 2c: Short further training courses increases the probability of staying in the current job.

Moreover, we expect to find country differences in the effect of training on job-to-job mobility. Germany features comparatively lower levels of occupational change over the career, presumably due to the strong focus on occupational skills in initial education (Allmendinger and Hinz 1998). Furthermore, many occupations in Germany require specific formal educational certificates, especially at the intermediate skill level (Bol and Weeden 2015). Thus, it is unlikely that short further training courses in Germany, which rarely lead to an upgrade of the level of formal qualification, will lead to occupational changes. In the UK, on the other hand, occupational skills are more often acquired on the job. Also, the percentage of workers in occupations that do not require a formal educational certificate is larger (Bol and Weeden 2015). There are even some short further training courses in the UK that lead to a formal certificate (Hefler and Markowitsch 2013). Therefore, it is likely that short further training will lead to higher rates of occupational mobility in the UK than in Germany.

The differences between the two countries may become even more pronounced when considering workers at a high risk of substitution by automation. While analysts have offered different predictions about the numbers of jobs at risk, they mostly agree that the current wave of technological change in the form of digitalization mainly affects the jobs of less-skilled workers (Dengler and Matthes 2018; Frey and Osborne 2017). Thereby, digitalization differs from the



computerization observed during the 1980s and 1990s that led to a “hollowing out” of the middle class (Autor, Katz, and Kearney 2006). Furthermore, workers in occupations with high automation risks do not have enough job training opportunities (see deliverable 3.6, chapters 2,3, and 4). Arguably, the differences between the German and the British labor market are larger for workers who do not have an academic degree. In Germany, most of these workers are in the vocational sector where the link between the field of their initial education and their occupation is high (DiPrete et al. 2017). Switching occupations is difficult for this group because they would need a new formal certificate. Further training may therefore be even less likely to lead to an occupational change in this group. Instead, further training may help them to adapt to new tasks on their current job. In the UK, on the other hand, occupation-specific credentials are even less common among the lower educational groups (Bol and Weeden 2015). Therefore, occupational change due to short courses may even be more likely in the UK than in Germany in occupations at risk. Conversely, training among vulnerable workers in Germany may more often lead to job stability than in the UK.

Hypothesis 3: The effect of short further training courses on changing occupations is larger in the UK than in Germany, especially when the current job has a high risk of substitution by automation.

Hypothesis 4: Among workers with a high substitution risk in the current job, the effect of training on job stability is larger in Germany than in the UK.

3. Data and Methods

For the empirical analyses, we use data from the National Educational Panel Study (NEPS), Start Cohort 6 (SUF 11.1.0) (Allmendinger et al. 2011; Blossfeld, Roßbach, and von Maurice 2011), and the Understanding Society: the UK Household Longitudinal Study (UKHLS). The NEPS captures educational processes, competencies, and educational outcomes across the lifespan. NEPS Starting Cohort 6 is a sample of birth cohorts 1944 to 1986 in Germany. We use the nine panel waves from 2009 to 2018 in the NEPS, as detailed information on non-formal courses is available here. The UKHLS is a large, nationally representative panel study for the UK that started in 2009/10, with annual follow-up. Adults (age 16+) are interviewed annually along with any new household members, in addition to household members who have turned 16 since the last interview. The UKHLS data are now available from wave 1 (2009-2010) to wave 9 (2017-19). We use eight panel waves from 2010 to 2019, because the first wave did not contain measures of job training. The two datasets are particularly well suited for analyzing non-formal training effects on labor market mobility, as extensive queries on training activities are made.

Since our analyses refer to (dependent) employees, we exclude all respondents who were self-employed at least once within the six waves. In addition, we restrict the sample to individuals



aged 25 to 55. After age 55, the complexity of labor market mobility increases, because retirement is possible. Within this subsample, all respondents are selected who were employed at least once during the observation period at the time of the panel interview and who continued to participate the following year. This results in 33,225 person-years in the NEPS data and 9,172 person-years in the UKHLS data.

Our dependent variable “job mobility” is assessed by the end of an employment episode and the subsequent state. The end of employment episodes is collected in both surveys by using supported queries. In each panel interview, the interviewer asks: “In our last interview at <time>, we noted that you were working at that time as <occupation mentioned at previous interview>. Until when did you hold this job with the same employer?”. In the UKHLS, the interviewer asks: “Is <occupation mentioned at previous interview> still an accurate description of your occupation in your main job?” and “Have you worked continuously for the same employer since the last interview date?” If the respondent indicates that one or both have changed, we record labor market mobility. This query excludes the possibility that job changes are erroneously caused by different coding of information on the occupation in two waves. On the other hand, it could also be that mobility is underreported because small changes in job tasks are not reported by respondents (Solga 2001).

Our variable on general labor market mobility has five categories (see table 1), depending on whether a change took place and what kind of episode after the end of an episode is current at the time of the interview: 1. immobility or no mobility, 2. internal mobility (change of occupation in the same company), 3. between-firm mobility without change of occupation, 4. between-firm mobility with change of occupation, and 5. exit from employment (= change to unemployment or labor market inactivity).

In Germany, we record occupational changes after the end of a job spell if the new job has a different 3-digit code in the Classification of Occupations 2010. The change of firms in Germany can unfortunately only be measured approximately due to a filtering error in the NEPS survey instrument. As an approximation, we coded the start of a new employment spell where the industry, region, and firm size are the same as the previous spell as within-firm changes. We record all other changes as between-firm changes. In the United Kingdom, occupational changes are operationalized as changes in the 3-digit version of the Standard Occupational Classification (SOC) 2000. Changes between firms are directly queried in the UKHLS questionnaire as indicated above.



Table 1: Forms of labor market mobility among employed persons

Labor market mobility	Change of occupation	Change of firm	Change to Inactivity
1. No mobility	No	No	No
2. Firm-internal mobility	Yes	No	No
3. Between-firm mobility in the occupation	No	Yes	No
4. Between-firm mobility & occupation change	Yes	Yes	No
5. Transition to unemployed / inactive	No	No	Yes

The central independent variable is participation in job-related further training. To exclude recall errors, the NEPS uses supported queries to record courses (Janik, Wölfel, and Trepesch 2016). Thus, for each individual life course episode (e.g., employment, unemployment, parental leave), respondents were asked about associated further training courses since the previous panel interview. In addition, at the end of the interview, they were asked again whether any further training had taken place that had not yet been reported. We use additional information to consider whether the course was job-related or not. This has been collected in most waves for a random sample of two courses. We also code all courses as job-related that were reported as part of employment episodes. The UKHLS asks respondents “In the last 12 months, that is since [interview month] [interview year - 1], have you done any [other] training schemes or courses, even if they are not finished yet? Please include any part-time or evening courses, training provided by an employer, day release schemes, apprenticeships and government training schemes.” Up to three training courses are recorded. We excluded courses that were for “hobby and leisure”. Since we also assume a longer-term effect of further training, we consider training participation for the two previous years. Thus, we record participation if a person participated in one or both of the previous two years.

We also consider whether the automation risk of current jobs affects an individual’s further training participation. We use a measure developed in the TECHNEQUALITY project (see Deliverable 1.1). The measure is based on a survey of HR professionals who were asked for different occupational tasks: “Based on the most recent technological developments (e.g., in the fields of robotics, computerization, machine learning), could you indicate how much time workers will spend on the following tasks for the occupation of [selected occupation] in the next five years?”. The data



was summarized on the level of ISCO 08 occupations. We use the share of tasks for which less time will be used as a proxy for automatability and merged it to the respective occupations in the NEPS and the UKHLS data sets.

Estimating the effect of training on mobility is complicated by confounders, that is, factors that influence both training participation and mobility. From previous research, it is known that participation in continuing education depends on initial education, gender, job characteristics, and firm characteristics (Bills 2005; Dämmrich, Vono de Vilhena, and Reichart 2014; Hubert and Wolf 2007; Schindler, Weiss, and Hubert 2011). Labor market mobility is also influenced by these factors (Erlinghagen 2006; Giesecke and Heisig 2010). To isolate the influence of further education from these confounding variables, we control for these factors in the models (for a summary, see Table A.2 in the Appendix). All control variables are measured before the potential change. Cases with missing values on any of the variables used are excluded. This procedure reduces the analysis sample from 33,225 to 28,159 person-years in the NEPS and from 9,172 to 6,156 person-years in the UKHLS for the analysis of labor market mobility.

We model labor market mobility as a time-dependent process in a competing-risks event history model for discrete time intervals. This specification has the advantage that time-varying independent variables can be included in the model. Since we do not observe total employment episodes during the panel waves for most respondents, we have both left- and right-censored episodes. Left-censoring is also known as the “delayed entry” problem: Respondents enter the sample after they have been “at-risk,” or in the job, for a while. However, this does not pose a problem for the calculation of the risk of changing jobs, since the duration of the current employment episode is known from the retrospective employment history questionnaire in both surveys. The first observation in our sample for individuals with “delayed entry” is assigned the current employment duration as the starting hazard (Rabe-Hesketh and Skrondal 2011:772). Right-censored cases, that is, employees without a change within the five-panel waves, represent the reference category in each case. Workers who experienced a mobility event re-enter the sample with their new job.

We calculate the risk of job mobility to the different destinations defined above using multinomial logistic regressions. The time-varying baseline hazard of ending a job spell (i.e. job mobility) is included in the model through categories of job tenure. The categories were chosen to represent the hazard curves of the target states. Model coefficients are reported as Average Marginal Effects (AME) to facilitate interpretation (Mood 2010). We adjusted the standard errors for clustering within individuals.



4. Results

Table 2 summarizes labor market mobility among employees in Germany and the UK as observed in our data sets. We calculated the share of individuals who experienced at least one of the mobility events over the observation period. Consequently, the row “no mobility” shows how many individuals did not change their job at all over the observed waves. In Germany, most individuals (61.9%) remained in their jobs across all waves. The most common type of job mobility is changing both firm and occupation (14.4%), while firm-internal mobility is least likely in Germany. Almost 11 percent of Germans in our sample experienced transitions to unemployment or inactivity at least once. In the UK, job stability is much less common. Only 30 percent remained in their jobs over all observed waves. Instead, the largest group, consisting of about 24 percent, experienced at least one job change within their firm. Furthermore, we find a large group (23.3%) of British people who experienced at least one transition to unemployment or inactivity. Also, job mobility across firms within occupations is much more common in the UK than in Germany. Only changes of both firm and occupation are more common in Germany than in the UK. In sum, we find a much more dynamic labor market in the UK in our data, as expected.

Table 2. Labor market mobility among employees in Germany and the UK (occurrence of at least one event, or none over the panel waves in % of individuals)

Type of mobility	Germany	UK
1. No mobility	61.9	30.2
2. Firm-internal mobility	4.8	23.8
3. Between-firm mobility in the occupation	8.3	17.1
4. Between-firm mobility & occupation change	14.4	5.7
5. Transition to unemployed / inactive	10.6	23.3

Sources: NEPS and UKHLS, own calculations

The upper part of Table 3 shows the results for the association between job-related training and labor market mobility in Germany from a competing risks event history model for discrete time intervals. The regression estimates that job-related training mainly reduces job-to-job-mobility in Germany, net of the control variables. The coefficient for training in the first row shows that the



probability of remaining in a job is significantly increased by about one percentage point for those who take part in further training. We also find a significant negative association with transitions to non-employment. The coefficient indicates that training participants have a 0.7 percentage point lower probability of becoming non-employed. Given the total rate of transitions to unemployment of about 11 percent shown in Table 2, this magnitude is small but not negligible. The associations with job-to-job mobility on the other hand are small and not statistically significant. Thus, Hypotheses 2a and 2b, which predicted mobility after training, are rejected in Germany.

Turning to the UK results, the lower part of Table 3 displays patterns similar to those seen in Germany. In the UK, job-related training is also significantly negatively related to the transition to non-employment: Workers who received job-related training are 2.1 percentage point less likely to become non-employed. This is even larger than in Germany but the relative magnitude is comparable, given the larger hazard of non-employment in the UK as indicated in Table 2. Interestingly, we find no significant coefficient for job stability. Yet, the direction of the coefficient shows that remaining in a job is slightly more likely in the UK, albeit at a lower level than in Germany. The estimates also suggest that there is no significant association between job training and job-to-job mobility, net of the control variables. If anything, we find some indications that internal mobility occurs more often after training as predicted by hypothesis 2b. However, coefficients are non-significant and so we have no evidence in favor of the hypothesis.

These findings show that job-related training prevents unemployment and works as a safety net for employees in the UK and Germany, though effect sizes are small. In sum, the findings in table 3 point in the direction of hypothesis 1, which stated that training should reduce transitions to nonemployment. Below, we will address whether this is especially the case for workers at high risk of automation. We also find support for hypothesis 2c: training participants are more likely to stay in their current jobs. This is most pronounced in Germany as predicted by hypothesis 4. Apparently, especially in Germany, employers train workers mainly for their current jobs. We also find weak evidence pointing towards hypothesis 3: The effect of further training on changing occupations is larger in the UK than in Germany. Yet, even though the coefficients of between-firm between occupation mobility show different signs in the two countries, the imprecisely estimated coefficients allow no confirmation of hypothesis 3.

Interestingly, table 3 suggests that substitution potential is associated with labor market mobility net of the control variables in Germany but not in the UK. The results indicate that German workers at high risk of substitution do not move within the firm or within the occupation but rather change both. Thus, they are apparently not able to make use of their firm and occupation specific skills and move to entirely new jobs. Transitions to non-employment are also slightly higher but here



the coefficient is not significantly different from zero. Thus, the TECHNEQUALITY measure shows plausible associations in Germany: Workers in jobs at high risk of automation move away from declining occupations and firms. In the UK we find no significant impact. If anything, there are slight increases of within-firm moves among those at risk of automation, but we cannot ascertain using this data whether this coefficient is significant. Thus, the TECHNEQUALITY measure does not affect job-to-job moves. It is not clear whether this results from measurement issues or labor market characteristics.

Table 4 displays the effects of job-related training on labor market mobility at low and high risk of substitution potential for the occupation. For Germany, the effects of job-related training do not differ much between workers at different risks of being replaced by machines: The AMEs of training participation at the highest value of substitution potential (57% of tasks will not be needed in the future) compared to the lowest (17% of tasks will not be needed in the future) are quite similar. If anything, the coefficients show some signs of larger mobility across firms and occupations and lower stability in the high-risk group. Yet, all differences are very small and do not reach any conventional level of statistical significance.

Similar to Germany, the difference between the AMEs of training participants at the lowest and highest risks of substitution potential in the UK are small and non-significant. Transitions to non-employment are more strongly reduced through training among the most vulnerable workers. This can be tentatively interpreted as evidence in favor of hypothesis 1. Yet, the difference is not statistically significant. We expected that among workers with a high substitution risk, the difference in the effect of further training on occupational mobility would be larger between the UK and Germany (hypothesis 3) and the effect of training on job stability and intra-firm mobility is larger in Germany (hypothesis 4). Our results suggest that neither hypotheses 3 nor 4 is supported. Instead, the lack of differences is evidence in favor of hypothesis 2c, which predicted effects on job stability regardless of automation potential. Accordingly, the data support the Job Competition Model where training occurs after mobility and substitution risk consequently has no impact because workers are already in new jobs when they train.



Table 3. The effect of job-related training and substitution potential on labor market mobility in Germany and the UK. Results from event history models controlled for individual and job characteristics calculated as average marginal effects

Germany					
	(1)	(2)	(3)	(4)	(5)
	Stability	Within-firm	Between-firm within occ.	Between-firm between-occ.	Non-employment
Job-related training	0.0112** (0.00383)	0.00180 (0.00143)	-0.00388 (0.00210)	-0.00261 (0.00243)	-0.00648** (0.00212)
Substitution potential	0.0000647 (0.000228)	-0.000166* (0.0000847)	-0.000450*** (0.000137)	0.000461*** (0.000138)	0.0000902 (0.000114)
N	28159	28159	28159	28159	28159
United Kingdom					
Job-related training	0.00500 (0.0115)	0.0102 (0.00730)	0.00340 (0.00640)	0.00405 (0.00406)	-0.0227*** (0.00668)
Substitution potential	-0.000681 (0.000630)	0.000825 (0.000443)	0.000159 (0.000354)	0.000109 (0.000230)	-0.000411 (0.000355)
N	6054	6054	6054	6054	6054

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controlled for: Education, gender, work experience, hourly wages, work hours, firm size, sector, household composition, migration background, job tenure

Source: NEPS and UHLS, own calculations

Table 4. The effect of the interaction between job-related Training and Substitution Potential on Labor Market Mobility in Germany and the UK. Results from event history models controlled for individual and job characteristics. Average marginal effects of training calculated at the lowest and highest observed value of substitution potential

Germany					
	(1)	(2)	(3)	(4)	(5)
	Stability	Within-firm	Between-firm within occ.	Between-firm between-occ.	Non-employment
Job-related training					
Substitution potential low	0.0137 (0.0101)	-0.000322 (0.00424)	0.000237 (0.00729)	-0.00714 (0.00451)	-0.00648 (0.00463)
Substitution potential high	0.00522 (0.00930)	0.00297 (0.00271)	-0.00606 (0.00406)	0.00425 (0.00692)	-0.00638 (0.00516)
N	28159	28159	28159	28159	28159
United Kingdom					
Job-related training					
Substitution pot. low	0.00769 (0.0262)	0.00844 (0.0165)	-0.00209 (0.0147)	0.00284 (0.00880)	-0.0169 (0.0177)
Substitution pot. high	0.000684 (0.0254)	0.0117 (0.0194)	0.00860 (0.0146)	0.00524 (0.00953)	-0.0263* (0.0129)
N	6054	6054	6054	6054	6054

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controlled for: Education, gender, work experience, hourly wages, work hours, firm size, sector, household composition, migration background, job tenure

Source: NEPS and UKHLS, own calculations



5. Conclusions

Ongoing debates on the risk of automation for jobs discuss whether and how job-related training can help employees adjust to structural changes in the labor market. In this chapter, we investigated the effects of job-related training on individual labor market mobility using German and British longitudinal data sets. Thereby, we aimed to find out whether the impact of training on labor market mobility differs between Germany and the UK. We especially focused our analyses on workers at high risk of substitution due to automation because such workers are most likely in need of new skills and jobs.

The core finding of our analysis suggests that job-related training prevents unemployment for employees in both Germany and the UK. The protection through training participation in the UK is even larger than in Germany. Nevertheless, compared to the observed transition rates to non-employment in both countries, the protection is not particularly strong. As a consequence, workers who do not participate in training face somewhat higher employment instability in both countries. This result is in line with what has been found by previous studies (Ebner and Ehlert 2018; Parent 1999).

We find that job-related training is not associated with increased within- or between-firm mobility, nor is it associated with occupation changes in either country. The results show that employees who participated in non-formal or short-formal job-related further training remain in their current jobs. While this might have been expected in the German labor market, where turnover is low and the prerequisites to change occupations are high, it is somewhat surprising to also find this for the UK. Apparently short training courses in these countries are mainly used to improve skills on the current job. This finding is in line with a firm-centered perspective on further training (Wotschack 2020) and the job competition model (Thurow 1975). In both countries, firms pay for most courses. Consequently, it would be inefficient for firms to move workers to different tasks after training them for their current tasks. Also, this finding suggests that training workers after they move to new positions is common in both Germany and the UK.

Our analyses examining the occupational risk of substitution by automation found hardly any differences. We assumed that the effects of training would be more pronounced among vulnerable workers because they are more likely to use training to stabilize their careers and increase job mobility. Also, we expected to find more pronounced differences between the UK and Germany among workers facing a high substitution risk. The assumption behind this hypothesis was that a high-turnover labor market and an education system with a focus on general skills, as in the UK, would enhance the role of short training courses for job-to-job mobility. Yet, the results do not confirm these assumptions.



The lack of findings when comparing workers facing different automation risk may of course be due to imprecise measurement of the probability that a job will become automated. In this paper, we relied on a novel measure developed in the TECHNEQUALITY project. It is based on human resources specialists' assessments of the time workers will spend on certain job tasks over the course of the next five years. It may well be that these trends do not apply to the workers in our sample, especially since our window of observation starts in 2010. Nevertheless, it is possible that this measure follows long-term trends already visible 10 years ago. At least in Germany, we find some evidence that the risk of changing both job and firm increases as substitution risk increases. Conversely, workers at high risk are less likely to stay in their firm and occupation. This fits the assumption that workers in occupations at risk of automation have to change jobs. The finding is in line with results by Nedelkoska (2013), who also found higher occupational change and higher unemployment among workers at risk of automation. The reason that we do not find higher unemployment in our sample may be that labor demand was much higher in Germany in the period under study compared to the previous study. Thus, workers looking for new jobs had a much higher chance of getting offers in the 2010s in Germany compared to before. Still the result that the TECHNEQUALITY measure of substitution risk does not predict labor market mobility in the UK is somewhat puzzling and requires further inquiry.

In terms of policy implications, the results first and foremost confirm that further training stabilizes careers, regardless of the risk of automation. Thus, policies that lead to higher and more equal participation in job-related further training are important to reduce employment insecurity. The cross-country comparison further suggests that this works regardless of the structure of labor market and educational institutions. The protective role of further training is observable in two countries with different institutions.

However, the finding that further training does not help vulnerable workers acquire new jobs in either country is sobering for those advocating further education as a solution. The most plausible reason is that short further training is often financed by the current employer. This implies that the skills learned are often job specific. Also, there may be reverse causality: Employers train those workers they want to keep. While this is good for employment stability, it does not enable workers in declining occupations to move to new jobs. Arguably, this is not the role of company-financed training. Thus, the results suggest that the organization of training needs to be changed before further training can actually help vulnerable workers.

Offering more state-funded further training courses would presumably be one option to provide training that is better geared towards transitions from declining to emerging jobs. Of course, these have to be in close cooperation with the firms so that the content is actually relevant in the



labor market. A role model for this could be the German apprenticeship system where employers, unions, and the state organize the curriculum. Furthermore, these courses should be accessible for full-time workers outside their work hours or leave regulations and funding should be developed

Even though the results in this paper are not in line with some hopes about what further training can do for vulnerable workers, we still confirmed a substantial “safety net” effect for participating workers. This is even the case in these two very strongly differing labor markets. Whether there are further positive effects from training should be the subject of future analyses that measure training in greater detail than was possible in this comparative paper.



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Appendix

<i>Variable</i>	<i>Mean</i>
<i>Job-related Training (2 prev. years)</i>	.5
<i>No voc./higher Edu.</i>	.05
<i>Vocational Edu.</i>	.64
<i>Higher Edu.</i>	.31
<i>Emp. experience (months)</i>	242.8
<i>TECHNEQUALITY substitution risk</i>	37.27
<i>Log hourly wage</i>	2.85
<i>>20 h/week</i>	.08
<i>20 - 35 h/week</i>	.25
<i>> 35 h/week</i>	.66
<i>Beamte</i>	.09
<i>>5 employees</i>	.06
<i>5 - 10 employees</i>	.09
<i>11 - 20 employees</i>	.1
<i>20 - 100 employees</i>	.27
<i>100 - 200 employees</i>	.11
<i>200 - 2.000 employees</i>	.26
<i>2.000 employees and more</i>	.11
<i>Sector: Industry/Agriculture</i>	.32
<i>Public sector</i>	.29
<i>Children <14 in hh</i>	.37
<i>Women</i>	.5
<i>Migration background</i>	.15
<i>Tenure at current job (months)</i>	120.84

Table 5: Germany, means of the control variables



Variable	Mean
<i>Job-related Training (2 prev. years)</i>	.48
<i>Low</i>	.32
<i>Med.</i>	.36
<i>High</i>	.32
<i>Emp. experience (years)</i>	79.58
TECHNEQUALITY substitution risk	38.29
<i>Log hourly wage</i>	9.8
<i>< 20 h/week</i>	.12
<i>20 - 35 h/week</i>	.3
<i>> 35 h/week</i>	.58
<i>1 - 9 employees</i>	.16
<i>10 - 24 employees</i>	.15
<i>25 - 99 employees</i>	.26
<i>100 - 199 employees</i>	.11
<i>200 - 999 employees</i>	.19
<i>1.000 employees and more</i>	.11
<i>Sector: Industry/Agriculture</i>	.17
<i>Public sector</i>	.14
<i>Women</i>	.53
<i>Children <14 in hh</i>	.61
<i>Migration background</i>	0
<i>Tenure at current job (years)</i>	2.43

Table 6: United Kingdom, means of the control variables



Chapter 6: Gender differences in ICT training participation in international comparison

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Extended Summary

The objective of this chapter is to understand gender differences in participation in information and communication technologies (ICT) related training in Europe, as this type of training has the potential to provide skills necessary for better adaptation to rapid technological innovation in the world of work but also in other domains of life. Surveys indicate that men use computers somewhat more frequently than women. However, there are considerable country variations, as the gender differences are more pronounced in Southern European countries. For example, in Italy in 2017 in the 12 months prior to the survey 65% of men compared to 57% of women use computers, average in Europe is 81% among men and 78% among women (Eurostat, data code: isoc_ci_cfp_cu). There are also studies indicating some disadvantage for women in ICT literacy skills (Jannsen et al. 1993; Kuhlemeier and Henker 2007; Volman et al. 2005), although some recent studies show less consistent gendered patterns (Eickelmann et al. 2019; Fraillon et al. 2019; OECD 2019). Many studies focus on gender differences in participation in adult education and training in general, revealing mixed results (e.g., more recent contributions by Dostie and Javdani 2020; Wotschack 2019; Boll and Bublitz 2018; Dämmrich et al. 2014; Wozny and Schneider 2014; Dieckhoff and Steiber 2011; Albert et al. 2010). However, there is little research on gender gap in participation in more specific type of adult education and training, such as ICT-related training (see for example Jannsen and Wölfel 2017). Based on the most recent wave of the Eurostat Adult Education Survey (AES) 2016, this report aims to fill this gap. Three following research questions are addressed:

Do men and women with comparative characteristics differ in participation in ICT-related training and what are the country variations?

How do household characteristic (marital status and presence of children) as well as workplace-related (occupational and sectoral) characteristics interact with the gender training gap?

Can country-specific characteristic contribute to explaining the country variation in gendered training participation? The focus is on four institutional characteristics: relative power of women in the labour force, family policies, gender culture and overall gender inequality index.

The analysis shows that women are somewhat disadvantaged in ICT training participation. Furthermore, results support gender segregation and gender role theories, as this disadvantage is more related to jobs than household context: occupational and sectoral gender segregation has a mediating impact on the gender training gap. However, a considerable gap in ICT training



participation appears also between men and women working in the same occupation and in the same sector.

The analysis clearly confirmed that gender differences in ICT training participation differ between sectors and occupational groups. Workplaces in sectors of professional, scientific and technical activities as well as in retail, accommodation and catering show higher gender ICT training gap. The training participation is rather equal in construction, mining, manufacturing and transportation. These results contradict previous findings about general gender training gap indicating that this gap is lower in female-dominated sectors and higher in male-dominated sectors. This could be explained by the variations in the content of training, as some studies indicate female disadvantage in more advanced ICT training (Janssen and Wölfel 2017). Yet AES data does not provide information on the specific type of ICT training. Same explanation could apply for female disadvantage in ICT training participation in high-skilled white-collar occupations. In terms of firm size, results indicate that participation in ICT training is more equal in smaller firms. Wotschak (2019) comes to similar conclusion and assumes that solidarity, fairness norms and social control are more important in smaller work settings.

Examining cross-country differences shows that women have highest ICT participation rate in Norway, Spain, Germany, France, Austria, Belgium, Sweden and the Netherlands. Moreover, it appears that gender gap in ICT training courses in favour of men tends to be higher in countries with rather high overall ICT participation rates, such as Norway, Luxembourg, the Netherlands, Switzerland and the United Kingdom. Evidence for differences between countries in terms of training predictors is less straightforward. Still, gender culture and overall gender inequality index (GII) comprising health, empowerment and economic status indicators tend to modify gendered ICT training gap. In countries with more egalitarian gender culture, participation in ICT training is higher, but this effect is stronger for men, therefore participation gap is relatively high. In the same vein, participation in ICT courses is higher in countries with lower GII, i.e., lower level of gender inequalities in different spheres of life, but again the effect is stronger for men. It has been suggested that in less gender-equal countries women are more likely to engage in the fields of science, technology, engineering and mathematics to find a way out of difficult living conditions (Stoet and Geary 2018). Accordingly, girls might feel the pressure to use new technologies and acquire ICT skills and thus this could explain why in more gender egalitarian countries gendered ICT training gap is higher.

These findings imply that there could be some role for supporting workplace female-friendly policies geared towards women with more training (see also Huffman et al. 2017; Wotschack 2019). Some previous studies conclude that gender occupational and sectoral segregation is very important predictor of gender training gap. However, results presented here indicate that ICT training gap is



wider in female-dominated occupations and sectors. Hence, paying attention to women's labour market opportunities should not be limited to their access to certain workplaces, occupations and sectors, but women should be supported also within workplaces.

Literature indicates that there is a considerable gender difference in expectations about working in ICT-related occupations among youngsters (OECD 2018) and social environment (family, school etc.) reproduces the traditional stereotypes about perceived masculinity of computers. Additionally, studies show girls being less confident about their computer competencies (Meelissen 2008). Therefore, teachers have a role in potentially narrowing this confidence gap. Initiatives to reduce gender-based stereotypes about ICT-related activities could increase girls' interest in programming and other computer applications and consequently reduce gender differences in ICT training participation.

Introduction

The labour market is in flux affected by a deep and rapid digital transformation as well as a globalization. Promoting a good match between the rapidly changing demand for skills with workers' competencies is crucial to harness the potential of these changes and ensure that no one is left behind (Autor et al. 2003). The ability to use computers is not only becoming an essential skill, but proficiency in computer use has an impact on the likelihood of participating in the labour force and on workers' wages. With the widespread diffusion of information and communication technologies (ICT) in all areas of life, the ability to manage information in digital environments and solve problems that involve the use of digital devices, application and networks is becoming essential for adults of both sexes (OECD 2012).

Surveys commonly find that men use computers somewhat more frequently than women do. Eurostat found that in 2017 81% of men aged 16–74 used a computer in the 12 months prior to the survey compared to 78% of women that age [Eurostat, isoc_ci_cfp_cu]. However, there are quite big country differences: the gender differences are bigger in Southern European countries (for example in Italy 65% men used computers and only 57% of women). Expectations about working in ICT-related occupations appear to be highly gender-biased. In 2018, on average across OECD countries, only 1% of girls reported that they want to work in ICT-related occupations, compared with 8% of boys who so reported (OECD 2018). In addition, the gender gap in interest in these occupations tended to widen over the past few years. The proportion of boys who reported that they expect to work as ICT professionals had increased between 2015 and 2018 by 1.1 percentage points, but the proportion of girls who reported so increased by only 0.2 percentage points during the same period (OECD 2018).



Most research in the 1990s and early 2000s show disadvantage for women in ICT literacy (Jannsen et al. 1993; Kuhlemeier and Henker 2007; Volman et al. 2005). In contrast, more recent studies reveal less consistent pattern. For example, some studies indicate that girls outperform boys in ICT skills (Eickelmann et al. 2019; Fraillon et al. 2019). Based on the 2018 PIAAC survey, men perform slightly better than women in problem solving in technology-rich environment. On average across OECD countries, 32% of men score at Level 2 or 3, compared to 28% of women, although a similar share of men and women have no computer experience or have failed the ICT score test (OECD 2019).

Adult education and training can provide opportunities to develop proficiency in problem solving in tech-rich environments. Various studies have compared men's and women's participation in adult education and training in general. The results are heterogeneous. In some studies, a gender training gap was identified, i.e., women were found to participate in training less likely than men (Dieckhoff and Steiber 2011; Evertsson 2004; Pischke 2001). However, there are also empirical evidence that women participate to a similar (Albert et al. 2010; Bassanini et al. 2005) or even higher extent (Dämmrich et al. 2014; Jones et al. 2008; Simpson and Stroh 2002). The question arises whether there exists important group heterogeneity among men and women, which is crucial in determining the participation incidence. Particularly, the household context, that is the presence of a partner and children, has been shown to significantly influence participation in training (Boll and Bublitz 2018). The gender training gap has been found to interact with the level of education (Wozny and Schneider 2014) as well as occupational and sectoral characteristics (Burgard 2012; Dostie and Javdani 2020; Wotschack 2019).

The gender training gap differs considerably between countries and several authors argue that gender differences in training participation arise due to country-specific institutional setups (Arulampalam et al. 2004; Dämmrich et al. 2015, Dieckhoff and Steiber 2011; Wozny and Schneider 2014). There are much less studies about gender differences in participation in more specific type of adult education and training, such as ICT-related training (see for example Jannsen and Wölfel 2017). Drawing on the most recent data from the Eurostat Adult Education Survey 2016, this report aims to fill this gap, by addressing the following research questions: first, do men and women with comparative characteristics differ in participation in ICT-related training? If so, how does this gendered training participation varies between countries? Second, how household characteristic (e.g., presence of children) as well as workplace-related (occupational and sectoral) characteristics interact with the gender training gap? Third, can country-specific characteristic contribute to explaining this country variation in gendered training participation? More specifically, we focus on four institutional characteristics: relative power of women in labour force, family policies, gender culture and overall gender inequality index.



Theoretical perspectives

The gender training gap

The gender training gap has been explained by human capital theory, 'doing gender' theories and discrimination theories. Human capital theory is concerned with the incentives for employers to invest in education and training (Becker 1975). It is expected that returns on training relative to its costs are most central in the skill investment decisions of both workers and employers. To explain differences between men and women in training participation, human capital theory refers to the variations in the labour force participation over the life course (Blau and Ferber 1992). Three differences between men and women have been argued to produce a gender training gap. First, as mothers spend considerable time outside the labour market, they are confronted with shorter time for recovering training investments. Second, in times of rapid technological change, women who return to the labour market after a prolonged period of leave face the problem of skill depreciation. This could reduce the incentive for women to train if they plan to have children in the near future, as they cannot be sure that this training will produce any return after a career break. Third, Becker (1985) argues that married women dedicate more time to household activities than married men. Investments in human capital that is of value in the labour market should be less attractive for women as they can reap lower returns. Theories of 'doing gender' postulate that gender roles are structured by practiced behaviour in the household context (West and Zimmerman 1987). During family building, the traditional gender roles are revitalized (Dieckhoff and Steiber 2011). From a gender role perspective, it is actual presence of care responsibilities that is the central mechanism affecting women's training participation.

Discrimination theories stress the perspective of employers. Taste-based discrimination against women implies a lower level of pay at which employers are willing to hire women (Becker 1957). One way to reduce pay is reducing training cost for women. Women may receive less training because of statistical discrimination (Arrow 1973; Phelps 1972). Employers perceive gender as a predictor of productivity. If women are predicted to be less productive, employers will invest less in training for women. Due to traditional division of work within couples, employers might perceive mothers as less committed to their jobs than women without children with similar characteristics. By contrast, fathers are assumed to be more attached to their work career than otherwise similar men (Correll et al. 2007). Employer discrimination against women might particularly evolve in the case of parenthood.



Gender segregation

According to a variant of human capital theory, women, because they anticipate career interruptions, choose occupations that require skills with low depreciation rates (Polachek 1981). Lower requirements for further training in female-dominated occupations would explain the gender training gap. Gender role theories predict that women choose occupations that require lower level of skill investments (Schwartz 1992). Employers' discriminatory practices in hiring might also prevent women from access to positions that are associated with greater opportunities for continuing training (Pfeffer and Ross 1990; Tomaskovic-Devey and Skaggs 2002). If women have no access to men's jobs, they do not have such training opportunities that relate to these jobs.

These approaches emphasize the importance of the type of job for training participation over and above of worker characteristics. If once selected into certain occupations, the amount of training is shaped firstly by skill requirements of the job and not so much by workers' skills and incentive structures. Previous studies indicate that training participation is higher in some occupations and sectors (Asplund 2005). The literature of occupational segregation suggests that the proportion of male workers in an occupation is positively related to the employment rewards (including training opportunities) that workers obtain, while a high proportion of women in an occupation is associated with lower levels of rewards (Reskin and Bielby 2005). However, some studies indicate that the demand for additional training is higher in education, health and social work sectors where many jobs are based on state-provided educational tracks and where women dominate (Estevez-Abe 2005). Wotschack (2019) argues that for female-dominated sectors and occupations higher rates of female training participation are often resulted from a stronger need for training and more legal regulations. Sectors and occupation related to ICT activities tend to be male-dominated. However, previous research in Germany have not shown significant gender differences in training participation in information and communication (Wotschack 2019).

According to model developed by Sap (1993) the proportion of women in the bargaining unit affects their bargaining power and could make women more capable of bargaining or competing for better training opportunities. Therefore, over-presentation of women in a sector or occupation could create specific conditions that could result in better training opportunities for women compared to men. A model of discrimination and segregation also assume that female-dominated industries or occupations might engage less in discriminatory behaviour of employers, while women in male-dominated industries and occupations might have to compete harder for training opportunities (Altonji and Blank 1999). On contrary Grönlund (2012) supposes that female-dominated occupations display a lower level of on-the-job training requirements than occupations dominated by men. Employers' deliberations on training investments may relegate women occupations with lower



training requirements. Her empirical analysis even provides some support for the hypothesis that on-the-job training is a mechanism of gender segregation.

Institutional context

Comparative studies on training participation have confirmed the importance of country-specific institutions in explaining gender differences in training participation (Dämmrich et al. 2016; Dieckhoff and Steiber 2011; Wozny and Schneider 2014). Institutions may also moderate the effect of individual characteristics on training participation. We focus on three country characteristics which have been found to have impact on gender differences in training participation: the relative power of women in the labour market, family policies and the gender culture.

Previous analysis confirms the importance of relative power of women in the labour market for female training participation (Wotschack 2019). When the work force and/or the management are composed of higher share of women, career and training interests of women should receive more attention and more power to be realized.

Family policies encouraging women's continuous participation in the labour market have been shown to positively affect women's and especially mothers' rate of labour market participation and also participation in training (Dieckhoff and Steiber 2011). In countries with more generous childcare facilities and shorter parental leave, females' labour market participation is higher (An 2013). In turn, higher labour market participation is linked to higher training participation (Estevez-Abe et al. 2001). Childcare tends to reduce the gender differences, as it enables women to return to the labour market. In contrast, longer parental leaves can have negative effects on women's training participation because these measures tend to keep mothers out of the labour market for longer (Estevez-Abe 2005).

Country-specific beliefs and norms about women's and men's roles in society and in the labour market may also have an impact on gender differences in training participation. Employers' discrimination against women has been found to be lower in more gender-egalitarian countries (Triventi 2013). In these societies men and women are also more equal in terms of labour market participation. Previous results indicate that employers in more gender-egalitarian societies are also less likely to discriminate women related to training participation than in societies with more traditional gender cultures (Dämmrich et al. 2015). Dostie and Javdani (2020) also explain women privileges to participate in training in non-profit sector by their over-presentation in this sector.

Data and methods

The analysis is based on the European Union Adult Education Survey (AES) 2016. This survey is part of the EU statistics on lifelong learning (formal, non-formal and informal) and is carried out every five years. AES 2016 is the latest wave available, conducted in 2016 and 2017 with the sample representative of 25- to 64-year-olds living in private households. In this report, data on 29 European countries is analysed (N = 187,884).

Participation in training related to information and communication technologies is defined by the field of the 1st and/or 2nd non-formal education and training activity twelve months prior to the interview. Hence, the analysis distinguishes between adults who have participated in ICT training either in their 1st or 2nd (or both) educational activity and those who have participated in training related to other fields or have not participated in any training. The AES 2016 questionnaire does not specify further the content of the ICT training, which could have been either in the form of courses, workshops and seminars, guided-on-the-job training or private lessons. Mainly, respondents have participated in ICT training in the form of courses and guided-on-the-job training.²²

The impact of independent variables is studied at micro-, meso-, and macro-level, i.e., at individual, workplace, and country level respectively. At the micro-level following characteristics are included: gender, age group (25–39, 40–49, 50–64), and educational level (ISCED 0–2, ISCED 3–4, ISCED 5–8). Additionally, from household composition analysis includes marital status (living or not living in a consensual union) and having children in the household (0–13 years old). From workplace-related characteristics analysis controls for occupation, firm size and sector (economic activity of the local unit). We distinguish four occupational groups: high-skilled white-collars (ISCO 1–3), low-skilled white-collars (ISCO 4–5), 'high-skilled blue-collars (ISCO 6–7) and low-skilled blue-collars (ISCO 8–9). Categories for firm size are following: 1–10 persons, 11–19, 20–49, 50 or more and no answer but 10 or more persons. Lastly, we distinguish between three economic sectors based on NACE classification: construction, mining, manufacturing, transportation etc. (A-F, H), sale, retail, accommodation, catering (G, I, T), professional, scientific, technical activities, administration and services, etc. (J-S, U).

To explore the impact of macro- or country-level characteristics on gender differences in participation in ICT courses, analysis includes aggregate data from various other sources:

²² According to AES 2016 pooled country data, the distribution of types of the 1st non-formal learning activity in the field of ICT is as follows: courses 40%, workshops and seminars 21%, guided-on-the-job training 37.5% and private lessons 1.7%.

Relative power: the share of female employees in the work force (Eurostat), the share of female in management (OECD)²³;

Gender culture: disagreement or strong disagreement with the statement that *when job's are scarce, men should have more right to a job than women* (World Values Survey (WVS));

Family policies: the share of children in childcare below the age of 3 years and between 3 and schooling age (Eurostat), the length of paid maternity and parental leave (OECD);

Gender Inequality Index (UNDP)²⁴, GII measures gender inequalities in three aspects of human development: (i) reproductive health, measured by maternal mortality ratio and adolescent birth rates; (ii) empowerment, measured by proportion of parliamentary seats occupied by females and proportion of adult females and males aged 25 years and older with at least some secondary education; and (iii) economic status, expressed as labour market participation and measured by labour force participation rate of female and male populations aged 15 years and older.

Macro-level characteristics from OECD and WVS have missing data in case of some countries (maximum 5 countries out of 29), thus the number of countries included in the analysis at this stage varies. Description of macro-level characteristics is provided in Appendix (Table 1a–4a).

To analyse micro-level determinants of participation in ICT-related training, binary logistic regression is used. Further, regression models control for interactions with gender by household and job-related variables to determine if the impact of these characteristics on ICT training varies for men and women. The effect of macro-level characteristics on participation in ICT training is analysed by applying multilevel logistic regression and controlling for individual-level characteristics. Additionally, to investigate possible modifying effect of macro-level variables on gender differences in participation in ICT courses interactions with gender are introduced (interactions are included step-by-step in separate models).

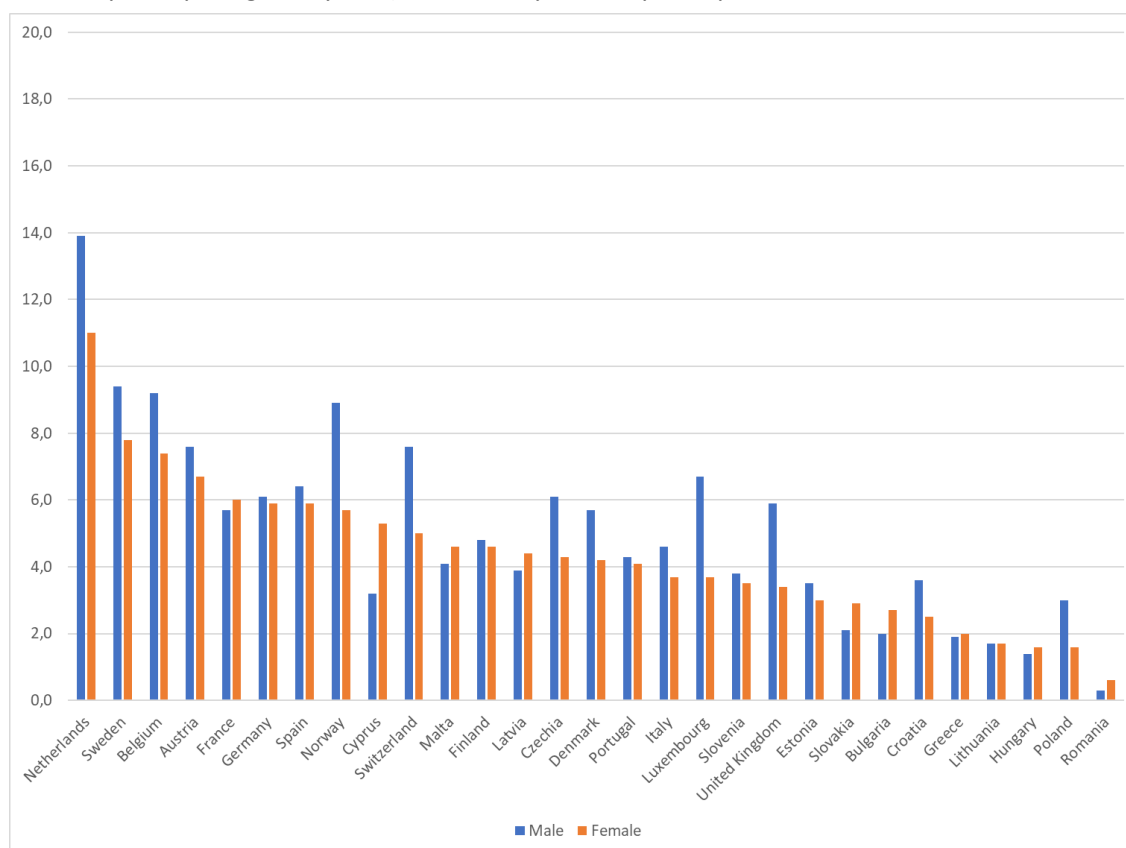
²³ Additionally, at the macro-level we controlled for the effect of the share of female engineers and scientists (Eurostat measure). However, this effect was in an unexpected direction, i.e., higher share of female engineers and scientists is associated with lower female ICT training participation. As this measure does not provide additional explanation to the gendered ICT training participation, we exclude it from the final analysis.

²⁴ For more details on the UNDP GII see <http://hdr.undp.org/en/content/gender-inequality-index-gii>

Results

According to the Adult Education Survey 2016, in EU-28 on average 37% of men and 34% of women participated in non-formal education and training (NFE). Focusing specifically on NFE courses in the field on ICT, it appears that in countries studied here, in the whole AES sample 5.4% of men and 4.6% of women report taking part in such training activities²⁵. Therefore, overall men are somewhat more often participating in NFE and also in ICT-related NFE. However, there are considerable country variations. Results in Figure 1 indicate that for women participation rate in ICT courses is the highest, about 6% to 11%, in Norway, Spain, Germany, France, Austria, Belgium, Sweden and the Netherlands. While at the other extreme, in Greece, Lithuania, Hungary, Poland and Romania ICT courses participation rate among women is only 2% or less.

Figure 1. Participation in ICT courses by gender: ICT training in the whole sample (vs other trainings and not participating in any NFE) [ordered by female participation rate]



Source: AES 2016

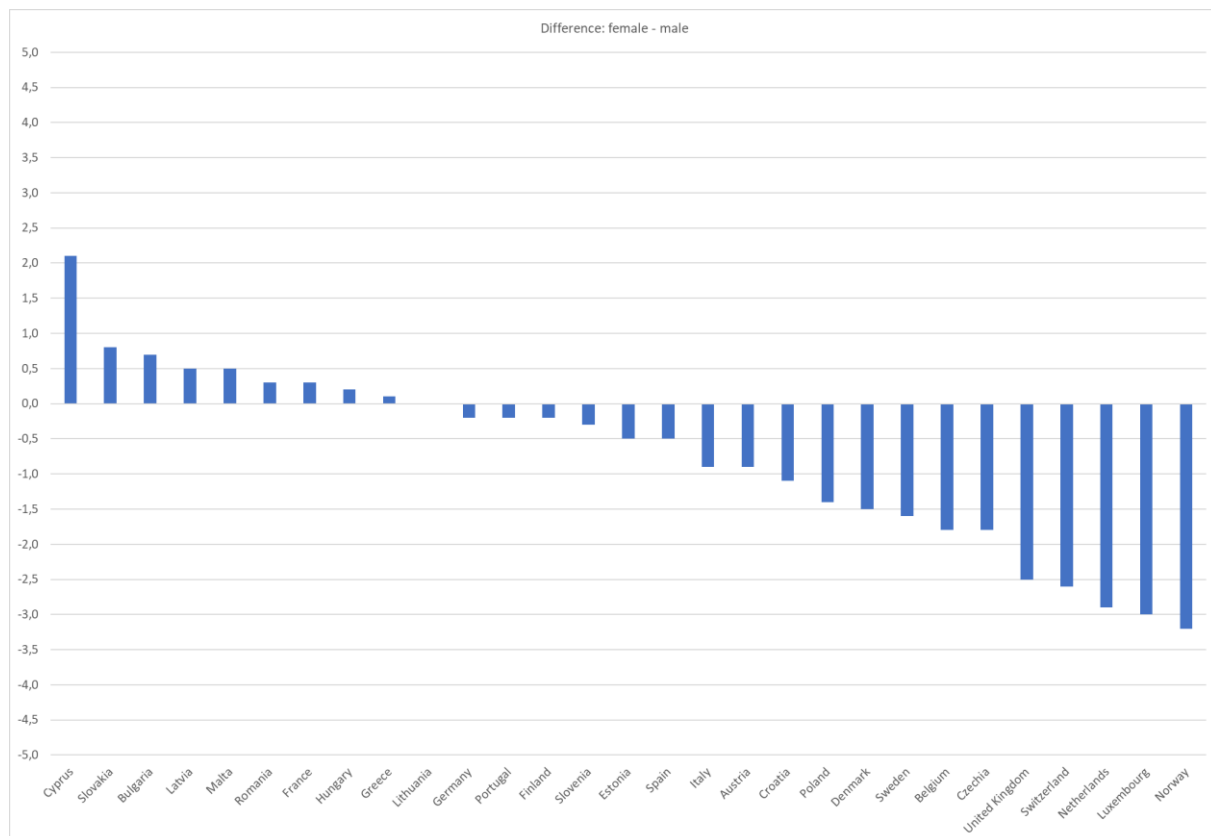
²⁵ If the sub-sample of those adults who have participated in NFE, 12.6% of men and 10.7% of women report that the field of their studies was related to ICT (excluding those who have not participated in any kind of NFE activity).



Additionally, it appears that among highly scoring countries, men tend to participate in the ICT courses more often than women, but gender differences seem smaller in countries with lowest levels of participation (apart from Poland).

Gender differences in taking up ICT courses are presented in further detail in Figure 2. Disadvantage of women is most pronounced in Norway, Luxembourg, the Netherlands, Switzerland and the United Kingdom, where men report participating in ICT related courses 3.2 to 2.5 percentage points more compared to women. Somewhat smaller difference in favour of men (around 2 to 1.5 percentage points) is apparent in the Czech Republic, Belgium, Sweden, Denmark and Poland. While only in Cyprus women are noticeably more often (2.1 percentage points) reporting ICT related training activities. Gender difference is in favour of women also in Slovakia, Bulgaria, Latvia, Malta and Romania, but in these countries difference in participation rates is less than 1 percentage point. Thus overall, in 17 countries out of 29, gender difference in ICT training participation is below 1 percentage point.

Figure 2. Gender difference in participation in ICT courses: female participation – male participation
The effect of individual and workplace-related characteristics on participation in ICT training



Country differences in gendered ICT training participation should depend on the content of training (whether it is targeted to improve customer service or database structure and programming, etc) and skills level (see also Jannsen and Wölfel 2017). However, AES does not provide such additional information.

Table 1. Participation in ICT-related courses: the effect of individual and job characteristics (odds ratios, standard error in parentheses)

	Model 1	Model 2	Model 3
Gender (ref male)			
female	0.87 (0.02) ***	0.82 (0.02) ***	0.75 (0.03) ***
Age (ref 25–39)			
40–49		1.10 (0.03) ***	1.04 (0.03)
50–64		0.88 (0.03) ***	0.99 (0.03)
Education (ref low)			
medium		2.50 (0.05) ***	1.38 (0.06) ***
high		6.10 (0.05) ***	1.61 (0.05) ***
Marital status (ref living in a cons. union)			
not living in a cons. union		1.03 (0.03)	1.03 (0.03)
Having 0–13 years old children (ref no)			
yes		1.06 (0.03) *	1.05 (0.03)
Occupation (ref high-skilled white-collar)			
low-skilled white-collar			0.74 (0.03) ***
high-skilled blue-collar			0.20 (0.07) ***
low-skilled blue-collar			0.15 (0.07) ***
Firm size (ref 1–10 persons)			
11–19			1.23 (0.05) ***
20–49			1.41 (0.05) ***
50+			1.82 (0.04) ***
no answer, but 10+			1.75 (0.07) ***
Sector (ref construction, mining, manufacturing, transportation etc)			
sale, retail, accommodation, catering			0.83 (0.05) ***
professional, scientific, technical activities, admin and services, etc			1.32 (0.03) ***
Intercept	0.05 (0.02) ***	0.01 (0.02) ***	0.05 (0.02) ***
N	205 382	194 696	110 442
BIC	70315.38	64212.31	46072.05
Pseudo R-squared	0.00	0.05	0.09

Note: * p < 0.05 ** p < 0.01 *** p < 0.001



Logistic regression results in Table 1 (p 13) indicate the impact of individual and workplace-related characteristics on participation in ICT courses. It appears that women compared to men have lower probability to participate in ICT courses (Model 1), this disadvantage increases after additional individual, occupational and sectoral characteristics are considered (Model 2–4). Differences in ICT courses participation by age group are significant when the model controls for individual characteristics (Model 2). Accordingly, 40–49-year-olds have higher probability and 50–64-year-olds lower probability to take up ICT-related courses than the youngest age group – 25-39-year-olds. However, age effect is not significant after adding workplace-related characteristics to the analysis. Expectedly, there are considerable differences according to highest completed education, as those with medium (ISCED 3–4) and particularly those with higher (ISCED 5–8) education participate in ICT training more compared to persons with lower educational attainment (ISCED 0–2).

From the household composition variables, having 0–13-years-old children tends to be associated with higher participation in ICT courses. However, when the model controls for occupation and other workplace-related characteristics (Model 3), having young children is not significantly associated with ICT training participation. The analysis would be more revealing and informative if data would differentiate between for instance 0–4-year-old children, but the AES 2016 does not provide such distinction.

All workplace-related characteristics included in the analysis have significant impact on the probability to participate in ICT training. According to occupational position, compared to high-skilled white-collars other groups have lower probability to take part in ICT courses (Model 3). Firm size appears to have considerable impact on the ICT training probability. Hence, participation in ICT courses increases with the firm size. Regarding economic sector or industry, results imply that compared to construction, mining, manufacturing and transportation participation in ICT-related training tends to be higher in the professional, scientific, technical activities, administration and services. In contrast, ICT training participation tends to be lower in retail, accommodation and catering sectors. Table 2 (p 14) presents interaction effects between gender and household and job-related characteristics. Results show that the impact of household characteristics on participation in ICT courses does not differ by gender. However, gender and job-related characteristics interactions are statistically significant. According to occupational group, women have considerably lower probability to participate in ICT courses compared to men in high-skilled white-collar positions (see Figure 3, p 15).

Table 2. Participation in ICT-related courses: interaction effects with gender by household and job characteristics (odds ratios, standard error in parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (ref male)					
female	0.74 (0.03) ***	0.77 (0.03) ***	0.62 (0.03) ***	0.88 (0.07)	1.08 (0.06)
Age (ref 25–39)					
40–49	1.04 (0.03)	1.04 (0.03)	1.04 (0.03)	1.04 (0.03)	1.04 (0.03)
50–64	0.98 (0.03)	0.98 (0.03) ***	0.98 (0.03)	0.99 (0.03)	0.99 (0.03)
Education (ref low)					
medium	1.38 (0.06) ***	1.38 (0.06) ***	1.38 (0.06) ***	1.38 (0.06) ***	1.38 (0.06) ***
high	1.61 (0.05) ***	1.61 (0.05) ***	1.61 (0.05) ***	1.61 (0.05) ***	1.60 (0.05) ***
Marital status (ref living in a cons. union)					
not living in a cons. union	1.03 (0.04)	1.05 (0.03)	1.05 (0.03)	1.04 (0.03)	1.04 (0.03)
Having 0–13 years old children (ref no)					
yes	1.05 (0.03)	1.10 (0.03) *	1.05 (0.03)	1.05 (0.03)	1.05 (0.03)
Occupation (ref high-skilled white-collar)					
low-skilled w-c	0.74 (0.03) ***	0.74 (0.03) ***	0.47 (0.06) ***	0.74 (0.04) ***	0.73 (0.04) ***
high-skilled b-c	0.20 (0.07) ***	0.20 (0.07) ***	0.18 (0.08) ***	0.20 (0.07) ***	0.21 (0.07) ***
low-skilled b-c	0.15 (0.07) ***	0.15 (0.07) ***	0.13 (0.09) ***	0.15 (0.07) ***	0.15 (0.07) ***
Firm size (ref 1–10 persons)					
11–19	1.23 (0.05) ***	1.23 (0.05) ***	1.24 (0.05) ***	1.33 (0.08) ***	1.24 (0.05) ***
20–49	1.41 (0.05) ***	1.41 (0.05) ***	1.44 (0.05) ***	1.48 (0.07) ***	1.42 (0.05) ***
50+	1.82 (0.04) ***	1.82 (0.04) ***	1.85 (0.04) ***	2.06 (0.06) ***	1.82 (0.04) ***
no answer, 10+	1.75 (0.07) ***	1.75 (0.07) ***	1.80 (0.07) ***	1.97 (0.10) ***	1.76 (0.07) ***



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Sector (ref construction, mining, manufacturing, transportation etc)

sale, retail, accommo., catering	0.83 (0.05) ***	0.82 (0.05) ***	0.83 (0.05) ***	0.83 (0.05) ***	0.94 (0.07) ***
professional, scientific, technical activities, admin and services, etc	1.32 (0.03) ***	1.32 (0.03) ***	1.32 (0.03) ***	1.32 (0.03) ***	1.32 (0.03) ***

Gender*Marital Status

female*not living in a cons. union	1.03 (0.06)
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Gender*Children

female*having 0–13 y o children	0.91 (0.05)
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Gender*Occupation

female*low-skilled w-c	2.12 (0.07) ***
female*high-skilled b-c	1.48 (0.18) *
female*low-skilled b-c	1.54 (0.14) **

Gender*Firm size

female*11–19	0.86 (0.10)
female*20–49	0.90 (0.09)
female*50+	0.79 (0.08) **
female* no answer, 10+	0.80 (0.14)

Gender*Sector

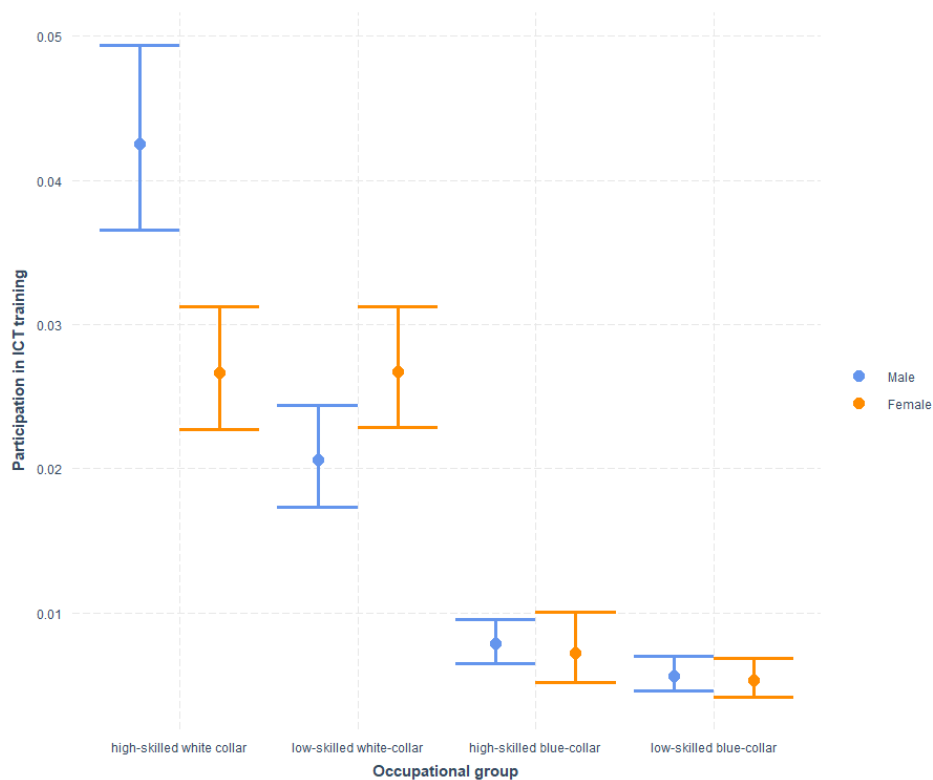
female* sale, retail, accommo., catering	0.68 (0.10) ***
female* professional, scientific, technical act. etc	0.62 (0.07) ***

Intercept	0.04 (0.08) ***	0.04 (0.08) ***	0.04 (0.08) ***	0.04 (0.08) ***	0.04 (0.08) ***
N	110 442	110 442	110 442	110 442	110 442
BIC	46083.35	46080.88	45972.31	46106.55	46044.98
Pseudo R-squared	0.09	0.09	0.09	0.09	0.09

Note: * p <0.05 ** p <0.01 *** p <0.001



Figure 3. Participation in ICT courses: interaction between gender and occupational group



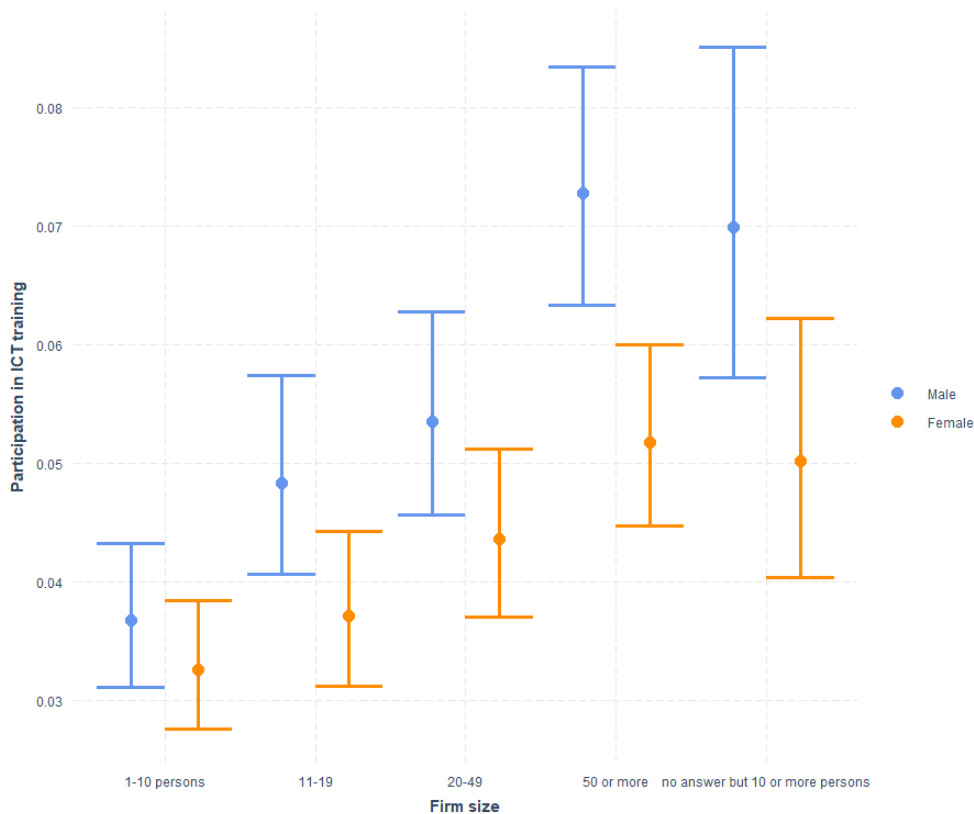
Yet among low-skilled white-collar workers women have the advantage in participating in ICT training. In the group of low-skilled white-collar workers, on average women are overrepresented, thus it seems that participation in ICT-related courses is more prevalent among women in female-dominated occupations. Among blue-collar occupations gender differences in ICT training participation are less pronounced. Interaction terms with firm size reveal that women have significantly lower probability to participate in ICT courses in larger firms (50 persons or more) (Figure 4). Thus, ICT training participation is more equal between genders in smaller firms, particularly those employing 1–10 persons (see also Wotschack 2019: 464).

Economic sector also has different impact on ICT participation probability depending on gender (Figure 5). Hence, women are most disadvantaged compared to men in ICT training participation in the sectors of professional, scientific and technical activities, and administration and services, but also in retail, accommodation and catering. While participation in ICT courses is rather equal in construction, mining, manufacturing and transportation – sectors dominated by male employees.

Multilevel regression results (presented in Appendix, Table 6A) explore the modifying effect of macro-, i.e., country-level characteristics on gender differences in participation in ICT training (for

results without interaction terms see Appendix, Table 5a). It appears that interaction terms with gender are significant in case of the share of female workers in the workforce, the share of women among managers, i.e., the relative power of women on the labour market²⁶, gender culture and overall gender inequality index (in case of GII $p < 0.1$). While the effect of provision of formal childcare and length of maternity-parental leave on ICT course participation do not differ by gender. However, examining confidence intervals, results show that interactions between gender and macro-level characteristics are clearer in case of gender culture and GII (see Appendix, Figure 1a and 2a for cross-level interactions by the share of female workers and managers by gender).

Figure 4. Participation in ICT courses: interaction between gender and firm size



²⁶ At the macro-level we also controlled for the effect of the share of female engineers and scientists. This resulted in a negative effect, i.e., higher share of female engineers and scientists is associated with lower female ICT training participation (similar to the effect of the share of female managers). We assume that this result might reflect the fact that AES data is capturing mainly rather basic ICT courses, while more complex training could be taking place on-the-job or via independent learning (including private lessons or informal learning).

According to Figure 6, more egalitarian gender culture (disagreement with the statement that when jobs are scarce, men should have more right to a job than women) tends to increase overall participation in ICT training, but the effect is stronger for men. So contrary to expectations, more equalitarian beliefs and norms regarding gender relations in a country, does not mitigate gender inequality in ICT courses participation. Additionally, Figure 7 shows that in countries with lower GII value, i.e., countries with fewer inequalities between females and males regarding health, empowerment and economic status, participation in ICT training is higher, but again, the effect is stronger for men.

Figure 5. Participation in ICT courses: interaction between gender and economic sector

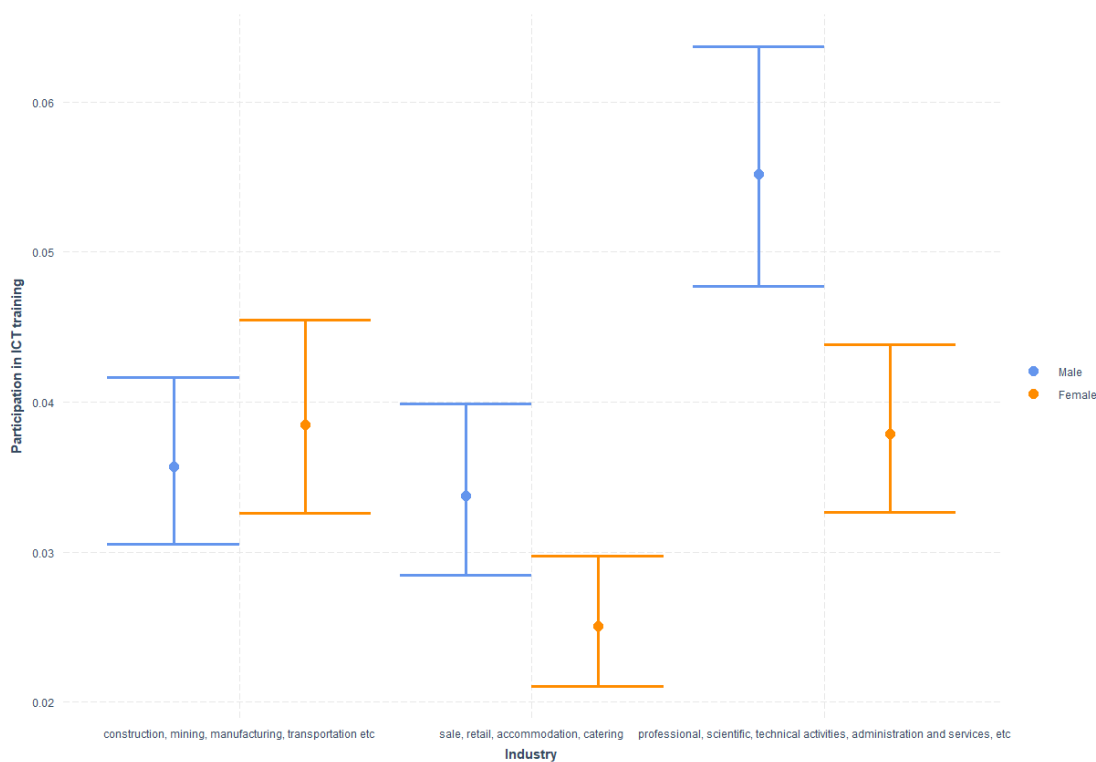


Figure 6. Cross-level interaction effect: participation in ICT training by gender culture and gender.

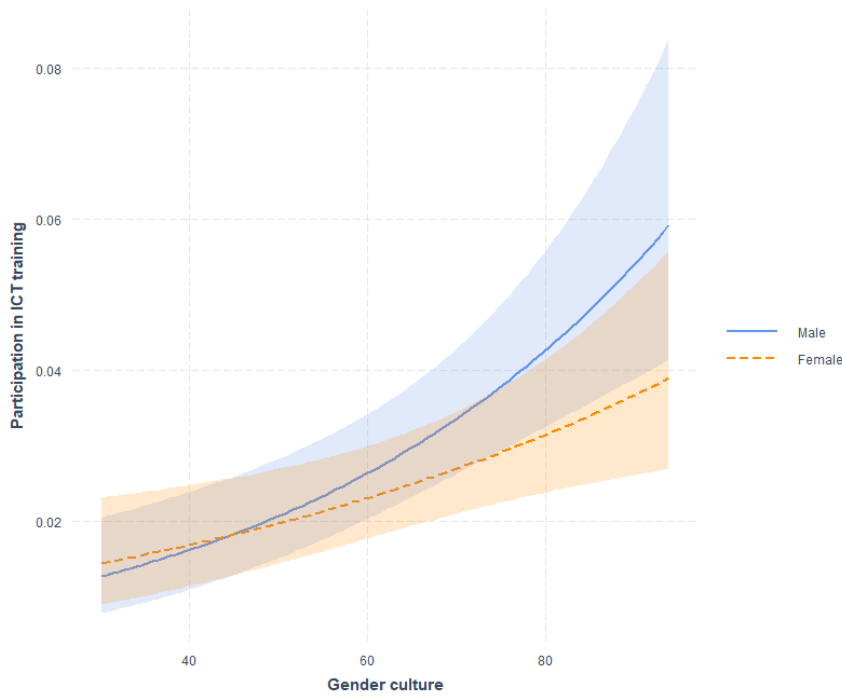
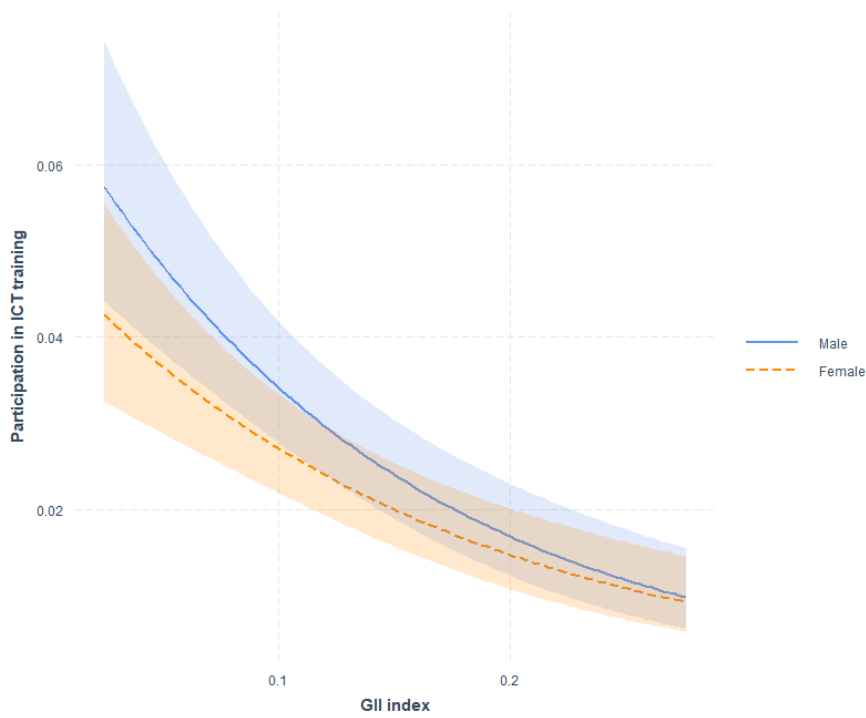


Figure 7. Cross-level interaction effect: participation in ICT training by the Gender Inequality Index and gender



Conclusions

The report aimed to explore gender differences in participation in ICT training. Despite previous surveys commonly finding that men use computers somewhat more frequently than women do as well as some disadvantage for women in ICT literacy so far surprisingly little research has been conducted on gender gap in ICT training. This study used the most recent data from the Adult Education Survey (2016) in order to investigate the effects of household characteristics as well as occupational and sectoral/industry characteristics on female ICT training participation and the gender training gap. Special attention is paid on country variation in gendered training participation and the contribution of country-specific institutional characteristics in this variation.

Following predominant theories in the field of gender training gap, it was assumed that employers tend to ascribe lower returns to training to female workers since women face a higher risk of career interruptions. Women are also often not willing to participate in training since they can reap lower and more risky returns to training. Our analysis revealed that women are somewhat disadvantaged in ICT training participation. However, these mentioned theories neglect the importance of macro-level institutional and meso-level, i.e., workplace-related differences.

Gender segregation and gender role theories emphasize the importance of the type of job for training participation over and above of worker characteristics. Our analysis indicated that gender difference varies more between jobs than between household context showing that occupational and sectoral gender segregation has a mediating effect on the gender training gap. However, a considerable gap in ICT training participation was found also between men and women working in the same occupation and in the same sector.

The analysis clearly confirmed that gender differences in ICT training participation differ between sectors and occupational groups. Organizations in sectors of professional, scientific and technical activities as well as in retail, accommodation and catering have higher gender ICT training gap. The training participation is rather equal in construction, mining, manufacturing and transportation. These results contradict previous findings about general gender training gap indicating that this gap is lower in female-dominated sectors and higher in male-dominated sectors. We explain this contradiction with content of training (whether it is targeted to improve customer service or database structure and programming, etc) in different sectors. Analysis presented by Janssen and Wölfel (2017) in Germany indicate that female disadvantage is the biggest in trainings connected with advanced ICT training and especially in programming but women have even advantages in task oriented training targeted to improve customer services. Unfortunately, we were not able to study gender gap by different types of ICT training. Disadvantage of women working in high-skilled white-collar occupations could also be explained by content of training.



Usually, it is assumed that large firms are more likely to have institutionalized human resource policies and/or a formal personnel office. They have more administrative resources and face a stronger need to invent formalized regulations in order to manage their larger work force. However, our results indicate that smaller firms show better outcomes. Regarding (equal) ICT training participation, it seems to be more advantageous for women to work in smaller firms. The analysis presented by Wotschak (2019) in Germany indicates also that gender training gap is smaller in small firms. He explained this result by the fact that solidarity, fairness norms and social control are more important in smaller work settings.

Regarding household composition, the expectations were that women with children are less likely to train. This prediction was, however, not confirmed by our analysis. Children up to 13 years of age in household do not show negative effect on women's ICT training participation. Analysis would be more revealing and informative if we could differentiate between for instance 0–4-year-old children, but the AES 2016 does not provide such distinction.

One of our aims was to investigate potential cross-country differences with regard to gendered ICT training participation. In line with previous research, we found evidence for cross-country variation in the level of ICT training participation and training gender gap. It appears that women have highest ICT participation rate in Norway, Spain, Germany, France, Austria, Belgium, Sweden and the Netherlands. Countries representing different institutional context, for instance in terms of welfare regime. Moreover, results indicate that gender gap in ICT training courses in favour of men tends to be higher in countries with rather high overall ICT participation rates, such as Norway, Luxembourg, the Netherlands, Switzerland and the United Kingdom. Evidence for differences between countries in terms of training predictors is less obvious. However, it seems that gender culture and overall gender inequality measured by the UNDP index – GII comprising health, empowerment and economic status indicators – tend to modify gendered ICT training gap. Namely, in countries characterised by more egalitarian gender culture, participation in ICT training is higher, but this effect is stronger for men, so participation gap is relatively high. Similarly, participation in ICT courses is higher in countries with lower GII, i.e., lower level of gender inequalities in different spheres of life, but again the effect is stronger for men. Stoet and Geary (2018) suggest that in less gender-equal countries women are more likely to engage in the fields of science, technology, engineering and mathematics to find a way out of difficult living conditions. Accordingly, in such countries girls might feel the pressure to use new technologies and acquire ICT competencies and thus this could explain why in more gender egalitarian countries gendered ICT training gap is higher.

These findings are important both for our understanding of gender differences in ICT training participation as well as policy making in the fields of ICT training and gender equality. Our results

indicate that there could be some role for supporting workplace female-friendly policies geared towards women with more training (see also Huffman et al. 2017; Wotschack 2019). Some previous studies conclude that gender occupational and sectoral segregation is very important predictor of gender training gap. However, our analysis indicates that ICT training gap is not lower but even bigger in female-dominated occupations and sectors. This result seems to suggest that paying attention to women's labour market opportunities should not be limited to their access to certain workplaces, occupations and sectors. In order to further improve females' opportunities for ICT training participation, policies that could continue to support women within workplaces are required.

Recent studies seem to indicate lessened gender gap in participation in computer-related professions (Lau and Yuen 2015). Also, the disadvantage of girls in terms of computer attitudes has become less self-evident. However, as mentioned in introduction there are big gender differences in expectations about working in ICT-related occupations among youngsters. Social environment (family, school etc.) is reproducing the traditional stereotypes about perceived masculinity of computers. Studies also indicate that girls feel less confident about their computers competencies and tend to underestimate their abilities, while boys tend to overestimate their achievements (Meelissen 2008). Teachers seem to have a role in this confidence gap. Therefore, initiatives to lessen gender-based stereotypes about ICT-related activities could increase girls' interest in programming and other computer applications and might help reduce differences in participation in ICT training.

Future research should pay more attention to the distribution of male and female employees to sectors and occupations with different ICT training requirements as well as the content of training. The data used in this study do not provide information on differences in terms of content of the ICT courses nor on returns to training. As other studies have shown, these differences provide another possible source of gender inequality (Green et al. 2016; Janssen and Wölfel 2017) and should be addressed in future research. Additionally, employers' calculations on training investments and social closure processes in the workplace deserve further attention



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Appendix

Table 1a. Relative power: Employment rate [LFSI_EMP_A__custom_539576], Eurostat; The share of female in management, OECD.

	Female employment rate	Female managers
Belgium	68.1	32.2
Bulgaria	68.8	Na
Czechia	79.0	25.3
Denmark	77.2	27.7
Germany	77.3	29.1
Estonia	77.4	35.8
Greece	65.1	24.7
Spain	73.7	30.9
France	73.4	32.4
Croatia	65.3	Na
Italy	59.0	27.2
Cyprus	73.8	Na
Latvia	78.6	46.8
Lithuania	79.7	39.1
Luxembourg	69.4	17.5
Hungary	68.0	39.2
Malta	60.8	Na
Netherlands	76.2	24.9
Austria	74.8	31.5
Poland	66.3	40.6
Portugal	75.8	35.7
Romania	60.3	Na
Slovenia	73.0	40.2
Slovakia	70.1	35.1
Finland	77.7	33.9
Sweden	84.1	39.2
United Kingdom	75.2	35.7
Norway	79.4	37.7
Switzerland	81.5	35.9



Table 2a. Gender culture: World Values Survey 2017/20, When jobs are scarce, men should have more right to a job than women: disagree + disagree strongly

	Disagree and disagree strongly
Belgium	83.8
Bulgaria	48.4
Czechia	59.4
Denmark	91.3
Germany	79.5
Estonia	75.8
Greece	43.1
Spain	76.7
France	80.3
Croatia	68.4
Italy	53.1
Cyprus	38.6
Latvia	Na
Lithuania	52.0
Luxembourg	Na
Hungary	56.6
Malta	Na
Netherlands	81.2
Austria	67.5
Poland	66.8
Portugal	66.7
Romania	35.7
Slovenia	77.3
Slovakia	30.2
Finland	87.4
Sweden	93.8
United Kingdom	83.4
Norway	92.1
Switzerland	68.8

Note: for Belgium ESS data



Table 3a. Family policies: Formal childcare % less than 3 years and from 3 years up to compulsory school age, 30 hours or over per week (Eurostat, EU-SILC survey [ilc_caindformal]); Total length of paid maternity and parental leave (weeks), OECD 2016

	Formal childcare < 3 years	Formal childcare > 3 up to compulsory school age	Length of paid maternity, parental leave
Belgium	28.5	73.3	32
Bulgaria	12.5	67.3	Na
Czechia	1.7	55.2	110
Denmark	62.2	84.3	50
Germany	21.4	53.2	58
Estonia	20.8	84.1	166
Greece	6.0	40.5	43
Spain	18.7	43.9	16
France	31.9	56.9	42
Croatia	13.5	46.9	Na
Italy	22.3	74.3	47.7
Cyprus	18.0	37.8	Na
Latvia	26.6	80.3	94
Lithuania	12.5	70.8	62
Luxembourg	33.0	55.4	42
Hungary	12.2	73.1	160
Malta	13.2	56.6	Na
Netherlands	5.4	19.5	16
Austria	5.6	23.7	60
Poland	5.6	45.7	52
Portugal	47.2	86.2	30.1
Romania	8.8	10.1	Na
Slovenia	35.7	81.4	52.1
Slovakia	0.5	65.0	164
Finland	22.9	60.2	161
Sweden	33.6	69.6	55,7
United Kingdom	4.4	27.2	39
Norway	47.0	78.3	91
Switzerland	5.9	13.0	14



Table 4a. Gender Inequality Index: the higher the GII value the more disparities between females and males and the more loss to human development (UNDP)

	Gender Inequality Index
Austria	0.069
Belgium	0.043
Bulgaria	0.206
Croatia	0.116
Czechia	0.136
Cyprus	0.086
Denmark	0.038
Estonia	0.086
Finland	0.047
France	0.049
Germany	0.084
Greece	0.116
Hungary	0.233
Italy	0.069
Latvia	0.176
Lithuania	0.124
Luxembourg	0.065
Malta	0.175
Netherlands	0.043
Norway	0.045
Poland	0.115
Portugal	0.075
Romania	0.276
Slovakia	0.191
Slovenia	0.063
Spain	0.070
Sweden	0.039
Switzerland	0.025
United Kingdom	0.118



Table 5a. Participation in ICT-related courses: the effect of macro-level characteristics (odds ratios, standard error in parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (ref male)					
female	0.75 (0.03) ***	0.78 (0.03) ***	0.77 (0.03) ***	0.75 (0.03) ***	0.77 (0.03) ***
Age (ref 25–39)					
40–49	1.01 (0.03)	1.01 (0.03)	1.02 (0.03)	1.01 (0.03)	1.02 (0.03)
50–64	0.92 (0.04) *	0.93 (0.04) *	0.92 (0.04) *	0.92 (0.04) *	0.92 (0.04) *
Education (ref low)					
medium	1.78 (0.07) ***	1.78 (0.07) ***	1.74 (0.06) ***	1.78 (0.07) ***	1.74 (0.06) ***
high	2.05 (0.07) ***	2.07 (0.07) ***	2.01 (0.07) ***	2.05 (0.07) ***	2.01 (0.07) ***
Marital status (ref living in a cons. union)					
not living in a cons. union	0.96 (0.03)	0.98 (0.03)	0.97 (0.03)	0.96 (0.03)	0.97 (0.03)
Having 0–13 years old children (ref no)					
yes	0.95 (0.03)	0.96 (0.03)	0.96 (0.03)	0.95 (0.03)	0.96 (0.03)
Occupation (ref high-skilled white-collar)					
low-skilled w-c	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***
high-skilled b-c	0.24 (0.08) ***	0.21 (0.08) ***	0.23 (0.08) ***	0.24 (0.08) ***	0.23 (0.08) ***
low-skilled b-c	0.18 (0.08) ***	0.17 (0.08) ***	0.17 (0.08) ***	0.18 (0.08) ***	0.17 (0.08) ***
Firm size (ref 1–10 persons)					
11–19	1.21 (0.05) ***	1.25 (0.05) ***	1.23 (0.05) ***	1.21 (0.05) ***	1.23 (0.05) ***
20–49	1.38 (0.05) ***	1.40 (0.05) ***	1.42 (0.05) ***	1.38 (0.05) ***	1.42 (0.05) ***
50+	1.78 (0.04) ***	1.81 (0.04) ***	1.81 (0.04) ***	1.78 (0.04) ***	1.80 (0.04) ***
no answer, 10+	1.44 (0.08) ***	1.40 (0.08) ***	1.38 (0.08) ***	1.44 (0.08) ***	1.39 (0.08) ***
Sector (ref construction, mining,					



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<i>manufacturing, transportation etc)</i>					
sale, retail, accommo., catering	0.81 (0.05) ***	0.82 (0.05) ***	0.81 (0.05) ***	0.81 (0.05) ***	0.81 (0.05) ***
professional, scientific, technical activities, admin and services, etc	1.18 (0.04) ***	1.19 (0.04) ***	1.20 (0.04) ***	1.18 (0.04) ***	1.20 (0.04) ***
Share of F in workforce	1.04 (0.02) *				
Share of F managers	0.96 (0.01) **				
Gender culture		1.02 (0.01) ***			
Childcare < 3 years			1.01 (0.01)		
Childcare from 3 years			0.99 (0.01)		
Parental leave weeks				1.00 (0.00) *	
GII index					0.00 (1.16) ***
Intercept	0.01 (1.16) ***	0.01 (0.39) ***	0.04 (0.30) ***	0.05 (0.18) ***	0.07 (0.16) ***
N	88 830	95 830	103 081	88 830	103 081
N country	24	26	29	24	29
BIC	40317.98	40179.56	43319.38	40309.31	43287.84
R-squared (fixed)	0.21	0.23	0.20	0.20	0.25
R-squared (total)	0.25	0.28	0.26	0.24	0.28

Note: * p <0.05 ** p <0.01 *** p <0.001



Table 6A. Participation in ICT-related courses: interaction effects with gender by macro-level characteristics (odds ratios, standard error in parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Gender (ref male)							
female	2.03 (0.34) *	1.21 (0.16)	1.49 (0.15) ***	0.81 (0.05) ***	0.83 (0.05) ***	0.76 (0.05) ***	0.71 (0.05) ***
Age (ref 25–39)							
40–49	1.02 (0.03)	1.02 (0.03)	1.01 (0.03)	1.02 (0.03)	1.02 (0.03)	1.01 (0.03)	1.02 (0.03)
50–64	0.92 (0.04) *	0.92 (0.04) *	0.93 (0.04) *	0.92 (0.04) *	0.92 (0.04) *	0.92 (0.04) *	0.91 (0.04) *
Education (ref low)							
medium	1.73 (0.06) ***	1.77 (0.07) ***	1.78 (0.07) ***	1.74 (0.06) ***	1.74 (0.06) ***	1.78 (0.07) ***	1.74 (0.06) ***
high	2.00 (0.07) ***	2.05 (0.07) ***	2.07 (0.07) ***	2.07 (0.07) ***	2.01 (0.07) ***	2.05 (0.07) ***	2.01 (0.07) ***
Marital status (ref living in a cons. union)							
not living in a cons. union	0.97 (0.03)	0.96 (0.03)	0.98 (0.03)	0.97 (0.03)	0.97 (0.03)	0.96 (0.03)	0.97 (0.03)
Having 0–13 years old children (ref no)							
yes	0.96 (0.03)	0.96 (0.03)	0.96 (0.03)	0.96 (0.03)	0.96 (0.03)	0.95 (0.03)	0.96 (0.03)
Occupation (ref high-skilled white-collar)							
low-skilled w-c	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***	0.75 (0.04) ***
high-skilled b-c	0.23 (0.08) ***	0.24 (0.08) ***	0.22 (0.08) ***	0.23 (0.08) ***	0.23 (0.08) ***	0.24 (0.08) ***	0.23 (0.08) ***
low-skilled b-c	0.17 (0.08) ***	0.18 (0.08) ***	0.17 (0.08) ***	0.17 (0.08) ***	0.17 (0.08) ***	0.18 (0.08) ***	0.17 (0.08) ***
Firm size (ref 1–10 persons)							

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11–19	1.23 (0.05) ***	1.21 (0.05) ***	1.25 (0.05) ***	1.23 (0.05) ***	1.23 (0.05) ***	1.21 (0.05) ***	1.23 (0.05) ***
20–49	1.42 (0.05) ***	1.39 (0.05) ***	1.41 (0.05) ***	1.42 (0.05) ***	1.42 (0.05) ***	1.38 (0.05) ***	1.42 (0.05) ***
50+	1.81 (0.04) ***	1.79 (0.04) ***	1.81 (0.04) ***	1.81 (0.04) ***	1.81 (0.04) ***	1.78 (0.04) ***	1.80 (0.04) ***
no answer, 10+	1.38 (0.08) ***	1.44 (0.08) ***	1.41 (0.08) ***	1.38 (0.08) ***	1.38 (0.08) ***	1.44 (0.08) ***	1.39 (0.08) ***
Sector (ref <i>construction, mining,</i> <i>manufacturing,</i> <i>transportation etc)</i>							
sale, retail, accommo., catering	0.81 (0.05) ***	0.82 (0.05) ***	0.82 (0.05) ***	0.81 (0.05) ***	0.81 (0.05) ***	0.81 (0.05) ***	0.81 (0.05) ***
professional, scientific, technical activities, admin and services, etc	1.20 (0.04) ***	1.18 (0.04) ***	1.19 (0.04) ***	1.20 (0.04) ***	1.20 (0.04) ***	1.18 (0.04) ***	1.20 (0.04) ***
Share of F in workforce	1.04 (0.02) **						
Female*Share of F in WF	0.99 (0.00) **						
Share of F managers Female*Share of F mngrs		0.98 (0.02) 0.99 (0.00) **					
Gender culture			1.03 (0.01) ***				

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Female*Gender culture			0.99 (0.00)				

Childcare < 3 years				1.01 (0.01)			
Female*Childcare < 3 years				1.00 (0.00)			
Childcare from 3 years					1.00 (0.00)		
Female*Childcare from 3 y					1.00 (0.00)		
Parental leave weeks						1.00 (0.00) *	
Female*Parental leave wks						1.00 (0.00)	
GII index							0.00 (1.20)

Fender*GII index							2.78 (0.56)
Intercept	0.00 (1.15)	0.08 (0.52)	0.01 (0.40)	0.03 (0.19)	0.03 (0.31)	0.05 (0.19)	0.07 (0.16)
	***	***	***	***	***	***	***
N	103 081	88 830	95 830	103 081	103 081	88 830	103 081
N country	29	24	26	29	29	24	29
BIC	43308.44	40312.34	40171.85	43318.91	43320.87	40320.69	43296.06
R-squared (fixed)	0.21	0.19	0.23	0.19	0.19	0.20	0.25
R-squared (total)	0.27	0.24	0.28	0.26	0.26	0.24	0.28

Note: * p <0.05 ** p <0.01 *** p <0.001

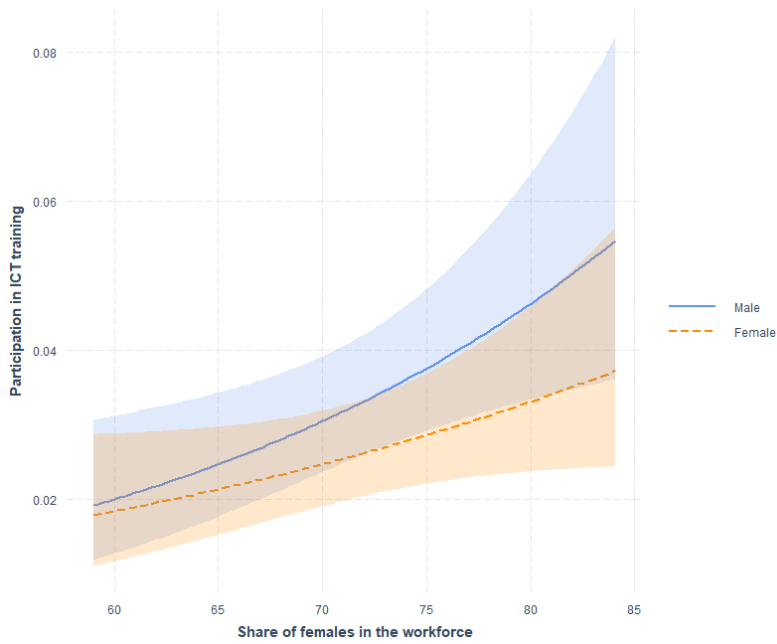


Figure 1a. Cross-level interaction effect: participation in ICT training by the share of females in the workforce and gender

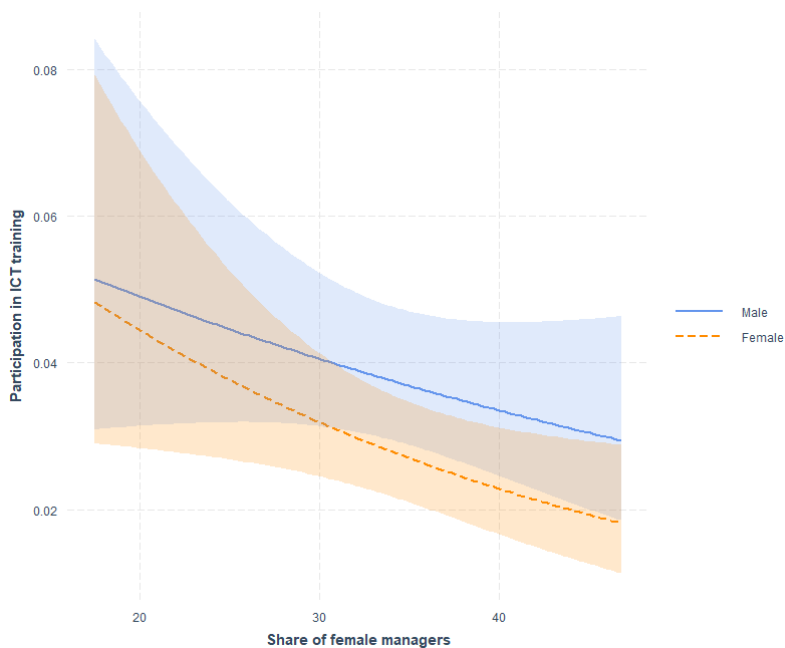


Figure 2a. Cross-level interaction effect: participation in ICT training by the share of females among managers and gender

Chapter 7A: The impact of family formation on women's and men's further training participation in Germany and the UK

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Extended summary

In this extended summary, we discuss our analyses in light of the larger TECHNEQUALITY framework, underline our key findings, and suggest possible policy options.

The TECHNEQUALITY deliverables of WP1 showed that technological innovations prompt a reconceptualization of traditional views of skills and education. Due to technological innovation, globalization, and demographic shifts, the demand for skills in the labor market is rapidly changing. As a result, workers' learned skills may become obsolete quickly. Job-related further training is one means of coping with changes in the labor market, and it helps employees to obtain crucial skills and knowledge related to their current professions. Furthermore, Chapter 5 (of Deliverable 3.6) found that job-related training is associated with better employment security. Further job-related training helps employees keep their skills up to date and supports the achievement of career aims, like higher productivity and income. Hence, job-related further training is an important tool for employees because it has the potential to increase employee competitiveness in the labor market.

In the next two chapters, we explain why parenthood (Chapter 7A) and partnership status (Chapter 7B) are major reasons for gender inequality in job-related training participation. We also discuss how the country context matters with regards to the gender gap in job-related training. Since the 1990s, women's participation in job-related further training has risen at an equal or higher rate than men's participation. Yet despite this progress in women's participation, little is known about the reasons for disparities in men's and women's training participation following family formation and dissolution, and whether family status influences gender inequality in job-related training participation. We contribute to answering the following two questions from task 3.5 of the grant proposal: *What is the impact of family formation on training gaps between men and women? What is the role of family dissolution in women's and men's further education?* Based on these two questions, our chapters highlight gender differences in lifelong education that are shaped by family formation and dissolution. Answering these questions also improves our knowledge about the role played by family policy and gendered norms in encouraging or discouraging workers from participating in training.

Focusing on two countries with different institutional and policy contexts, namely Germany and the United Kingdom, the next two chapters look at the transition to parenthood and the transition to divorce or separation as sources of change in an individual's job-related training



participation. We use data from the 2010–2018 round of the German National Educational Panel Study (NEPS) and the 2011–2019 round of Understanding Society: the UK Household Longitudinal Study (UKHLS). Our chapters shed light on the crucial role of family formation or dissolution in producing gender inequality in job-related training participation, and it elucidates how country context matters with regards to the gender gap in job-related training.

We employ two-way fixed-effects models with step impact functions and an event-study design in our analyses. For Chapter 7A, this approach requires the assumption of parallel time trends between treatment (transition to parenthood) and control groups (constantly childless during our observational window). For Chapter 7B, the treatment group experienced the transition to divorce with children, while the control group was permanently married with children. We calculate separate models for women and men because we assume that the impact of family formation and dissolution on job-related training participation will differ by gender. We also examine the time path of the family formation or dissolution effect by scrutinizing whether childbirth (chapter 7A) or divorce (Chapter 7B) have a constant and permanent effect on training participation or if the effect changes over time. We therefore also implement two-way fixed-effects models in the event-study designs and compare them to step impact models. We do this to see whether the overall family formation effect is driven by having very young children in the household (Chapter 7A) and the immediate family dissolution effect (chapter 7B), or whether the effect remains stable over time.

Main findings

Gender differences: We find gender differences in job-related further training participation following parenthood. Women suffer a substantial and statistically significant motherhood penalty in job-related training participation, while men seem to be only weakly affected by parenthood.

Between-country differences: Women’s job-related training participation decreases following parenthood in both countries, but this decline is steeper in Germany. In Germany, first childbirth decreases women’s job-related training participation by 29 percentage points. The fatherhood penalty is substantial and statistically significant, but it appears to be smaller for men. Following first childbirth, men’s training participation decreases by 7 percentage points in Germany. In the UK, motherhood decreases women’s training participation probability by 8 percentage points, while the effect of fatherhood on training participation is neither substantial nor statistically significant (see section 3.2.).

In Germany, the negative effects of motherhood on job-related further training participation last for about four years following first childbirth, thus remaining impactful beyond the early stage of parenthood. In the UK, the negative effect of motherhood on women’s job-related further training participation persists for a shorter period of time than in Germany. While the negative effects of

motherhood on job-related further training participation last for about two years following first childbirth, there is no significant negative effect of having children after two years. For men, there is a small negative effect of having a first child on training participation in Germany, and no effect in the UK.

Institutions matter: Our analyses suggest that the negative effect of childbirth on women's job-related training participation is larger in Germany than in the UK due to Germany's lower levels of support for maternal employment. In terms of work-family policy, Germany's approach is based on conservative assumptions about women as secondary earners. New mothers in Germany enjoy a long maternity leave but face a lack of childcare options prior to kindergarten, a combination that incentivizes the traditional family model. Germany's social policy discourages paid employment among secondary earners and may thereby foster traditional gendered specialization. While recent trends suggest that women are now taking shorter leaves from employment after childbirth in Germany, strong expectations of men acting as the breadwinner remain. The UK is generally considered a liberal welfare regime. However, universal paid family leave and child allowances are also available in the UK, unlike in the United States. Family policy in the UK is characterized by restricted, gender-neutral, and market-based defamilization. In terms of gender regimes, work-family policy in the UK promotes the "one and a half earner" model, which encourages women to take up part-time work and to use public part-time childcare services. Moreover, flexible work schedules have become a policy tool used by companies to attract and retain working parents.

Family dissolution matters in the UK: Our findings show that both men's and women's participation in further training declines following divorce in the UK, while further training participation does not change following divorce in Germany. Based on the results of previous studies, we took account of the fact that divorce or separation can lead to changes in an individual's economic well-being and labor market activities. The presence of a partner can encourage job-related training because partnered individuals are able to share housework or childcare, thereby facilitating subsequent job-related further training. We see that in the UK, men's and women's job training participation declines following divorce. In Germany, all *differences* based on *pre-post* divorce status in job-related training participation are very small and do not reach conventional levels of statistical significance.

Policy recommendations

1. Targeted policies based on women's diverse contexts

In order to close gender gaps in women's access to skill development and further training participation, a well-directed policy must go beyond solely increasing overall participation rates of further training among women. Knowing details about the training participation behavior of different

subgroups of women, such as mothers, is crucial. Childless women's further training participation is equal to or even higher than men's, whereas mothers fall behind in further training participation after first childbirth. Any intervention aimed at closing gender gaps in skill development should be based on a good understanding of how different groups of women are affected by the institutions, the market, and the household. Data should not only be disaggregated by sex but also by other relevant factors, such as parenthood status.

II. Offer more flexible or shorter training courses

Mothers are less likely to participate in further job training due to time constraints and family care responsibilities. Policy makers therefore need to identify barriers to equal access for women and men, and they need to do this particularly for women with young children. Further training programs should be designed with the aim of removing existing barriers for mothers, such as the timing and the length of the training, and of responding flexibly to different needs. Further training courses should be more flexible—there should be shorter or modular training courses that allow women to reduce their time away from work or home. In addition, mothers' participation rates may increase if further training is scheduled during core working hours (e.g., between 9 am and 3 pm).

III. Offer childcare for further training participation

Our findings suggest that family care responsibilities severely constrain women's choices regarding further training participation. Employees need institutional support for childcare to continue participation in further training. Employers should be committed to helping their employees balance their work and family responsibilities. This commitment includes all aspects surrounding childcare and caregiving. Offering childcare and social services for further training participation affects women to a greater degree than men because women bear the greatest burden of family care responsibilities.

IV. Promote the return to work for women

Further training programs should also aim to promote the return to work for women either after childbirth, following a period of parental leave, or as a result of long-term unemployment due to unpaid family care responsibilities. Further training programs should also provide advice, counseling, and networking for mothers, thereby helping women return to the labor market after parental leave.

V. Create gender-sensitive training environments

Employers are more reluctant to train mothers than men or childless women because employers often deem mothers less worthy of investment. Instructors and managers in training institutions should receive gender awareness training to raise and address gender issues and to avoid

stereotypes. These individuals can then help sensitize employers and encourage them to offer further job training to both women and men, and especially to women with children. Employers and training providers all have a role to play in creating a supportive and motivating environment that is conducive to the recruitment of mothers into further training.

1. Introduction

Despite decades of increases in women's labor market participation, motherhood still has a disruptive effect on women's careers. After the birth of a first child, women's earnings, market-related work hours, and childcare and housework hours change because women tend to reduce their working hours and spend more time on housework (Baxter et al. 2008; Killewald and García-Manglano 2016; Musick et al. 2020; Sanchez and Thomson 1997). Most research on the motherhood penalties for labor market outcomes has concentrated on estimating wage changes (Budig and England 2001; Musick et al. 2020) or working hours (Killewald and García-Manglano 2016). However, empirical evidence on the existence of a motherhood gap in participation in job-related training programs is lacking.

Due to technological innovation, globalization, and demographic shifts, the demand for skills in the labor market is rapidly changing and workers' learned skills may become obsolete. Job-related further training is one means of coping with changes in the labor market and helps employees obtain crucial skills and knowledge relevant to their current professions (Dämmrich et al. 2016). Consequently, participation rates in job-related non-formal training have increased in recent years. In 2007, 25.3% of employees participated in job-related further training. By 2016, these rates had increased to 34.6% across the 27 EU member states (Eurostat 2020). Furthermore, job-related training is associated with better employment security (Ebner and Ehlert 2018), higher productivity (Hansson 2008), and wage increases (Büchel and Pannenberg 2004; Haelermans, and Borghans 2012). Hence, job-related further training is an important tool for employees because it has the potential to increase employee competitiveness in the labor market.

Previous studies show that job-related further training is not distributed equally between genders (Knoke and Ishio 1998; Simpson and Stroh 2002). Since the 1990s, however, women's participation in job-related nonformal training has risen at an equal or higher rate than men's participation. Despite this progress, we know little about whether gender differences in relation to parenthood shape participation in job-related further training. Many workers have reported that childcare and other family responsibilities operate as a major barrier to participation in job-related further training, especially for women (Cedefop 2015; Sussman 2002). As previous research suggests a possible association between parenthood and women's training disadvantage, our chapter examines whether these associations are based on causal effects of family formation (transitioning

from childlessness to first childbirth) on training participation and whether the effects of parenthood are markedly stronger for women than for men.

Examining two countries with different institutional and policy contexts, namely Germany and the United Kingdom, this chapter focuses on the transition to parenthood as a source of change in an individual's job-related further training participation. This chapter aims to answer the following questions: (1) Are men's and women's job-related further training participation affected differently by the transition to parenthood? (2) How do men's and women's job-related further training participation trajectories after parenthood differ according to each country's institutional and policy context? We use data from the 2010–2018 round of the German National Educational Panel Study (NEPS) and from the 2011–2019 round of Understanding Society: the UK Household Longitudinal Study (UKHLS). We employ two-way fixed-effects models with step impact functions and event-study designs.

Our findings suggest that women's job-related training participation decreases after parenthood in both countries, but this decrease is steeper in Germany. The negative effects of motherhood on job-related further training participation last for about two years after first childbirth in the UK, but any significant negative effect disappears after two years. In Germany, however, the negative effect of motherhood on women's job-related further training participation persists for a longer period of time, lasting beyond the early stage of parenthood. There is a small negative effect of having a first child on men's training participation in Germany and no effect of this in the UK. Our chapter sheds light on gender differences in the family formation effect on job-related training participation, and it elucidates the impact of country context on these effect differences.

2. Theoretical Framework

2.1. Parenthood and Job-related Further Training

We argue that there are gendered effects of family formation on job-related training participation. Although the gender gap in training participation seems to be closing, many of the underlying mechanisms still come into play after family formation processes. The literature has offered different theoretical explanations for the well-established finding of a gender gap in training participation (Knoke and Ishio 1998; Simpson and Stroh 2002) and the wage penalty for motherhood (Budig and England 2001; Correll et al. 2007; Gangl and Ziefle 2009; Musick et al. 2020). Previous studies suggest that women are less likely to participate in job-related further training due to (1) gendered household specialization, (2) career breaks and shorter working hours, (3) occupational segregation, and (4) discrimination against mothers.

Becker's theory of gendered household specialization argues that it is rational for men to increase their comparative advantage in market-related work while it is rational for women to increase their comparative advantage in household activities (Becker 1981). According to human capital theory (Becker 1964) and the theory of optimal energy allocation (Becker 1985), women have less incentive to participate in supplemental training as a means to increase their market-related human capital compared to men due to their relative advantage in household production. If women's average work experience is shorter and more discontinuous than men's average work experience, employers are less likely to offer training to women. Yet the gendered household specialization theory does not fully reflect trends in today's labor market. Since the 1990s, both women's labor force participation and the share of female sole and primary earners have increased (Wang et al. 2013). Several studies have found that women's training participation is equal to or greater than men's (Green and Zanchi 1997; Wooden et al. 1997).

In the UK and Germany, women's participation in job-related further training has increased at an equal or higher pace than men's over the past years. Although the gender training gap seems to be closing, a motherhood gap in job-related further training may persist. Studies show that women's earnings, working hours, and childcare and housework hours change after parenthood because women are more likely to reduce their working hours and to increase housework and childcare hours (Baxter et al. 2008; Killewald and García-Manglano 2016; Musick et al. 2020; Sanchez and Thomson 1997). Participating in job-related further training can be expensive and time-consuming, making participation less attractive to workers juggling work and family responsibilities (Lebert and Antal 2016). Hence, we might expect mothers' job-related further training participation to decline following parenthood due to a work-family conflict.

There is some evidence to support the assumption that women fall behind in job-related training participation after becoming mothers. For instance, research suggests that having preschool-aged children reduces job-related training participation by mothers but not fathers (Green 1993; Harris 1999; Lebert and Antal 2016). However, to date, little attention has been paid to changes in workers' job-related training participation before and after childbirth, and it is unclear whether the transition into parenthood influences women's and men's job-related training participation differently. Parenthood might be a trigger event that fosters gendered household specialization. Therefore, our first two hypotheses related to the total causal effect of family formation on training participation are:

Hypothesis 1: We expect first motherhood to decrease training participation probability.

Hypothesis 2: We expect first fatherhood to have either no effect or a positive effect on men's training participation probability.

Parental leave and reduced working hours resulting from childcare should affect job training participation. Taking a more extended period off from paid work for childcare is referred to as the central mechanism of motherhood penalties (Aisenbrey et al., 2009). Although the right to maternity leave is related to higher rates of female employment and a higher proportion of mothers returning to paid work after childbirth (Rønsen and Sundström 2002), longer maternity leave discourages women from reentering employment (Pettit and Hook 2005) and increases the motherhood wage penalty (Misra et al., 2007; Mari and Cutuli 2021). Although paternity and parental leave are offered in most EU member states, fathers' uptake of paternity and parental leave is low. On average, only 10% of fathers take paternity leave across 23 EU countries (Van Belle 2016). The gender differences in the length of parental leave are even more pronounced since most fathers only take a short period of parental leave after childbirth (Van Belle 2016). For example, the Additional Paternity Leave (APL) was introduced in the UK in 2011, permitting fathers to access up to 26 weeks of parental leave in addition to the two weeks of ordinary parental leave. Yet only 29% of fathers took more than two weeks of leave, and less than 1% of fathers took the APL in its first year (Kaufman 2018). Most job-related training courses take place at the workplace (Cedefop, 2015), leading us to expect parental leave to mediate the effect of family formation for women but not for men in both countries.

Hypothesis 3: We expect the parenthood effect on training participation to be mediated via parental leave for women but not for men in both countries.

Gender differences in working hours are often used as an explanation for the possible gender gap in job-related training. Studies document that the most common obstacle for training participation among women is lack of time (Tuor and Backes-Gellner, 2009), especially due to family obligations (Cedefop, 2015). Work-family conflicts foster part-time employment for women. Research shows that working part-time is associated with fewer training opportunities at workplaces (Arulampalam and Booth 1998; Sobaih 2011). Comparing Germany, Italy, and the Netherlands, Boll and Bublitz (2018) find that in Germany, women with part-time employment have a lower rate of job training participation than women with full-time employment. In terms of training intensity, German women in part-time employment report fewer training course hours at a rate of 5.5 hours per annum. By contrast, in Italy and the Netherlands, women's training course hours were unaffected by their weekly working hours. For women, parenthood is associated with reduced hours in paid labor, while men's hours in paid labor stay the same or increase slightly after becoming a parent (Glauber 2008; Lundberg and Rose 2000, Kühhirt 2012). Kühhirt (2012) additionally finds that men contribute to housework at the same rate as they did before the birth of their child, while women experience long-term increases in housework regardless of the resources and earning situation within the household. Childbirth seems to foster gender specialization via negative effects on working hours for women but not for men (Kühhirt, 2012; Glauber 2008; Lundberg and Rose 2000). We thus derive the following hypothesis:

Hypothesis 4: We expect the family formation effect on job-related training participation to be mediated via working hours for women but not for men in both countries.

Previous research shows that the number of children affects women's labor market outcomes (Budig and England 2001; Markussen and Strom 2022). Having an additional child has a significant negative impact on women's employment, working hours, and wages, but not on men's (Cools et al. 2017). Having a second and third child might have a much larger effect on women's labor supply because increased work-life conflicts and childcare costs discourage women's employment (Budig and England 2001). Consequently, the birth of a second child might have a more substantial impact on a traditional division of household labor than the first (Markussen and Strom 2022). This might further reduce women's available time for participating in job-related training.

Hypothesis 5: We expect the first motherhood effect on job-related training participation to be mediated via second childbirths.

Even after controlling for all of the mechanisms mentioned above, we expect to find a direct effect of family formation on training participation. We want to offer at least two major reasons for why we expect to find a residual effect of family formation on job-related training participation: (1) changes in occupation and (2) discrimination against mothers. Occupational segregation by gender has been the dominant model for explaining gender differences in wages (Blau and Kahn 2017) and training (Simpson and Stroh 2002). Occupational segregation by gender refers to the tendency of men and women to work in different occupations. Occupational segregation by gender may contribute to the gender gap in job-related further training because female-dominated occupations offer fewer training opportunities (Simpson and Stroh 2002). However, recent trends show that occupational sex segregation declined substantially during the 2000s and women started moving into new types of jobs and occupations (Blau et al. 2013). However, gender segregation today might depend on parenthood status. Previous research has further shown that motherhood is associated with occupational segregation (Hook and Pettit 2016), which might lead mothers into occupations with fewer training opportunities.

Likewise, occupational discrimination can generate a motherhood training penalty. As research by Correll et al. (2007) suggests, employers might perceive mothers as less productive and less labor-market-oriented than fathers after the transition into parenthood. In a laboratory experiment, Correll et al. (2007) find that evaluators perceive mothers to be less competent and less committed to paid work. As a result, mothers are rated as less hireable and as less suitable for promotion and management training courses. We therefore expect to find a direct effect of the transition into first motherhood even after controlling for all the previously mentioned mechanisms.

Hypothesis 6: We expect first childbirth to have a negative and direct effect on job-related training for women but not for men in both countries even after controlling for parental leave take-up, part-time work, and second childbirths.

Job-related training is particularly important for mothers since it is associated with lower motherhood wage penalties (Staff and Mortimer 2012) and better employment security (Kahn et al. 2014). Job-related training participation increases mothers' employment continuity and has positive effects on women's wages and occupational prestige (Kahn et al. 2014). Although mothers take time off from paid work after childbirth, participating in additional education or job-related training during these periods helps mothers avoid the motherhood wage penalty when they return to the labor market (Staff and Mortimer 2012).

Grip and van Loo (2002) differentiate between technical and economic skill obsolescence. While technical skill obsolescence describes a loss of human capital due to atrophy (non-use of skills), economic skill obsolescence describes changes in the value of workers' skills due to external developments (Grip and van Loo, 2002). For young mothers, this would mean that the non-use of skills due to employment breaks might cause skill loss, while external developments like technological changes might devalue their remaining skills. As a result, skill-adaption through participation in job-related training might be an important means to counterbalance the disruptive effects of motherhood on careers.

2.2. Institutional Differences in Job-related training Participation in Germany and the United Kingdom

Institutional factors might moderate the effect of parenthood on differences in job-related training participation. For example, a strong male-breadwinner female-caregiver norm, which is enforced both culturally and institutionally, may foster shifts in the traditional household specialization pattern in couples after childbirth, or it may increase employer bias in favor of fathers (Correll et al. 2007). These factors may have negative effects on women's job-related training participation after childbirth. By looking at Germany and the UK, we compare two countries with different welfare state regimes (Esping-Andersen 1990; Korpi 2000). Different institutional contexts may contribute to resource availability for parents and gendered expectations regarding who should do what in the family (Musick et al. 2020; Zoch and Schober 2018).

According to Esping-Andersen's typology of welfare capitalism, contemporary Western welfare states can be classified into three types: liberal regimes, conservative regimes, and social democratic regimes (Esping-Andersen, 1990). A conservative regime such as Germany is often

characterized as a male-breadwinner state (Esping-Andersen, 1990). Liberal regimes, such as the UK or the US, include countries where care is seen as a private family responsibility.

Korpi (2000) suggests a different welfare state typology based on three types of gendered family policies: (1) the general family support model (e.g., Germany), (2) the dual earner support model (e.g., Scandinavian countries), and (3) the market-oriented model (e.g., the US and the UK). In this typology, Germany is categorized as a country that generally supports families while maintaining a traditional gendered household specialization. The UK, on the other hand, is described as market-oriented because citizens must rely on their market resources or informal help from family for the supply of care services. Misra et al. (2007) categorize both countries in similar ways. They describe Germany as a country with a carer strategy, exemplified by support for women's caregiving through care allowances, subsidized pension contributions for caregivers, and part-time employment opportunities. By contrast, the UK is characterized as pursuing an earner strategy, evidenced by the minimal policy support for families with children and resulting requirement for market-based care solutions (i.e., day care centers and after school programs).

In terms of work-family policy, Germany's approach is based on conservative assumptions about women as secondary earners (Lohmann and Zigel 2016). New mothers in Germany enjoy a long period of maternity leave but face a lack of childcare options prior to kindergarten, a combination that incentivizes the traditional family model. Germany's social policy discourages paid employment among secondary earners (Bick and Fuchs-Schündeln, 2017; Smith et al, 2003), and may thereby foster traditional gendered specialization. While recent trends suggest that women take shorter employment breaks after childbirth in Germany, strong expectations based on the male breadwinner model remain (Lang and Groß 2020). While the UK is considered a liberal welfare regime, it still offers universal paid family leave and child allowances, unlike the US. Family policy in the UK is characterized as restricted, gender-neutral, and market-based defamilization (Lohmann and Zigel 2016). In terms of gender regimes, work-family policy in the UK promotes the "one and a half earner" model, which encourages women to engage in part-time work and to use public part-time childcare services. Moreover, flexible work schedules have become a policy tool that companies adopt to attract and retain working parents (Cooke 2011).

Culturally, male-breadwinner norms have been stronger in the federal states that used to form West Germany than in the UK (Knight and Brinton 2017; Trappe et al. 2015). Studies show that institutional and cultural contexts shape maternal employment (Budig et al. 2012; Boeckmann et al. 2015; Kleven et al. 2019). Budig et al. (2012) find that both parental leave and public childcare are associated with higher earnings for mothers when cultural attitudes toward maternal employment are positive. However, in countries where cultural attitudes towards maternal employment are negative, parental leave and public childcare have less positive associations with maternal earnings,

and in some cases even negative ones. These findings suggest that working-family policies are most effective when they are accompanied by strong cultural support for maternal employment.

Recent studies have examined how men's and women's earnings change after first childbirth from a cross-national perspective (Kleven et al. 2019; Musick et al. 2020). A study by Kleven et al. (2019) shows that, while women's wages decrease both in Germany and the UK after childbirth, the decline is greater in Germany. However, men's earnings are not affected by childbirth across six countries with different welfare regimes (social democratic regimes include Denmark and Sweden, liberal regimes include the US and the UK, and conservative regimes include Austria and Germany). By using gender norm measures from the International Social Survey Program (ISSP), Kleven et al. (2019) suggest that this finding is correlated with conservative gendered ideologies since Germany exhibits less support for maternal employment than the UK. Based on these findings, we expect that transitioning into parenthood has a larger and longer-lasting negative effect on women's job-related further training participation in Germany than in the UK.

Hypothesis 7: We expect to see a steeper decline in women's training participation following parenthood in Germany relative to their counterparts in the UK.

Hypothesis 8: We expect the negative effect of first childbirth on women's training participation to persist longer in Germany than in the UK.

3. Data and Method

3.1. Data

To test the four hypotheses, we used the starting cohort 6 data (SUF 12.0.0) of the National Educational Panel Study (NEPS) (Allmendinger et al. 2011; Blossfeld et al. 2011) for Germany and Understanding Society: the UK Household Longitudinal Study (UKHLS) for the UK analyses. Since our analyses refer to dependent employees, we excluded all respondents who were not employed or who were self-employed at least once during our observational period. For both datasets, we restricted our sample to continuously employed prime-age workers aged 25–55.

NEPS collects detailed information about educational trajectories, competencies, and returns to education over the life course of people born between 1944–1986. We used waves 2–12, which contained detailed information on non-formal training participation. In contrast to the German Socio-Economic Panel (SOEP), NEPS has much more precise information regarding course characteristics, contents, and participation timing. This is why NEPS is best suited to doing research on training participation in Germany. Understanding Society: the UK Household Longitudinal Study (UKHLS) is a large, nationally representative panel study for the UK that started in 2009–10, with annual follow-up with all study members. Adults (aged 16+) are interviewed annually along with any

new household members, in addition to household members who have turned 16 since the last interview. The UKHLS data are available from wave 1 (2009–10 survey year) to wave 10 (2017–19 survey years). We used waves 2–10 because the first wave did not contain measures for job-related training participation.

3.2. Method

We implemented two-way-fixed-effects (TWFE) regression models with standard errors clustered at the individual level. Through the process of demeaning, fixed-effects models eliminate all time-constant observed and unobserved factors a_i that might influence our independent and dependent variables (Brüderl and Ludwig 2015) and hence cause spurious correlation. Thereby only the idiosyncratic error term ε_{it} remained in the error term. This is the primary advantage of our approach over comparison between estimators. FE estimators are consistent under the assumption of strict exogeneity with respect to ε_{it} , meaning that in each time period t there is no correlation between ε_{it} and the independent variables $Parentstat_{it}$ and X_{it} of the same time period and all other time periods.

Since the fundamental problem of causal inference (Holland 1986) means that within estimation is only possible when observing individuals over time, we need to be sure that changes in our outcome variable are exclusively based on changes in the treatment status. This means that we had to ensure that outcome changes are not based on period effects (training participation increases for all) or aging (change in training participation is based on becoming one year older).

A requirement for this approach is the assumption of parallel time trends between treatment and control groups. To weaken this assumption and make our argument more plausible, we included a control group of nontreated individuals (constantly childless during our observational window) for each estimation. They contributed to the estimation by providing an estimate of the time trend that we are trying to measure via wave fixed-effects (μ_t) and age fixed-effects (γA_{it}). Since we further aimed to decompose the total effect of family formation on training participation, we additionally conducted static analyses in which we included variables via stepwise modeling. We calculated separate models for women and for men since we assume that the impact of family formation processes on job-related training participation differs by gender.

$$Y_{it} = a_i + \gamma A_{it} + \mu_t + \beta Parentstat_{it} + \delta X_{it} + \varepsilon_{it} \quad (1)$$

We also examined the time path of the family formation effect and analyzed whether childbirth has a constant and permanent effect on training participation, or whether the effect changes as the child ages. We therefore additionally implemented TWFE models in event-study designs and compared them with step impact models to see if the overall family formation effect is

driven by having very young children in the household or if the effect remains stable over time. Our event-study specification further allowed us to test our parallel trends assumption. Although a saturated model with a full set of leads and lags based on treatment timing cannot be seen as a direct test of the parallel trend assumption, it at least shows whether treatment and control groups have comparable dynamics in the pre-treatment period (Cunningham 2020).

$$Y_{it} = \alpha_i + \gamma A_{it} + \mu_t + \sum_{k=T_0}^{-2} \beta_k \times Parentstat_{ik} + \sum_{k=0}^{T_1} \beta_k \times Parentstat_{ik} + \delta X_{it} + \varepsilon_{it} \quad (2)$$

A recent strand of literature on difference-in-differences approaches under “differential timing” of treatment shows that under certain conditions, TWFE models might be biased due to problematic weighting procedures in the estimation (Goodman-Bacon 2021; Callaway and Sant’Anna 2020; Sun and Abraham 2020). This is especially true if early treated individuals take up the role of the control group for later treated units. Although we did not expect this to be a problem in our analyses due to the large share of “never-treated” control units, we implemented new robust estimators as robustness checks that consider the possibility of negative weighting processes. For our step impact functions, we use the TWFE estimator developed by Goodman-Bacon (2021), and we implemented the estimator developed by Sun and Abraham (2020) as robustness checks for our TWFE event-study models.

3.3. Variables

Dependent variable

We focused on non-formal job-related further training participation. For both Germany and the UK, we coded a binary variable that indicates whether a person has participated in at least one job-related training course during two waves. Job-related non-formal training is an organized learning program that helps employees upgrade and expand their skills without gaining an educational qualification such as a college or vocational training degree. In the German National Educational Panel Study (NEPS) data, for each individual life course episode (e.g., employment, unemployment, parental leave), respondents were asked about associated further training courses since the previous panel interview. In the Understanding Society: the UK Household Longitudinal Study (UKHLS) data, respondents were asked, “In the last 12 months, that is since [interview month] [interview year - 1], have you done any [other] training schemes or courses, even if they are not finished yet? Please include any part-time or evening courses, training provided by an employer, day release schemes, apprenticeships and government training schemes.” We excluded courses that were for “hobbies and leisure”.

Independent variable

The independent variable on our main interest is the transition to parenthood upon first childbirth. Childless workers are coded 0 and workers with children are coded 1.

Mediators

We coded a binary variable for parental leave take-up to see whether a person is on maternity, paternity, or parental leave. Part-time work indicates working less than 35 hours per week. Second childbirth indicates an extra child after first childbirth.

Confounders

We controlled for age (fixed-effects) and marital status (cohabiting, married, divorced).

4. Results

4.1. Descriptive Results

The upper part of Table 1 displays descriptive statistics of the German National Educational Panel Study (NEPS) data, separated by gender and parenthood status, for the dependent and independent variables in our models (more detailed in table A1 in the appendix). The sample incorporates 1,229 men who remained childless and 193 men who became fathers during our observation, and 953 women who remained childless during our observation period and 147 women who eventually became mothers. Constantly childless men and women served as the control group, allowing us to control for aging and period effects.

In Germany, the job-related training participation rate is 31% for men and 38% for women in our sample. We see heterogeneous participation rates: Men who became fathers during the observation period have a higher training participation rate (32%) than those who constantly remain childless (30%). As expected, there are large parenthood differences in job-related training participation among women in Germany. Constantly childless women have by far the highest training participation rates (40%) compared to women who eventually become mothers (31%). At the descriptive level, mothers are less likely to participate in job-related further training than their childless counterparts.

Table 1 shows that women who make the transition into first parenthood spend 54% of their person-years during our observation period as mothers. This is comparable to men who become fathers in our sample (55% of their person-years as fathers). Transitions into second childbirth are not common in our sample (see Table A1 in the Appendix). Among those men and women who become parents, only 17% of person-years are spent with a second child.

Table 1. Descriptive statistics

	Constantly childless men	Becoming fathers	Men total	Constantly childless Women	Becoming mothers	Women total
Germany						
Job-related further training participation	.3	.32	.31	.4	.31	.38
Parenthood status	0	.55	.12	0	.54	.11
Number of persons	1229	193	1442	953	147	1,100
% total	86.43	13.57	100	86.64	13.36	100
Number of person-years	5,282	1,407	6,689	3,993	966	4,959
% total	78.97%	21.03%	100%	80.52%	19.48%	100%
Mean person- years per person	6.8	8.52	7.16	6.75	7.76	6.95
UK						
Job-related further training participation	.26	.31	.27	.3	.27	.29
Parenthood status	0	.56	.16	0	.57	.18
Number of persons	2,451	682	3,133	1,866	758	3,154
% total	78.2	21.8	100	76.0	24.03	100
Number of person-years	10,296	4,074	14,370	10,239	4,534	14,773
% total	71.65%	28.35%	100%	69.31%	30.7%	100%
Mean person- years per person	5.48	6.92	5.89	5.57	6.99	6.00

Table A1 (in the Appendix) further shows that the share of highly educated people is higher among those groups of men and women who eventually become parents, indicating that differences in educational levels do not reflect the motherhood gap in training among women. In terms of partnership status, most constantly childless men (57%) and women (44%) are single. In our treatment groups, by contrast, men (61%) and women (62%) spent most of their person-years married. With regard to parental leave take-up, women who became mothers spent 28 % of their person years on parental leave,²⁷ while men only spent 4 % of their person-years on parental leave in Germany.

The lower part of Table 1 displays an overview of our UK Household Longitudinal Study (UKHLS) sample. In the sample, we have 2,451 childless men, 682 men who became fathers during the observation period, 1,866 women who remained childless, and 758 women who made the transition into first childbirth. Men who transitioned to parenthood show a training participation rate of 31%, while constantly childless men seem to train less (26%). Women who make the transition into first parenthood have a training participation rate of 27%, while the female control group of has a participation rate of 30%. Women and men who eventually make the transition into first parenthood spend about half of their person-years as parents (56% and 57%). Constantly childless people are slightly older than those who make the transition into first parenthood.

Similar to what we observed in our German groups, our UK treatment groups (becoming parents) seem to be more highly educated than our control groups (constantly childless) for both men and women (see Table A1 in the Appendix). Being single is the most common status among those who remain childless, while those who make the transition to parenthood spend the majority of their person-years married. Men who transitioned into parenthood spend 14% of their person-years on parental leave. By contrast, women who eventually become mothers spend much more time on parental leave (27% of their person years). With regard to working hours, we find a clear gendered pattern. Women spend more time working part-time in our sample than men. We find that men in the treatment group (men who have ever been fathers throughout the observation period) spend less time working part-time than constantly childless men. For women, we see that the treatment group (women who have ever been mothers throughout the observation period) spends a higher share of their person years working part-time compared to the control group.

²⁷ Duration of parental leave following first childbirth is not necessarily the same as the period that the national policy mandates from time off following the birth of a child.

4.2. Multivariate Results

4.2.1. Step Impact Functions Analysis of Job-related further training Participation by Country

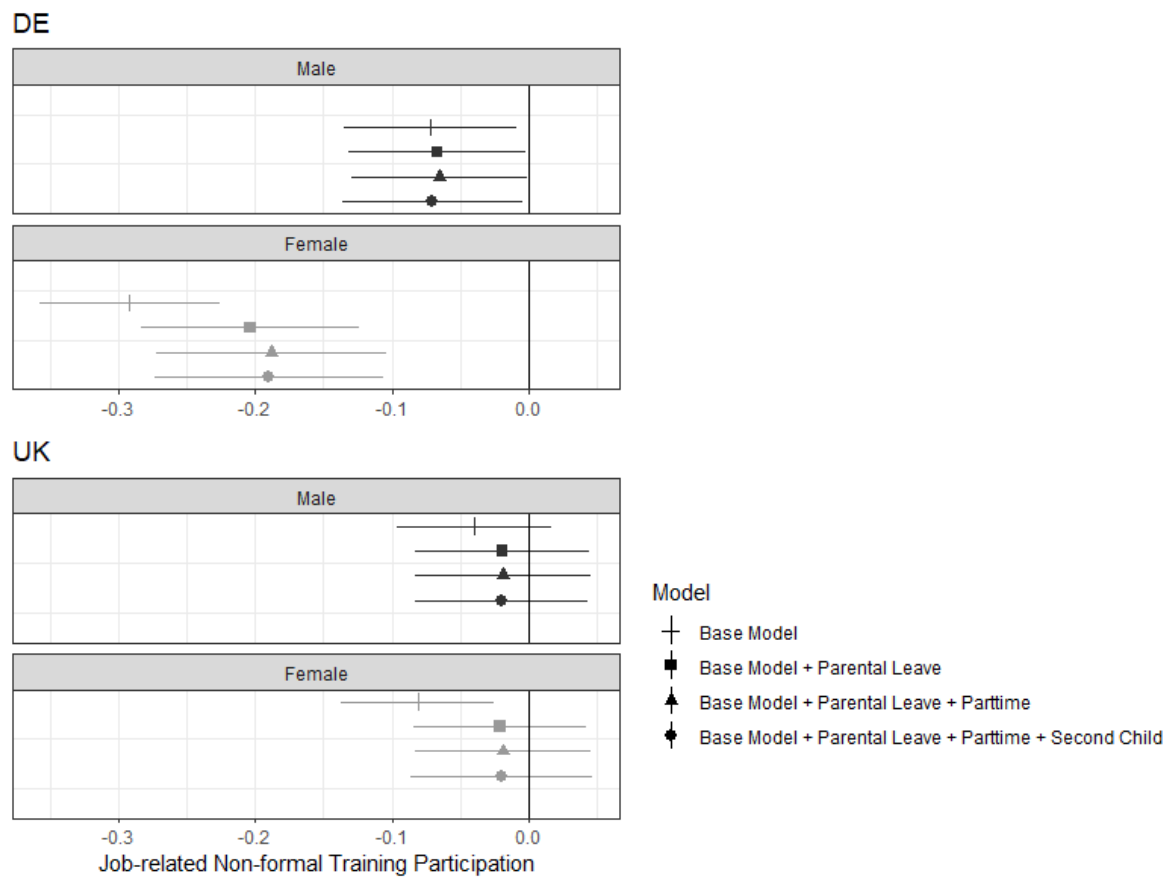
Figure 1 illustrates our results from the static analyses of the effect of the transition into parenthood on job-related training participation, using TWFE step-impact models. In Germany, first childbirth decreases women's job-related training participation by 29 percentage points (pp.). Following first childbirth, men's training participation decreases in Germany by about 7 percentage points. Men's training participation declines after first childbirth as well, although the effects seem to be lower in substantial terms than motherhood effects.

Likewise, we find gender differences in job-related further training participation following parenthood in the UK. Here, women suffer a substantial and statistically significant motherhood penalty in job-related training participation, while men seem to be only weakly affected by parenthood. In the baseline model (controlling for age and marital status), motherhood decreases women's training participation probability by 8 percentage points, while we find no statistically significant fatherhood effect. Thus, our findings support Hypothesis 1: First motherhood decreases training participation probability. Hypothesis 2: First fatherhood has either no effect or a positive effect on men's training participation probability, is partially supported in the UK. We found a fatherhood penalty in Germany and no significant effect of parenthood on men's training participation in the UK. Findings also support Hypothesis 7: We expect to see a steeper decline in job-related training participation in Germany than in the UK after first motherhood.

We further analyzed the role of potential mediators of the family formation effect. For women in Germany, we find that controlling for parental-leave take-up decreases the effect of childbirth on further training to 20 percentage points. Including an additional indicator for part-time work reduces the family formation effect on training participation to 19 percentage points for women. Thus, even after controlling for parental leave and part-time work, motherhood effects still persist. Further, the effect of family formation does not seem to be mediated via second and subsequent childbirths.

In contrast to our results for women, we find that fatherhood effects seem to remain stable after controlling for different mediators. Controlling for parental leave take-up, part-time work, and second childbirths does not decrease our estimated fatherhood effect for men in Germany (7 percentage points in all models). In line with our German results for motherhood, we find that parental leave take-up seems to be the main driver of the motherhood penalty in the UK. Parental leave reduces the motherhood effects from 8 to 2 percentage points, which thereby turns statistically insignificant. Additionally, controlling for part-time work and second childbirths does not change the coefficient of the motherhood effect in the UK.

Figure 1. Effects of transition to first childbirth on job-related training participation by gender and country, based on two-way-fixed-effects with step impact functions.



In sum, the impact of parenthood on training participation is more substantial in Germany than in the UK. Furthermore, the gender gap in job-related further training participation is larger than in the UK since women’s job-related further training participation following first childbirth declines more sharply in Germany than in the UK. In both countries, parental leave partially explains why most mothers are less likely to participate in job-related further training after first childbirth. Thus, our results confirm Hypothesis 3, which states that the parenthood effect is mediated via parental leave take-up for women but not for men in both countries. Neither part-time work nor second childbirths seem to be the mediator of the total effect of family formation. We therefore cannot confirm Hypotheses 4 and 5. In accordance with our expectations, we found a residual effect of family formation for women in both countries after controlling for parental leave take-up, part-time work, and second childbirths. We also find a significant direct effect of family formation for men in Germany. Based on these results, we can only partly confirm Hypothesis 6: First childbirth has a negative effect on job-related training for women but not for men in both countries even after controlling for parental leave take-up, part-time work, and second childbirths.

4.2.2. Event Study Analysis of Job-related further training Participation by Country

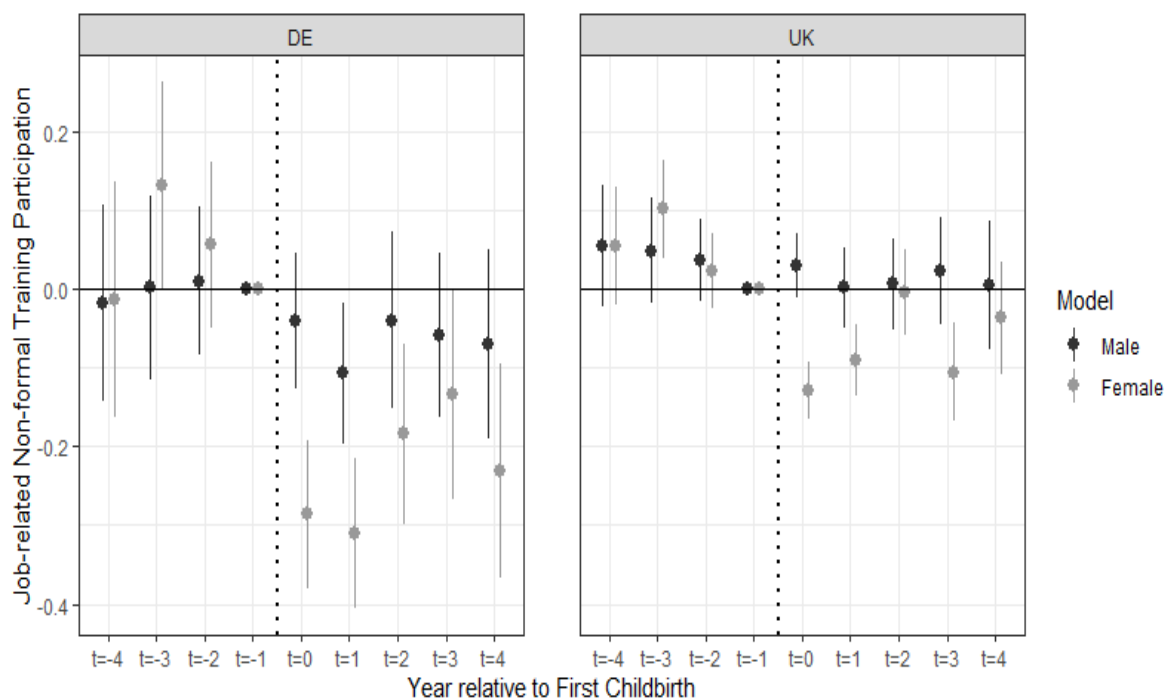
Next, we examine whether our identified parenthood effects are short-term or whether the effects remain stable over time. Figure 2 shows findings from the two-way-fixed-effects (TWFE) estimations in event-study specifications. We focus on potential violations of the parallel trend assumptions. Indeed, we find that there might be anticipation processes regarding family formation. In both countries, women who became mothers during our observational period trained more in the third year before childbirth than constantly childless women in the same time-period, although the effect only achieves statistical significance in Germany. It may be that (1) training participation is already lower one year before childbirth ($t = -1$) due to anticipation and pregnancy effects or (2) women who plan to become mothers and who hope for a smooth return to work increase their training participation in anticipation of a return to the labor market. In the remaining pre-treatment periods, we do not find significant differences in training dynamics between treatment groups and control groups. In accordance with our step impact model, we also find that in both countries, women participate less in job-related further training after first childbirth than men.

The time path patterns between Germany and the UK are quite different. In Germany, motherhood effects seem to last longer. While the motherhood penalty gets weaker at $t=2$ and $t=3$, training participation behavior never returns to the pre-motherhood baseline. In the first interview after childbirth, women report 29 percentage points lower training participation probability. Our findings suggest that the motherhood penalty seems to get slightly stronger one year after childbirth (at $t=1$, 31 pp.). In the following two years, the effect of parenthood starts to fade out. In the second year after first childbirth ($t=2$), motherhood decreases training participation probability by 18 percentage points, while in the third year following first childbirth ($t=3$), job-related training participation probability seems to be 13 percentage points lower than in the pre-motherhood period ($t=-1$). Still, the training participation probability never returns to the pre-motherhood baseline.

In the UK, we find that mothers report a lower training participation rate in the first two interviews after first childbirth. During the year of first childbirth, training participation probability decreases by 13 percentage points. One year after the transition into parenthood, women still have 9 percentage points lower training probability in comparison to $t=-1$. After two years, women do not seem to participate less in job-related further training anymore. While our findings in Germany support Hypothesis 4, our findings for the UK do not. This is the case because we expect the negative effect of first childbirth on women's training participation to persist over the years. In Germany, the training participation probability of women never returns to its original level after the initial drop. Four years after the birth of a first child, women's training participation is 23 percentage points below its level just before childbirth. In the UK, two years after the first childbirth, we do not see the negative effects of childbirth on women's training participation.

Considering the time-paths of fatherhood effects, we find no relative time-period with a significant effect of first childbirth in the UK. In Germany, our results indicate no fatherhood penalty in the first interview after childbirth. However, a negative and statistically significant effect at $t=1$ (-11 pp.) becomes insignificant over time. In sum, we find (1) long-term negative effects of childbirth on women's training participation in Germany, (2) short-term negative effects on men in Germany and women in the UK, and (3) no effects on men in the UK.

Figure 2. Predicted change in job-related training participation before and after first childbirth by gender and country, based on two-way-fixed-effects with an event-study design.



5. Robustness checks

We also used our event-study specifications to see whether the time path pattern changes while controlling for parental leave in comparison to the time path of the total causal effect of first childbirth. Results can be seen in Figure 3 in the appendix. The effect sizes get smaller after controlling for parental leave, but the time path patterns are comparable to the time paths of the total causal effects.

6. Concluding discussion

This chapter examined how the transition to parenthood changes an individual's job-related training participation. Our chapter sheds light on parenthood as a source of gender inequality in job-related training participation, and it illuminates the impact of country context on the gender gap in job-related training. These findings do not bode well for gender equality in job-related further training

participation. Following parenthood, women face a motherhood penalty in job-related further training in Germany and the UK. Patterns of job-related further training participation also differed across countries following parenthood, with German women faring worse than their counterparts in the UK. In Germany, women never fully catch up on job-related further training participation rates as their children get older, while men tend to return to their previous participation rates after the early stages of parenthood. Since we do not find a consistent gender gap in training participation prior to first childbirth, our findings suggest that entry into parenthood is the critical factor behind the remaining gender gap in job-related training participation.

We found similarly gendered patterns of job-related further training participation following parenthood in Germany and the UK, although they differed in length and magnitude. We found steeper declines following first childbirth in women's job-related further training participation relative to men's training participation in Germany. Additionally, women experienced a long-term child penalty in job-related further training participation in Germany. This is in line with previous literature which showed that women experienced a larger wage penalty for motherhood in Germany than in the UK (Kleven et al. 2019; Musick et al. 2020). Despite a major policy reform in 2007 in Germany, studies show that work-family policies based on the male-breadwinner norm are still prevalent in Germany, such as long maternity leaves and a lack of childcare options for children under 3. These policies are linked to larger motherhood wage penalties and higher levels of gender segregation in the labor market in Germany (Aisenbrey and Fasang 2017; Gangl and Ziefle 2009).

To close gender gaps in women's access to skill development and further training participation, policies seeking to increase women's further training participation need to focus on improving mothers' participation rates. Childless women's further training participation is equal to or higher than men's, while mothers fall behind in further training participation after first childbirth. Any interventions aimed at tackling gender gaps in skill development should be based on a good understanding of how different groups of women are affected by the institutions, the market, and the household. Data should be disaggregated not only by gender but also by other relevant factors, such as parenthood status. It is thus important to know details about training participation rates of different subgroups of women, including mothers.

Policies should encourage and enable mothers to participate in further training opportunities. Policy makers, therefore, need to identify barriers to equal access for women and men, and particularly for women with young children. Further training programs should be designed to overcome existing barriers for mothers, such as timing and childcare facilities, and to respond flexibly to different needs. Our findings suggest that family care responsibilities severely constrain women's choices in further training participation. Public expenditure cuts in childcare and social

services affect women to a greater degree than men because women tend to bear the greatest burden of household responsibilities.

There are several approaches to increasing mothers' access to and participation in further job training. First, further training programs should be more flexible, for instance by offering shorter or modular training courses that allow women with children to reduce the time away from work or home. Second, further training programs should also aim at promoting the return to work for women either after childbirth, following a period of parental leave, or after long-term unemployment due to unpaid family care responsibilities. Lastly, instructors and managers of training institutions should receive gender awareness training to raise and address gender issues and avoid stereotypes. They can help sensitize employers and encourage them to offer further job training to both women and men, and especially to women with children. Employers and training providers all have roles to play in creating a supportive and motivating environment conducive to the recruitment of mothers into further training participation.

A number of limitations need to be considered. First, we lacked data to differentiate the federal states of the former East Germany from the federal states of the former West Germany, although there might be persistent East–West differences in maternal employment patterns and gender ideologies (Zoch and Schober 2018). Second, studies showed that women are less likely to participate in employer-sponsored training (Dämmrich et al. 2015). It is possible that mothers are even more disadvantaged in employer-sponsored training participation compared to all types of further job training. Third, the NEPS and the UKHLS are not longitudinal surveys of youth, meaning that many respondents have already undergone their transition to first parenthood before our observational window. Lastly, the UKHLS only provides information on maternity leave, not parental leave in general, while family or care-related leave is a separate category on the current economic activity status.

Despite these limitations, our findings have implications for discussions about the persistence of gender inequality in job-related further training participation following childbirth. Although descriptive statistics suggest that women are more likely to participate in job-related further training than men, our estimates show that mothers reduce training participation to a greater extent than fathers. It is also important to underscore the implications of the motherhood penalty in training participation for broader questions of social inequality. The long-term implications are clear: Parenthood will likely exacerbate inequalities between women and men in job-related further training participation, occupational attainment, and lifetime earnings. As this parenthood gap persists, governments must weigh the gendered consequences of parenthood to develop policies to support women's, and especially mothers', job-related further training participation.

TECHNEQUALITY Deliverable D3.6

Table A1: Descriptive statistics: Germany

	Constantly childless men	(sd)	Becoming fathers	(sd)	Men total	Constantly childless Women	(sd)	Becoming mothers	(sd)	Women total
DE										
Job-related further raining participation	.3	(.46)	.32	(.47)	.31	.4	(.49)	.31	(.46)	.38
Parenthood status	0	(0)	.55	(.5)	.12	0	(0)	.54	(.5)	.11
Birth of 2nd child	0	(0)	.17	(.38)	.04	0	(0)	.17	(.38)	.03
Age	40.52	(8.51)	36.18	(5.6)	39.61	41.39	(8.49)	33.53	(4.16)	39.86
High education	.55	(.5)	.76	(.43)	.60	.59	(.49)	.79	(.4)	.63
Medium education	.28	(.45)	.17	(.37)	.25	.33	(.47)	.19	(.39)	.30
Low education	.17	(.38)	.07	(.26)	.15	.09	(.28)	.02	(.13)	.07
Single	.57	(.5)	.1	(.3)	.47	.44	(.5)	.1	(.3)	.37
Cohabiting	.19	(.39)	.29	(.45)	.21	.21	(.41)	.28	(.45)	.23
Married	.23	(.42)	.61	(.49)	.31	.33	(.47)	.62	(.48)	.39
Divorced / Widowed	.01	(.1)	0	(.07)	.01	.02	(.13)	0	(0)	.01
Parental leave take-up	0	(0)	.04	(.19)	.01	0	(0)	.28	(.45)	.06
Part-time work	.06	(.24)	.03	(.18)	.06	.18	(.39)	.31	(.46)	.21
Number of persons	1229		193		1442	953		147		1,100
% total	86.43		13.57		100	86.64		13.36		100
Number of person-years	5282		1407		6,689	3993		966		4,959
% total	78.97		21.03		100%	80.52		19.48		100%
Mean person-years per person	6.8		8.52		7.16	6.75		7.76		6.95

Source: NEPS SC6 SUF 12.0.0, authors' calculations. Note: Statistics shown are mean values for unweighted data

TECHNEQUALITY Deliverable D3.6

Table A2: Descriptive statistics: UK

	Constantly childless men	(sd)	Becoming fathers	(sd)	Men total	Constantly childless Women	(sd)	Becoming mothers	(sd)	Women total
UK										
Job-related further raining participation	.26	(.44)	.31	(.46)	.27	.3	(.46)	.27	(.44)	.29
Parenthood status	0	(0)	.56	(.5)	.16	0	(0)	.57	(.49)	.18
Birth of 2nd child	0	(0)	.17	(.38)	.05	0	(0)	.18	(.38)	.06
Age	37.57	(9.26)	33.63	(5.19)	36.45	37.51	(9.35)	32.44	(4.66)	35.95
High education	.44	(.5)	.53	(.5)	.47	.54	(.5)	.65	(.48)	.58
Medium education	.33	(.47)	.32	(.47)	.32	.29	(.45)	.28	(.45)	.29
Low education	.24	(.43)	.15	(.35)	.21	.16	(.37)	.08	(.27)	.14
Single	.47	(.5)	.08	(.28)	.36	.41	(.49)	.09	(.29)	.31
Cohabiting	.21	(.41)	.2	(.4)	.21	.21	(.4)	.22	(.42)	.21
Married	.28	(.45)	.7	(.46)	.40	.32	(.47)	.66	(.47)	.43
Divorced / Widowed	.04	(.2)	.01	(.12)	.03	.07	(.25)	.02	(.14)	.05
Parental leave take-up	0	(.09)	.14	(.35)	.05	0	(.16)	.27	(.44)	.10
Part-time work	.07	(.25)	.02	(.15)	.05	.11	(.31)	.22	(.42)	.15
Number of persons	2451		682		3133	1866		758		3,154
% total	78.2		21.8		100	76.0		24.03		100
Number of person-years	10,296		4,074		14,370	10,239		4,534		14,773
% total	71.65%		28.35%		100%	69.31%		30.7%		100%
Mean person-years per person	5.48		6.92		5.89	5.57		6.99		6.00

Source: UKHLS, authors' calculations. Note: Statistics shown are mean values for unweighted data

Table 2. Two-way Fixed-Effects Event Study Estimation: Family Formation and Job-related Training Participation Germany

	Women	Men
Time Relative to First Childbirth		
T-10	-0.25 (0.22)	-0.36*** (0.10)
T-9	0.17 (0.25)	0.04 (0.18)
T-8	-0.37** (0.14)	0.10 (0.11)
T-7	-0.28** (0.11)	0.18+ (0.11)
T-6	0.07 (0.14)	0.16* (0.08)
T-5	-0.06 (0.09)	0.03 (0.07)
T-4	-0.01 (0.08)	-0.02 (0.06)
T-3	0.13+ (0.07)	0.00 (0.06)
T-2	0.06 (0.05)	0.01 (0.05)
T0 (First interview after childbirth, T-1 is reference year)	-0.29*** (0.05)	-0.04 (0.04)
T+1	-0.31*** (0.05)	-0.11* (0.05)
T+2	-0.18** (0.06)	-0.04 (0.06)
T+3	-0.13* (0.07)	-0.06 (0.05)
T+4	-0.23*** (0.07)	-0.07 (0.06)
T+5	-0.24* (0.10)	0.08 (0.07)
T+6	-0.06 (0.13)	0.00 (0.09)
T+7	-0.18 (0.15)	0.00 (0.09)
T+8	0.09 (0.18)	0.07 (0.13)
T+9	0.20 (0.23)	-0.20* (0.08)
Family Status		
Single	0.00	0.00

	(0.00)	(0.00)
Cohabiting	-0.01	-0.02
	(0.04)	(0.03)
Married	-0.03	-0.01
	(0.05)	(0.03)
Divorced	-0.13	-0.09
	(0.11)	(0.08)
Constant	-0.19	-0.43+
	(0.25)	(0.22)
N	.	.
R2 (Within)	.	.
Age Fixed-Effects	YES	YES
Wave Fixed-Effects	YES	YES

Notes: Standard errors in parentheses. + p < 0.10, * p < 0.05, ** p < 0.01, , *** p < 0.001.

Source: NEPS SC6 SUF 11.0.0, authors' calculations.

	Women	Men
Time Relative to First Childbirth		
T-8	0.16	0.09
	(0.19)	(0.17)
T-7	0.29**	0.11
	(0.11)	(0.10)
T-6	0.06	0.06
	(0.07)	(0.06)
T-5	0.05	0.04
	(0.05)	(0.05)
T-4	0.05	0.05
	(0.04)	(0.04)
T-3	0.10**	0.05
	(0.03)	(0.03)
T-2	0.02	0.04
	(0.02)	(0.03)
T0 (First interview after childbirth, T-1 is reference year)	-0.13***	0.03
	(0.02)	(0.02)
T+1	-0.09***	0.00
	(0.02)	(0.03)
T+2	-0.01	0.01
	(0.03)	(0.03)
T+3	-0.11***	0.02
	(0.03)	(0.03)
T+4	-0.04	0.00
	(0.04)	(0.04)
T+5	-0.03	-0.03
	(0.04)	(0.05)

T+6	-0.01 (0.06)	-0.07 (0.06)
T+7	0.06 (0.07)	0.00 (0.09)
Family Status		
Single	0.00 (0.00)	0.00 (0.00)
Cohabiting	-0.03 (0.02)	-0.03 (0.02)
Married	-0.02 (0.03)	0.01 (0.03)
Divorced	-0.01 (0.05)	-0.03 (0.04)
Constant	0.50*** (0.12)	0.31* (0.15)
N	.	.
R2 (Within)	.	.
Age Fixed-Effects	YES	YES
Wave Fixed-Effects	YES	YES

Notes: Standard errors in parentheses. + p < 0.10, * p < 0.05, ** p < 0.01, , *** p < 0.001.

Table 3. Two-way Fixed-Effects Event Study Estimation: Family Formation and Job-related Training Participation UK

Source: UKHLS, authors' calculations.

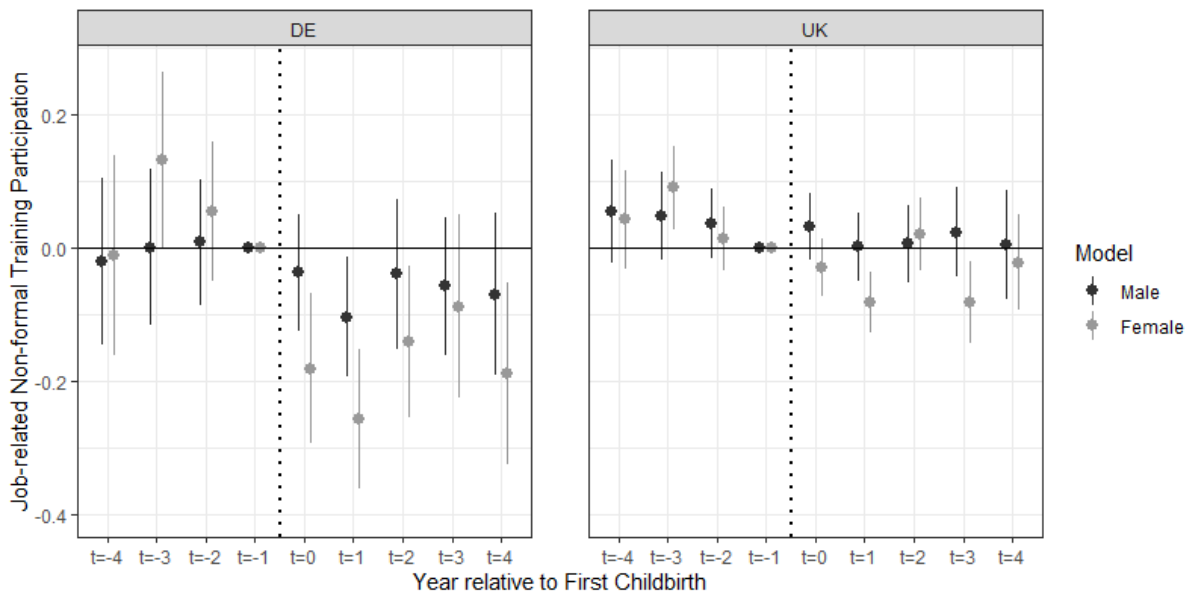


Figure 3. Two-way Fixed-Effects Event Study Estimation: Family Formation and Job-related Training Participation UK controlled for parental-leave take-up

Chapter 7B: The role of family dissolution in women's and men's further training participation in Germany and the UK

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1. Introduction

There has been a great deal of concern about the relationship between changes in families and the rise in economic inequality in recent years (Esping-Andersen 2007; McCall and Percheski 2010; McLanahan 2004). Notably, the increase in the number of families headed by single mothers has been linked to rising family income inequality (McCall and Percheski 2010). Previous studies have shown a wide range of economic costs of divorce for women, such as declines in household income (Smock 1994) and increases in the risk of poverty (Hübgen 2020; Leopold 2018; Smock and Manning 1999) because single mothers work fewer hours and earn less than other families (McCall and Percheski 2010).

In the previous chapter, we found that women experience a substantial decline in job-related training participation after first childbirth (see Chapter 7A) due to work interruptions, gendered household specialization, and discrimination against mothers. In this chapter, we analyze the causal relationship between family dissolution and job-related training participation. After a divorce, women might need to reinforce their labor market orientation through full-time work and regular training participation to maintain economic security. Research has shown that participation in job-related training can reduce unemployment risks, meaning that such training can have a career stabilizing effect (see Chapter 5 of Deliverable 3.6). Hence, the relationship between family context and further job training participation deserves attention in work, gender, and family scholarship.

As outlined in Chapter 7A (Deliverables 3.6), previous findings suggest a possible association between family-related factors and the gender gap in training participation. Previous studies focusing on partnership or marital status effects on job-related training participation provide mixed results (Elman and O'Rand 2002; Green 1993; Harris 1999; Lebert and Antal 2016). In terms of marital status, married women (Green 1993) or single men (Harris 1999) are less likely to participate in job training. According to Zhang and Palameta (2006), both married and divorced workers are less likely to engage in job training than single workers. However, Elman and O'Rand (2002) find no impact of marriage on an employee's likelihood of participating in job training. Studies show that the presence of a partner can be positively associated with an employee's probability of participating in job training if the employee's partner provides childcare and housework (Greenhaus and Powell, 2012; Lebert and Antal 2016; Maurer, Weiss, and Barbeite, 2003). These studies suggest that divorce might be an extremely salient factor in relation to job-related training participation. Since



chapter 7A showed that family formation processes have strong causal effects on job-related training participation, the effect of family dissolution might differ from the effect of divorce.

However, studies focusing on the effect of family dissolution on job-related training are rare. Indeed, to our knowledge, not a single study to date has explicitly analyzed whether and how much family dissolution affects job training participation. We contribute to this growing field of research by analyzing how family dissolution changes a worker's job training participation. Family events like divorce (DiPrete and McManus 2000) have effects on employment behavior and income, meaning that differences in their incidence can shape inequality in job training participation as well. Core unresolved questions are (1) whether family dissolution is primarily associated with job training participation, (2) whether the effect of family dissolution varies by gender, and (3) whether the institutional context matters for the relationship between family dissolution and job-related training.

2. Background

2.1. Divorce and Labor Supply

A large body of literature shows that divorce or separation is associated with an individual's economic well-being and labor market activities (Hauser et al. 2016; DiPrete and McManus 2000; Leopold 2018; van Damme et al. 2009). For women, divorce and separation are associated with a substantial decline in household income (Smock 1994). A large income drop after a divorce is explained by the loss of the partner's income, the lack of human capital investment by women, and children after divorce (van Damme et al. 2009).

At the individual level, employment status, weeks worked, and work experience have all been linked to marital dissolution (Spitze 1988). Studies show that divorce increases women's employment rates. Tamborini et al. (2015) find that women's employment and average earning increased following divorce. Raz-Yurovich's (2011) findings suggest that women's employment stability, number of jobs held, and monthly salary increases after divorce.

Women's employment is a possible response to the increased risk of marital dissolution. Married women's investments into the labor market are often limited due to childcare and housework responsibilities. Marital instability may increase married women's labor supply, meaning that there might be an anticipation effect of divorce on women's labor supply (Ozcan and Breen 2012). Research has also shown that married women tend to increase their labor supply when perceived marital risk is increased (Blau and Kahn 2007). As a result, we see positive correlations between women's employment and divorce rates. In sum, studies on the relationship between divorce and women's labor supply find that divorce or the risk of divorce leads to an increase in women's employment and working hours.



However, some studies have found opposing results, especially in the UK. For example, in the UK, divorce led to a decrease in women's employment by 5 percentage points in 1991–1997. After the policy change that offered incentives to work in 1998, women's employment dropped by 2 percentage points in 1998–2003 (Jenkins 2008). Van Damme et al. (2009) also found that women's employment dropped by 4.9 percentage points in the UK in 1994–2001, while there was a small but significant increase in women's employment rates following divorce in the Netherlands, Denmark, Italy, Portugal, France, Belgium, Spain, and Germany. Van Damme et al. (2009) explain that different public policies, such as welfare benefits and public childcare provision, matter for changes in women's employment after divorce.

Employment patterns after divorce look different in Germany and the UK. In the case of Germany, previous research shows that women increased their employment after a divorce (Hauser et al. 2016; Bröckel and Andreß 2015; Van Damme et al. 2009). Hauser et al. (2016) find that divorce increased women's employment rates by 8 percentage points in the period between 1990 and 2006. Using more recent data from 2000–2012, Bröckel and Andreß (2015) suggest that women's employment participation rates went up by 6 percentage points after a divorce. Van Damme et al.'s (2009) study also confirms that women are more likely to participate in the labor market after a divorce in Germany. Unlike in the UK, women in Germany tend to increase their engagement in employment. Since country variations between Germany and the UK were substantial, we estimate the effect of divorce on job-related training participation to be significant both in Germany and the UK.

2.2 Divorce and Participation in Job-related Training

Many studies have examined the effect of divorce on women's employment and income, but little attention has been paid to changes in women's job-related training participation after family dissolution. Lebert and Antal (2016) found that the presence of a partner is a resource for job-related training because partnered individuals can share housework or childcare to invest their time in job-related further training. Using the Swiss Household Panel Study in the period between 2004 and 2013, they show that partnered employees are more likely to participate in further training than employees without a partner.

However, research also suggests that the effect of divorce on further job training is different by gender. Using the 1995 UK Labor Force Survey, Harris (1999) finds that single men are less likely to participate in further training than men living with a partner. By contrast, having a partner does not change women's further training participation rates. Using the 1987 General Household Survey in the UK, Green (1993) finds that married women and women with children are less likely to participate in further job training due to family care responsibilities. Employers are more reluctant to train married women and mothers than single or childless women because they often deem married women and mothers less worthy of investment (Green, 1993).



Considering the effect of partnership status on job-related further job training by gender and country, findings are contested. We do not know whether individuals' training participation changes before or after divorce. If the presence of a partner is a resource for job training participation (Lebert and Antal 2016), an individual's job training participation rates might decline after family dissolution. Further research has shown that divorce might have a causal temporary effect on life satisfaction, mental health, and body mass index (Leopold 2018), which are all factors which by themselves might reduce training participation probability. If marriage is a barrier to job training participation for women (Green 1993), we might find higher job training participation rates after family dissolution among women.

2.3. Research Questions and Hypotheses

The purpose of this chapter is to examine the effects of family dissolution on job-related training participation in Germany and the UK. Although some studies (e.g., Elman and O'Rand 2002; Green 1993; Lebert and Antal 2016; Green 1993) have acknowledged the effect of marriage/cohabitation on job training participation, the effect of family dissolution on job training participation might be different.

The research questions are (1) Does family dissolution (divorce or separation) affect an employee's job-related training participation? (2) If so, do different work-family policies in Germany and the UK contribute to the effects?

We contribute to the existing literature in the following way: We estimate the "treatment effect" of family dissolution on further job training participation. This means that we compare dissolution effects to job training participation based on before-after estimations. To our knowledge, we are the first researchers to examine the causal effect of family dissolution on job training participation.

Hypothesis 1: We expect family dissolution to *increase* women's training participation probability due to increased female labor supply.

Hypothesis 2: We expect family dissolution to *decrease* women's and men's training participation probability due to increased work-life conflict.

Hypothesis 3: We expect to see a steeper decline in women's and men's training participation following family dissolution in the UK compared to their counterparts in Germany.



3. Data and Method

3.1. Data

To analyze the relationship between family dissolution and job-related training participation, we used starting cohort 6 data (SUF 12.0.0) of the National Educational Panel Study (NEPS) (Allmendinger et al. 2011; Blossfeld et al. 2011) for Germany and Understanding Society: the UK Household Longitudinal Study (UKHLS) for the UK. For both datasets, we restricted our sample to continuously employed prime-age workers living in a household with a partner and children (before dissolution takes place), aged 25–55.

The National Educational Panel Study (NEPS) collects detailed information about educational trajectories, competencies, and returns to education over the life course of people born between 1944 and 1986. We used waves 2–12, which contain detailed information on non-formal training participation. Understanding Society: the UK Household Longitudinal Study (UKHLS) is a large, nationally representative panel study for the UK that started in 2009–10 with annual follow-ups with all study members. The UKHLS data are now available from wave 1 (2009–10 survey year) to wave 10 (2017–19 survey years). We use waves 2–10 because the first wave did not contain measures of job training participation. For more details, please see the data section in Chapter 7A.

3.2. Method

As previously mentioned in Chapter 7A, we implemented two-way-fixed-effects (TWFE) regression models with standard errors clustered at the individual level. FE estimators are consistent under the assumption of strict exogeneity with respect to ε_{it} , meaning that in each time period t there is no correlation between ε_{it} and the independent variables $Dissolution_{it}$ and X_{it} of the same time period and all other time periods. A requirement for this approach is the assumption of parallel time trends between treatment and control groups. To weaken this assumption and to make our modeling design more plausible, we included a control group of non-treated individuals (permanently married) for each estimation. They contributed to the estimation by providing an estimate of the time trend that we are trying to measure via wave-fixed effects (μ_t) and age-fixed effects (γA_{it}). We calculated separate models for women and for men since we assumed that the impact of family dissolution processes on job-related training participation might differ by gender.

$$Y_{it} = \alpha_i + \gamma A_{it} + \mu_t + \beta Dissolution_{it} + \delta X_{it} + \varepsilon_{it}$$



3.3. Measures

Dependent variable: Following the measures in Chapter 7A, we focused on non-formal job-related further training participation. Job-related non-formal training is an organized learning program that helps employees upgrade and expand their skills without resulting in an educational qualification such as a college or vocational training degree. For both Germany and the UK, we coded a binary variable that indicates whether a person has participated in at least one job-related training course during the two waves.

Independent variable: Our primary independent variable was the transition into family dissolution. We define family dissolution as an event of household dissolution. This means that moving out, divorce, and widowhood are all considered events of family dissolution. People living together with a partner and children in one household were coded 0, while people who do not cohabit with their partner anymore were coded 1.

Confounders: We controlled for age (fixed-effects) and period effects (wave-fixed effects)

4. Findings

4.1. Descriptive Results

The upper part of Table 1 shows descriptive statistics for Germany, separated by gender and treatment/control group status, for the dependent and independent variables in our models. In Germany, we see slightly higher participation rates in job-related training in our treatment groups in comparison to our control groups. Our male control group is 45 years old on average while our male treatment group has a mean age of 43 years. Constantly cohabiting women and women who at some point experienced a family dissolution event are 44 years old on average. Our male control group consists of 2,599 constantly cohabiting or married men with children in the household, and the treatment group contains 700 men who experienced a family dissolution event during our observation period. In our female sample, we find 2,695 women who continued to live with a partner with children in the household, and 109 women who eventually stopped living with their partner. In both samples, the share of individuals in our control groups is much higher than in the treatment groups.

The lower part of Table 1 displays an overview of the UK data. Our sample consists of 7,017 constantly cohabiting men with children, and 123 men who at some point experienced an event of family dissolution with children. For women, we have 6,359 constantly cohabiting women and 222 women who experienced family dissolution with children. Likewise, in our German data, we find different participation rates between the treatment (constantly cohabiting) and control groups (those who eventually experience a dissolution event) than in the UK. Among men, our control group exhibited a 27% training participation rate, while our male treatment group spent 29% of their person-years with job-related training. Among women, constantly cohabiting women have a training rate of 31%, while women who transitioned into family dissolution have a



participation rate of 32%. We do not find large age differences between treatment and control groups. Our UK sample is slightly younger than the German sample.

Table 1. Descriptive statistics

	Men		Women	
	Constantly Cohabiting	Eventually Separated	Constantly Cohabiting	Eventually Separated
Germany				
Job-related Training Participation	.32	.34	.31	.32
Family dissolution	0	.47	0	.50
Age	44.96	43.23	43.85	43.49
Number of persons	2599	104	2695	109
% total	96.15%	3.85%	96.11%	3.89%
Number of person-years	12,111	700	12,490	735
% total	94.54%	5.46%	94.44%	5.56%
Mean person-years per person	6.96	7.97	6.88	7.99
UK				
Job-related Training Participation	.27	.29	.31	.32
Family dissolution	0	.45	0	.50
Age	40.50	40.38	39.51	40.17
Number of persons	7017	123	6359	222
% total	98.28%	1.72%	96.63%	3.37%
Number of person-years	27,873	751	25,002	1292
% total	97.38%	2.62%	95.09%	4.91%
Mean person-years per person	5.74	7.19	5.65	6.72

Source: NEPS SC6 SUF 12.0.0 and UKHLS, authors' calculations. Note: Statistics shown are mean values for unweighted data.



Figure 1. Effects of transition to family dissolution on job-related training participation by gender and country, based on two-way-fixed-effects with step impact functions.

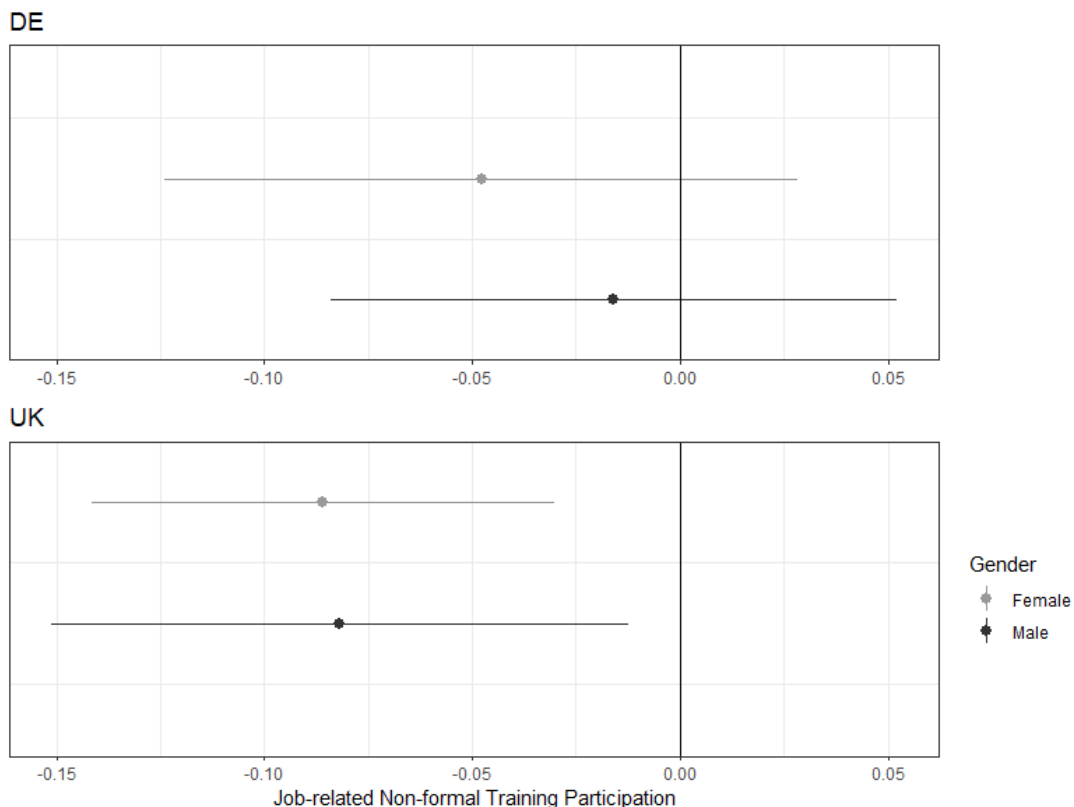


Table 2. Two-way Fixed-Effects (Step Impact): Family Dissolution and Job-related Training Participation

	Germany		UK	
	Men	Women	Men	Women
Dissolution	-0.02 (0.04)	-0.05 (0.04)	-0.08** (0.03)	-0.09** (0.03)
Constant	0.21 (0.26)	-0.21 (0.29)	0.25+ (0.15)	0.55*** (0.16)
N
R2
Age Fixed-Effects	YES	YES	YES	YES
Time Fixed-Effects	YES	YES	YES	YES

Notes: Standard errors in parentheses. + p < 0.10, * p < 0.05, ** p < 0.01, , *** p < 0.001.

Source: NEPS SC6 SUF 12.0.0 and UKHLS, authors' calculations.

4.2. Multivariate Results

Figure 1 illustrates our findings from the static analyses of effects of family dissolution on job-related training participation. Our multivariate models show substantive effects of family dissolution on job-related training participation for women and for men in Germany, but they do not reach statistical significance. Statistical insignificance in Germany might be explained by very low case numbers in our treatment groups. Our models show slightly higher coefficients for women than for men.

In the UK, we find substantial and statistically significant effects of family dissolution for men and women. Family dissolution decreases women's training participation probability by about 9 percentage points (pp.). Likewise, experiencing a family dissolution event decreases the job-related training participation probability of men by 8 percentage points. Previous studies find that in the UK, women's employment decreases following divorce (Jenkins 2008; Van Damme et al. 2009), which is in line with our findings. In contrast to Germany, divorce leads to a decrease in both women's and men's training participation in the UK. We assume that different public policies in Germany and the UK, such as public childcare provision, might explain the decline in training participation following divorce in the UK. Until 2015, parents could access 15 hours of free public childcare per week in the UK (UK Department of Education, 2015). The presence of a partner could be a resource for job-related training because partnered individuals can share housework or childcare to facilitate job-related further training. After losing a partner's care support, it might be difficult for workers to participate in job training with only part-time public childcare support.

5. Concluding discussion

In this chapter, we addressed the question of whether family dissolution impacts men's and women's training participation differently and whether different work-family policies in Germany and the UK contribute to the effects of family dissolution on job-related training participation. By applying two-way fixed-effects models with step impact functions, we paid particular attention to the effect of family dissolution on further training participation.

Previous findings suggest that the presence of a partner can be a resource for job training participation because partnered individuals can share housework or childcare responsibilities, allowing them to invest their time in job-related further training. In this case, employees are more likely to participate in further training than employees without a partner (Lebert and Antal 2016).

Our findings show that both men's and women's participation in further training appear to change following family dissolution in Germany, although the effects did not reach statistical significance. In the UK, by contrast, we found negative and statistically significant effects of family dissolution on training participation for



both women and men. Training participation behavior in the UK seems to be negatively affected by family dissolution events to a considerable extent.

There are some limitations to this study. First, we needed to deal with the problem of having very few transitions into family dissolution in both our data sets. While our approach might have benefits regarding internal validity, external validity might be more problematic due to few transitions. Also, we are not able to investigate the time path of the family dissolution effect due to the very small case numbers. Second, both the NEPS and UKHLS data sets do not provide information on housework or childcare hours, and therefore we were unable to measure the direct impact of housework or childcare hours on further training participation. As time-use studies suggest, unpaid work hours may indicate a gendered division of household labor, even when both spouses are employed. If there is a couple with more egalitarian division of unpaid working hours, particularly in dual-earner households, family dissolution might have a more significant impact on further training participation. Third, we do not have a measure for public childcare availability. If employees mainly rely on formal childcare for young children, family dissolution has less impact on further training participation.

Despite these limitations, our results contribute to a better understanding of how family-related factors affect employee's job training participation. Although studies have examined the effect of marriage on job-related training participation (Green 1993; Harris 1999; Lebert and Antal 2016), little attention has been paid to changes in workers' job training participation after family dissolution. We find that losing the benefit of having a partner might decrease an individual's job-related training participation in the UK, while we find substantial but not statistically significant results in the German context.

From a policy perspective, our findings show the importance of offering childcare for further training participation. In the UK, we find that both men's and women's further training participation declines after family dissolution. Institutional support for childcare should be provided for employees with children, especially for single parents. Employers should be committed to helping their employees balance work and family responsibilities. This commitment includes all aspects surrounding childcare and caregiving. Policymakers need to adopt work-family policies that address the needs of all families, while also supporting employees' positions as workers and/or caregivers.



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Chapter 8: Differences in formal adult education participation due to gendered influence of family life

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ABSTRACT

Formal adult education is often associated with updating and upgrading of skills and knowledge, the reflection of needs of the labour market, and a provision of the welfare state. Additionally, it is a platform where individual motivation for better labour market returns and limitations of one's life situation meet. Hence, this paper examines how family life and labour market factors impact participation in formal adult education, and whether this varies by gender. With Finnish register data and panel data from the UK, we study the influence of family life factors in formal adult education enrolment among the 1965-1985 birth cohorts. The results of the fixed effect regression models reveal that mothers are more constrained than fathers to enrol in formal adult education. However, the results vary between the two countries; mothers with small children, or single mothers, in the UK have much lower likelihood to enrol than others, whereas in the Finnish adult education these are not strong restraining factors. Overall, the study shows variation in who takes up formal adult education depending on the family and labour market situation, stressing the institutional support from the welfare state in promoting opportunities for those otherwise restricted by their situations.

INTRODUCTION

During the individual adult life course, there are three main factors that have been extensively studied in sociological literature: education, labour market attainment and family life. Existing evidence on the two-dimensional associations of these factors is inadequate in responding to the complex connections of education-work-family. Specifically, there is one aspect which all three factors influence both directly and through their connections – adult education (AE). Formal adult education can be seen as the attainment of skills and knowledge, a reflection on the needs of the labour market, and (often) a public policy provided by the welfare state. All of these are influenced by technological changes which alter tasks, jobs and occupations, creating needs for new and updated skills among the labour force and putting pressure on the welfare state to provide means to adapt to this changing labour market. From a life course perspective, formal education is an outcome of individual motivation derived from different labour market situations and life events such as unstable careers or family formation. Therefore, this paper takes a multidimensional approach and examines how family life and labour market factors impact participation in formal adult education.



Globalisation and technological changes have increased the need for skilled labour, putting more pressure to match jobs with skills, but also to maintain and update skills and knowledge as the changes in jobs and tasks require continuous learning. This can be partially achieved via non-formal or job-related training, but life-long learning has been increasingly adopted across western societies within the formal educational framework as well (OECD 2021). While non-formal adult education provides opportunities for short and skill-focused training, formal adult education equips the individual with further formal educational qualifications. Thus, the formal AE programmes require more resources from the participant (time out-of-work, adequate finances during studies etc.), but it also provides higher labour market returns (Stenberg 2010; McMullin & Kilpi-Jakonen 2014; Triventi & Barone 2014). Non-formal adult training is also often provided by the employer and is obtained by those with good labour market standing and high educational attainment, often promoting cumulative advantage (Bukodi 2017) and requiring employment to begin with, while formal education is often motivated by personal needs and interests. As a result, individuals with unstable labour market attainment, unemployment, poverty and other types of resource inadequacy, such as those created by family formation, may have a higher need for skill improvement and qualifications via formal adult education to improve their situations. Hence, the focus of this paper is on the individual factors influencing participation in formal adult education.

While adult education decisions are derived from individual motivation and needs, the degree to which various aspects of life, i.e. educational attainment, labour market activity and family responsibilities are structured differently between genders creates both different needs and opportunities for men and women for adult education. One of the biggest gender equality achievements within the past decades is increased female employment and independence, which has led to an advantage for women in higher education attainment. Both men and women often consider the completion of education a necessity before family formation (Settersten & Mayer 1997), although distance learning environments may alter this requirement (Andersson 2019). However, educational attainment is still largely stratified by social origin and segregated by gender as women and men attend gender-typical fields (Barone 2011; Charles & Bradley 2002). This has been proven to result in gendered occupations and unequal labour market attainment (Gundert & Mayer 2012; Smyth & Steinmetz 2008). Further, as mothers devote more time for family responsibilities and childcare than fathers, and are more likely to take up part-time work, this puts more time constraints on employed mothers (Evertsson & Neramo 2004). All these gendered factors can be assumed to form varying pathways for men and women, and different needs to re-enrol in formal education throughout their careers. Hence, this paper studies the gender differences in the association between family life and participation in formal adult education.

As formal adult education is provided by public (educational) institutions, welfare state regulations and provisions are vital in creating the opportunities for participation. One goal of adult education is to promote



the labour market attainment and employment of low-skilled or otherwise marginalised populations (Stenberg 2011a; Vono de Vilhena et al 2016). Financial support for further education can be seen to alleviate the obstacles of attending formal adult education, and diminishing the dependence of the current individual economic situation. However, often family commitments are one of the main barriers for adult education participation (Massing & Gauly 2017; Pont 2004), and thus the interplay between labour market regulations and family policies are also vital. In the European context, participation in formal adult education is among the highest in the Nordic countries (Eurostat 2020), where financial support for AE participation and families is provided but labour market regulations are also high, which may limit job turnover. However, in the United Kingdom participation rates are at similar levels to Northern Europe although less support is provided for participation and the labour market has higher job turnover. Hence, this paper analyses two countries, Finland and the United Kingdom, both with high participation rates in formal adult education but with very different institutions.

This paper benefits from two longitudinal datasets; Finnish register data for Finland, and the British Household Panel Survey (BHPS) for the United Kingdom. To study the impact of various individual factors, i.e. gender, family life and resources, in formal adult education enrolment, we apply linear panel regression modelling with fixed effects over the individual life course after obtaining their initial educational attainment. The paper contributes to the literature in three ways. First, we examine the differences between two contexts, Finland and the UK, that consist of different educational systems (both initial and adult education), labour market regulations, family policies and gendered norms, but on the macro-level have similar outcomes in formal adult education participation levels. Second, we combine multiple individual factors in analysing inequalities in the labour market, focusing on the impact of family life and gender differences in formal adult education within the framework of technology-driven labour markets. Third, we provide evidence on how gendered roles within the household influence the decision to enrol in formal adult education differently for men and women. The results demonstrate clear differences between how the Finnish welfare state supports disadvantaged and marginalised populations towards adult education while in the UK the possibilities to participate in formal adult education are mainly provided for those with already high resources and human capital.

FURTHER SKILLS WITH ADULT EDUCATION

Formal adult education can operate as a way to update, upgrade or replace one's initial educational qualifications and credentials. Many factors in the early career can determine the needs and motivations for further education at later stages of individual careers. People's labour market positioning and particularly unstable or unsatisfying careers and jobs may raise a need and motivation for further skills, either by horizontal or vertical movements within the labour market with new qualifications obtained through adult education.



Wolbers (2003) found that those who have a poor match between their education and job are more likely to participate in further vocational training than those with matching jobs. This is also supported by Hällsten (2011), whose findings demonstrate that those whose labour market situations were disadvantaged to a moderate extent (in terms of earnings) and experienced some unemployment were most likely to participate in tertiary education at later life.

One institutional factor creating instability and a need for new skills in the job market is technological change. Particularly, mid-level occupations are thought to be seeing a transformation, but automation, robotisation and other technological innovations and advanced techniques are altering tasks and jobs throughout the occupational strata (Goos et al 2009). Although technological changes may increase the need for non-formal forms of adult education to update technical skills for new tasks, it can also increase the need to enrol in formal adult education to obtain new qualifications and re-educate into different occupations. The mid-level labour force could be assumed to be the most prone to attend adult education as they have lower financial thresholds than those with lower wages, but they are also able to upgrade their educational qualifications more than those with advanced degrees.

A substantial part of adult education literature looks at the individual returns to adult education. Adult education is thought to increase individual productivity and thus have a positive influence in a person's labour market attainment and career progress (Triventi and Barone 2014; Kilpi-Jakonen et al 2015). In relation to formal adult education, previous literature has concluded that formal education has a positive influence on employment outcomes, such as earnings (Stenberg 2010; Triventi & Barone 2014), prestige (McMullin & Kilpi-Jakonen 2014), and being in non-precarious employment (Vono de Vilhena et al 2016). In cases where individuals with low-skilled jobs, low educational attainment or unemployment attended formal adult education, positive returns have been found for individual earnings (Stenberg 2010).

From a broader perspective, adult education is often seen as a public policy through which the marginalised and low-skilled labour force can obtain higher labour market attainment and further promote their life situations (European Commission 2007; Stenberg 2011a). The participation of marginalised individuals in formal adult education is considered beneficial for both the individual and society. Stenberg and Westerlund (2008) found that when individuals with long-term unemployment enrol in upper secondary level adult education, their earnings increase even with a short enrolment. Further, Knipprath and De Rick (2014) found that a lack of human capital encourages participation in adult education, more commonly in formal education for women and in work-related training for men. People from disadvantaged backgrounds with high cognitive ability often obtain further educational qualifications. However, instead of acquiring further academic qualifications (which would provide better chances for upward mobility) they often pursue further vocational qualifications (Heiskala et al 2021).



There is criticism of whether adult education as a labour market booster for marginalised and disadvantaged people is an efficient policy goal (Stenberg 2011b). Some studies argue that adult education maintains labour market inequalities through cumulative advantage promoting better outcomes for those who are already from advantaged backgrounds (Bukodi 2017). This would also be in line with the argument of relative risk aversion, where people with high parental education are very likely to obtain higher educational attainment themselves (Breen & Goldthorpe 1997; Holm & Jæger 2008), and for some individuals this can take place through adult education if it has not been achieved through their initial education. For example, Virdia & Schindler (2019) found that even though individuals from disadvantaged backgrounds have a higher risk for adult education, those from advantaged social backgrounds are more likely to enrol, and they obtain higher premiums from adult education. Overall, Kilpi-Jakonen et al (2015) conclude in their comparative paper that as no country is able to promote clear equalising impacts via adult education policies, more emphasis should be put on improving the equality in participation in adult education in the first place.

GENDERED FAMILY LIFE, WORK AND FURTHER EDUCATION

While initial educational attainment is significant in determining a person's labour market position, it also shapes the gender differences in the labour market through female advantage in higher education, school-to-work transitions and gendered occupations. In most societies women are attaining tertiary education degrees in equal numbers, and in some countries, such as Finland, the educational attainment of women has overtaken that of men (Barro & Lee 2013; Pekkarinen 2012). However, there are significant gender inequalities within education, particularly in relation to the quality differences of the educational institution attended and in fields of study (Barone 2011; Charles & Bradley 2002). Gender differences in occupational attainment together with unequal pay and other gender inequality issues, such as women experiencing more unstable early careers with weak employment protection (Struffolino 2019), may result in gendered motivation and need for further skills through formal adult education.

Career opportunities, or lack of them, can motivate people to obtain further educational qualifications. Overall, occupational mobility and career progress is usually most prominent during the first few decades of an individual's career (Härkönen & Bihagen 2011), but the entry job influences career progress to a large degree, particularly if the career start is not successful, with women suffering more from such situations (Bukodi & Dex 2010). While career progression is connected with re-enrolment in formal education, it is skewed to those in advantaged positions (Virdia & Schindler 2019). With global educational expansion, and particularly the increase in higher education attainment among women, career patterns between men and women have become more alike and women are achieving higher prestige (Bukodi & Dex 2010; Härkönen et al 2016). However, women are less likely to recognise their career aspirations, and are thus more affected by the gendered educational (vocational) system (Aisenbrey & Brückner 2008). This, in turn, could reflect a higher



probability to enrol in adult education if women's occupational aspirations become clearer at a later stage of their career.

Female disadvantages in the labour market may act as boosters for women to attend adult education, to keep up with job and income competition with men. Aisenbrey & Brückner (2008) found that women's returns to human capital, even if obtained at similar or higher levels than men, are lower in regard to wages. High gender segregation in education contributes to gendered occupational destinations (Gundert & Mayer 2012), although gender differences in occupations are only partially explained by the positive changes in female educational attainment (Härkönen et al 2016). Some studies on the returns to adult education have shown that women benefit more from attending formal adult education as the upgraded educational attainment results in better employment opportunities (Kilpi-Jakonen et al (2015) but the earning returns are somewhat similar between men and women (Stenberg 2010). Although career processes and labour market activity has also obtained evidence in relation to gender differences (Van Winkle & Fasang 2017), adult education is still left out of the picture.

Together with labour market activity and attainment, family formation processes and family life influence the possibilities and motivation of adult education. Although research often focuses on either of these two, there are some advancements that provide evidence on the gendered multidimensional processes of life courses (Aisenbrey & Fasang 2017). One mechanism of how family life influences adult education is that family formation and childbearing introduces tasks and duties and thus require more time resources. Family responsibilities were found to be one of the biggest obstacles for adult education participation (Pont 2004). As women still use more time for childcare and household tasks, this obstacle is bigger for women than men (Massing & Gauly 2017). In addition to women bearing the childbearing time-use, women are also more likely to alter their labour market position, to take up part-time work and devote more time for family responsibilities and childcare (Evertsson & Neramo 2004). This is in line with the results by Massing & Gauly (2017) that in all other countries of their study, except the UK (although this outlier was not statistically significant) women with children aged under 13 were less likely to participate in any kind of training.

Another resource constraint imposed by family formation is increased financial costs and thus pressure on the monetary resources of the family. If an individual is unable to obtain more resources through changing their job, adult education could be seen as a valid option. Attaining either a higher educational degree or re-education at a similar level to initial education but in a different field (that has higher returns or more stable employment prospects) could provide better labour market attainment for the parent. This mechanism for adult education participation may not be strongly gendered as improvement in the labour market returns of either parent would improve the family's livelihood. However, with the persistent motherhood penalty and fatherhood advantage in career progression and labour market position (Aisenbrey et al 2009; Aisenbrey &

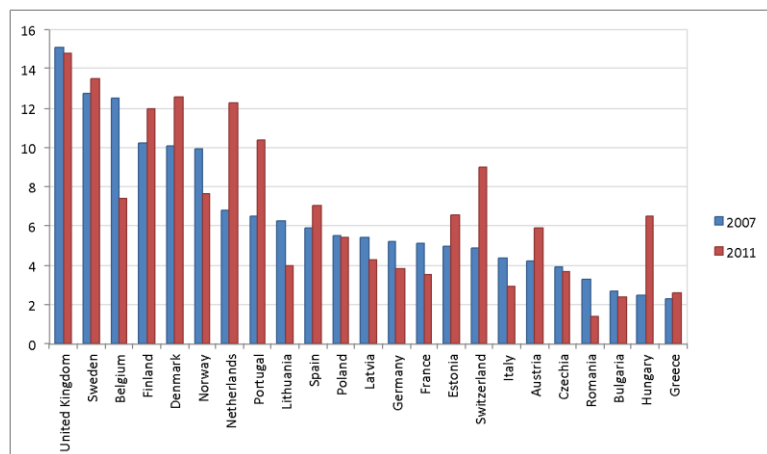


Fasang 2017; Härkönen et al 2016), mothers might be more prone to enrol in adult education in pursuing higher labour market returns, to avoid risking the male-breadwinner provision of the household.

INSTITUTIONAL APPROACH TO ADULT EDUCATION

The institutional contexts regarding adult education in the two countries studied, Finland and the United Kingdom, are diverse but also share some similarities. First, individuals can attend any educational level in formal adult education, ranging from compulsory school certificates to professional degrees and apprenticeship to academic qualifications. The format of studying and learning can also be more versatile for adult education students than traditional degree students, with more online courses, self-learning or even part-time studies to accommodate the myriad of family and work needs of adult participants. Second, in both countries, the participation rate in formal adult education is among the highest in Europe (see Figure 1); the UK had the highest rate in both 2007 and 2011, while Finland remained in the top 5 countries for both years. However, the main differences are in how these two countries provide support and opportunities for individuals to participate, and how individual constraints for adult education might be alleviated or maintained by the existing educational, labour market and family policy institutions.

Figure 1: Participation rate in formal adult education in EU countries, years 2007 and 2011 (Eurostat 2020)



In the Finnish formal adult education context, many individuals are eligible for financial support for adult education. Adult education benefit is attached to previous income level and thus requires (somewhat lengthy) employment experience and studying full time. If individuals are not eligible for this, they may receive normal student benefits if they do not hold that level of qualifications yet. Also, employers are required to permit study leaves for full-time studies if the employee requests it and the employee has been employed for at least a year. In addition, formal adult education programmes do not have high fees or costs, as formal

education is tuition-free in Finland. All this provides support for participation and alleviates both the financial and time constraints of the individuals to participate in formal adult education. In the United Kingdom, on the other hand, participating in formal adult education often has tuition and fees, and in some programmes relatively high ones. However, individuals can apply for grants or financial support, although public student finance is complemented with grants from various organisations, and both have varying eligibility criteria making the system complex and difficult to steer in.

The degree of support for adult education participants also reflects on who is able to participate in the adult education system, putting pressure on the individual resources. For example, Kilpi-Jakonen et al (2015) found that in Finland the mid-level educated are most likely to participate in formal adult education, whereas in the UK selectivity skewed towards those with already high educational attainment. Further, this indicates the importance of labour market regulations and employment protection shaping AE participation opportunities. Both job turnover and the annual rate for occupational changes are much higher in the UK than in Finland (Bachmann et al 2020), indicating the strong occupational regulations and employer protection with strong labour unions in Finland, while these affect the UK labour market to a lesser extent.

Female participation in education and employment, and the provision of childcare, explains how much gender-typical educational attainment leads to gender-typical labour market position (Smyth & Steinmetz 2008). Due to the interconnected nature of all these factors and institutions, they can be assumed to also influence the gender differences in formal AE participation. In Finland, expansion in female educational attainment has been very rapid but both educational and occupational gender segregation are the highest in Europe (Smyth and Steinmetz 2008). In the UK, only occupational gender segregation is at a higher level (but still around the EU-average), while educational or income differences between men and women are lesser (Smyth and Steinmetz 2008). These differences can create different processes of motivation for formal adult education between men and women if the labour market standing is at a desired level.

In addition to educational and labour market institutions, family policies can be expected to influence participation in adult education, and particularly the gender differences in participation. In Finland, every child is eligible for child benefit until the age of 17 and families have various support services available for financial, health, wellbeing or time needs of the family. Further, a parent may stay at home, full or part-time, until the child is three years old with financial assistance. This policy makes the Finnish system more conservative than the other Nordic countries as mainly women, particularly low-skilled mothers with unstable employment histories, stay at home for longer periods after childbirth (Karhula et al 2017; Närvi 2014). These extended periods outside the labour market weaken the opportunities for returning into the labour market and lowers the labour market attainment of mothers (Napari 2010). As returning to work after extensive periods at home may be problematic, there is an increased need for updating or upgrading skills and knowledge, which could



motivate adult education participation. In the United Kingdom the support for families is heavily based on the tax system, relying on employment and earnings of the family, although some family policies are targeted to alleviate poverty and other social problems (Daly 2010). Some parents are eligible to apply for childcare support (if in hardship or attending higher education full time) when participating in formal adult education resulting in a qualification.

In light of all these differences in educational, labour market and family policy institutions between Finland and the United Kingdom, we assume that family life constraints in participating in formal adult education are more gendered in the UK than in Finland. Further, financial constraints prevent participation in the UK due to high cost of attendance and lack of support for families, whereas in Finland low resources are compensated with public policies and thus they enable formal adult education participation.

DATA AND METHODS

This study benefits from two longitudinal datasets Finnish register data and the British Household Panel Survey (BHPS), including the birth cohorts 1965-1985. The Finnish registers cover the total Finnish population since 1987, and provide detailed information on individual, household and intergenerational factors. Because the polytechnics (universities of applied sciences) were established in 1996 and the adult education system experienced a comprehensive reform in 1997 in Finland, the observation period starts from 1998 and continues until 2017. The BHPS is an annual survey from 1991 to 2009 of which (due to data limitations) we use the waves commencing from 1998 onwards. We are also in the process of getting data from Understanding Society, which continues from BHPS as a bi-annual survey, and would then match the observation years of the Finnish registers. Currently the shorter observation period (until 2009) leaves some possible later life events of individuals uncovered, particularly among the younger cohorts.

In order to observe enrolment in formal AE, the observation period begins when the individual is not in (initial) education. Age-appropriate educational enrolment is considered as the initial educational attainment of a person, the measure allowing a few years of flexibility in obtaining a degree, thus also counting possible gap years. The samples are limited to those whose first out-of-education year is on or after 1998 (left censoring). Overall, this results in a sample of 630 000 individuals and over 10 million person-years in Finland, and almost 4 000 individuals and over 23 000 person-years in the United Kingdom.

The outcome variable is enrolling in formal adult education. For Finland, the variable has been calculated from graduation and registration years of formal educational qualifications. Since registration year is available only for the highest degree obtained (not the most recent), in these cases the expected/average time of completing the degree in question was calculated to observe the most likely starting (enrolment) year. In the



United Kingdom, the survey includes information on enrolment and in what type of education the person enrolls, which has been used to determine enrolment in formal adult education programmes (leaving out work-place training, non-formal education etc) that has taken place after initial educational attainment. The outcome variable has been measured in time $t+1$ to observe the independent variables at the time of the application/enrolment decision rather than the actual enrolment (which would then affect labour market status, income of the year of enrolment etc).

The main independent variables consider the family situation of the individual, particularly measuring the factors related to children in the household. We use the number of children (under age 16) and the age of the youngest child (0=no children, 1=0-3 years old, 2=4-16 years old) in the household to derive the possible impacts of time and financial constraints on adult education. Because the constraints from family life and responsibilities most likely differ according to other resources available, we include interaction effects between the family life factors and both income (individual monthly income in Finland, household income in the UK) and relationship status (married, cohabiting, single) in the models. The results of these interactions are presented as graphs of predictive margins (full results by request from the authors). Unfortunately there are no comparable measures in the two datasets in regards to workplace or working hours and thus income is the best available measure for labour market attainment. Further, the data does not provide time use information which could be used to test time constraints. As we expect the family life constraints to be different for men and women, the sample in all of the models is split by gender.

Other family, labour market and demographic factors of interest that are expected to influence the adult education enrolment decision are controlled in the models: initial educational attainment (categories based on the national educational system, considering all different levels), labour market activity (employed, unemployed, outside the labour force), age (and age squared), and country (only for the UK sample). Detailed information and descriptive statistics on the main independent and control variables are provided in Appendix Table A1 for both countries.

The analytical approach relies on linear panel regression modelling (the hierarchy of same individuals across observed years) analysing how family life influences the probability to enrol in adult education, considering various labour market and demographic factors over individual life courses. However, many individual factors are not static but change over time within the individual life course, and a change in one may influence another: for instance, having a child will influence the financial resources available. Moreover, there might be some stable unobserved factors (i.e. religion or region) that could influence how family factors shape enrolment decisions in formal adult education and also more directly the possibilities of adult education enrolment. For these reasons, we apply individual fixed effects to counter the unobserved heterogeneity within the individual life course during the observation period. In other words, this approach fixes all time-



invariant factors (i.e region, religion), and thus provides more robust results on the time-varying factors affecting formal adult education enrolment. Fixed effects thus focus on the changes in the observed factors within the individual life course across the observation period, focusing on different life events and situations considering also the previous situations of the individual. Naturally, applying fixed effects does not delete all unobserved heterogeneity particularly on those factors that do change over time but we cannot observe (i.e. geographical location or housing situation).

RESULTS: GENDER DIFFERENCES IN ADULT EDUCATION

To get a picture of the overall gender differences in formal adult education participation, Figures 2 and 3 demonstrate the results from a simple logistic regression with clustered SEs by individuals (no control variables in these models). Figure 2 shows the gender differences in formal AE over an individual's age. In both countries the trend seems to be a decreasing one for both men and women; older people are less likely to attend formal AE than younger ones. However, the gender differences seem to diminish at later ages to a greater extent in Finland than in the UK. Previous studies have found that women participate in adult education more, and this is also the result we find for both countries.

Figure 3 shows the gender differences in formal AE by initial educational attainment level (crude categories used to represent the level of attainment rather than each separate qualification, i.e. no division for general and vocational secondary education). The figure presents a clear division of formal adult education participation depending on individuals' initial educational attainment in both countries. However, the results are opposite; in Finland individuals with higher educational attainment are less likely to attend formal AE while in the UK the probability increases with higher educational attainment. This can indicate at least two things. First, the formal adult education system in the UK provides more opportunities for participation among the highly educated, suggesting updating or adding skills among those who already have high human capital, while in Finland the system is used more by those with lower-level qualifications, suggesting that individuals upgrade their educational qualifications to improve labour market attainment rather than update or accumulate existing high qualifications. The gender differences seem to follow the opposite trends as they are highest among the basic educated in Finland and most clearly visible among the tertiary educated in the UK.



Figure 2: Participation in formal adult education by gender across different ages

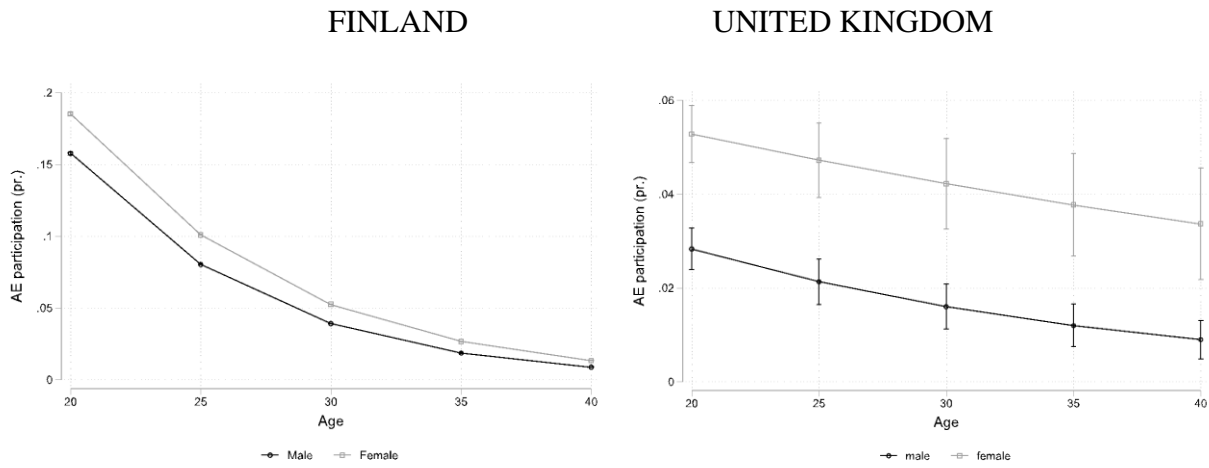
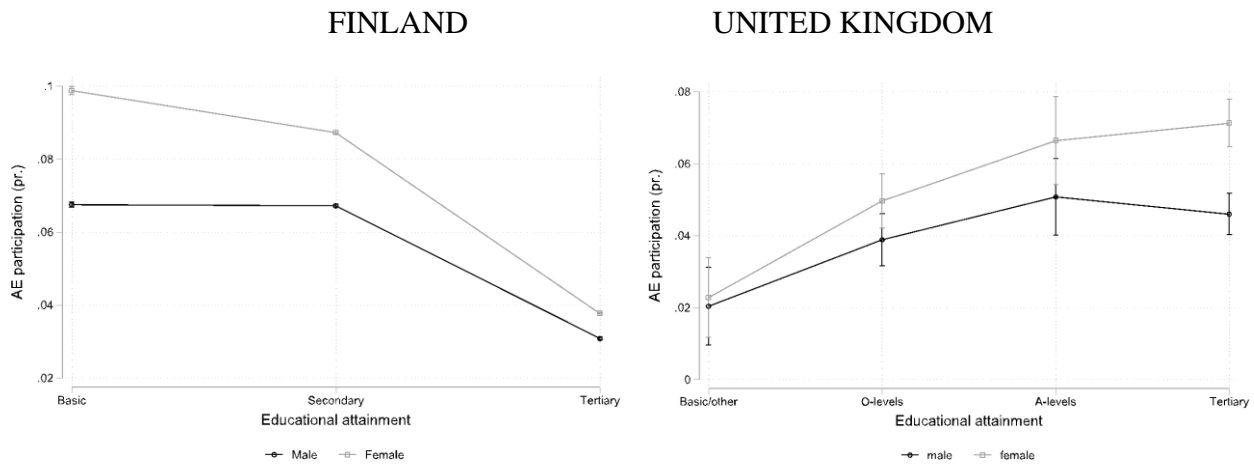


Figure 3: Gender differences in formal AE participation by initial educational attainment level



RESULTS: FAMILY LIFE AND FORMAL ADULT EDUCATION

To examine the relationship between family life and enrolment in formal adult education, we use multilevel linear regression models with fixed effects. Tables 1 (Finland) and 2 (the UK) report the results of the main variables of interest as average marginal effects (AMEs); Model 1 shows the impact of the number of children in the household on enrolment in formal AE, Model 2 the impact of the age of the youngest child in the household and Model 3 includes both of these main independent variables. All models control for marital status and income (reported) and other individual labour market and demographic factors (not reported in the tables).

The results for Finland (Table 1) show that family life does impact on the enrolment in formal adult education, and in similar directions for both men and women. The number of children is negatively associated with enrolment, i.e. the more children you have the less likely you are to enrol in formal AE. However, when looking at the age of the youngest child in the household, the comparison between the childless and those with children of any age seems to point towards having children increases enrolment prospects. These results are similar for men and women, although the impact among men seems to be lower.

The results for the United Kingdom (Table 2) on the other hand, draw a somewhat more varied picture of the impacts of family life on formal AE enrolment and on gender differences in them. First, the impacts of family life and children are the opposite of Finland; the number of children has a positive influence (when controlling for the age of the child) and having young children has a negative impact. One clear result in the UK is the negative effect of having small children in the household compared to childless households, and this is particularly visible among women. Considering the low statistical power of the UK sample, the fact that this result is statistically significant shows that it is a very important factor in AE participation, particularly affecting the mothers of young children. For fathers with older children, the impact on AE is positive, rather than negative as it is for women, indicating less restrictions from family life for men.

To further examine how family life influences enrollment in formal adult education, particularly considering the resources available for individuals and households, we added an interaction effect in the models. The results of these interactions are presented as graphs of predictive margins (full results by request from the authors). First, we tested if the effect of children varies by marital status, particularly being interested in single parents (Figures 4 for Finland and 5 for the UK). Second, we tested if there are income differences in the impact of having children on enrolling in formal adult education (Figures 6 Finland and 7 UK). The age of the child is used in the interactions to measure family situations to derive impacts of income also in households with no children.



Table 1: Impacts of family life factors on enrolment in formal adult education, results of panel regression models with fixed effects (AMEs, SEs in brackets), Finland

	Men				Women		
	Model 1	Model 2	Model 3		Model 1	Model 2	Model 3
Number of children in the hh	- 0.009*** (0.000)		- 0.009*** (0.000)		- 0.015*** (0.000)		- 0.016*** (0.000)
Age of the youngest child (ref: no children)							
0-3 years		0.000 (0.000)	0.001*** (0.000)			0.005*** (0.000)	0.006*** (0.000)
4-16 years		0.002*** (0.000)	0.003*** (0.000)			0.006*** (0.000)	0.007*** (0.000)
Marital status (ref: Single)							
Cohabiting	- 0.002*** (0.000)	- 0.001*** (0.000)	- 0.002*** (0.000)		- 0.006*** (0.000)	- 0.006*** (0.000)	- 0.006*** (0.000)
Married	- 0.002*** (0.000)	- 0.002*** (0.000)	- 0.003*** (0.000)		- 0.003*** (0.000)	- 0.005*** (0.000)	- 0.005*** (0.000)
Income (individual, logged)	- 0.001*** (0.000)	- 0.001*** (0.000)	- 0.001*** (0.000)		0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Constant	0.207*** (0.001)	0.202*** (0.001)	0.207*** (0.002)		0.184*** (0.002)	0.188*** (0.002)	0.197*** (0.002)
N (person-years)	5463350	5463350	5463350		5607106	5607106	5607106

Note: all models control also for income, employment status, educational attainment, age, and age square.

Table 2 Impacts of family life factors on enrolment in formal adult education, results of panel regression models with fixed effects (AMEs, SEs in brackets), the United Kingdom

	Men			Women		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Number of children in the hh	0.001 (0.004)		0.001 (0.006)	-0.004 (0.005)		0.006 (0.006)
Age of the youngest child (ref: no children)						
0-3 years		-0.001 (0.008)	-0.002 (0.010)		-0.027** (0.008)	-0.033*** (0.010)
4-16 years		0.013 (0.011)	0.012 (0.013)		-0.007 (0.010)	-0.012 (0.011)
Marital status (ref: Cohabiting)						
Married	0.000 (0.008)	-0.001 (0.008)	-0.001 (0.008)	-0.000 (0.009)	-0.005 (0.009)	-0.005 (0.009)
Single	0.004 (0.010)	0.003 (0.010)	0.003 (0.010)	0.012 (0.011)	0.008 (0.011)	0.009 (0.011)
Income (household, logged)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	-0.006 (0.004)	-0.007 (0.004)	-0.007 (0.004)
Constant	-0.106* (0.049)	-0.105* (0.049)	-0.104* (0.049)	-0.177** (0.057)	-0.167** (0.057)	-0.162** (0.057)
N (person-years)	11243	11243	11243	12129	12129	12129

Note: all models control also for income, employment status, educational attainment, country, age, and age square.

Figure 4: The interaction effect of marital status and age of the youngest child on AE enrolment (predictive margins of multilevel fixed-effects linear regression models), Finland

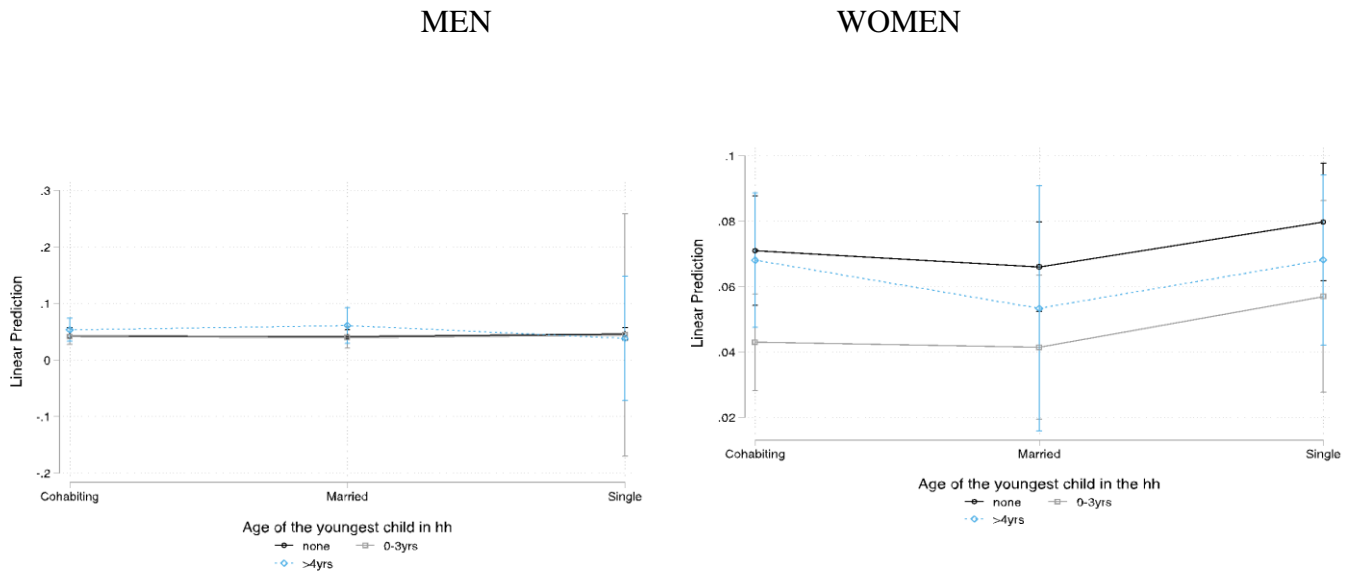


Figure 5: The interaction effect of marital status and age of the youngest child on AE enrolment (predictive margins of multilevel fixed-effects linear regression models), the United Kingdom

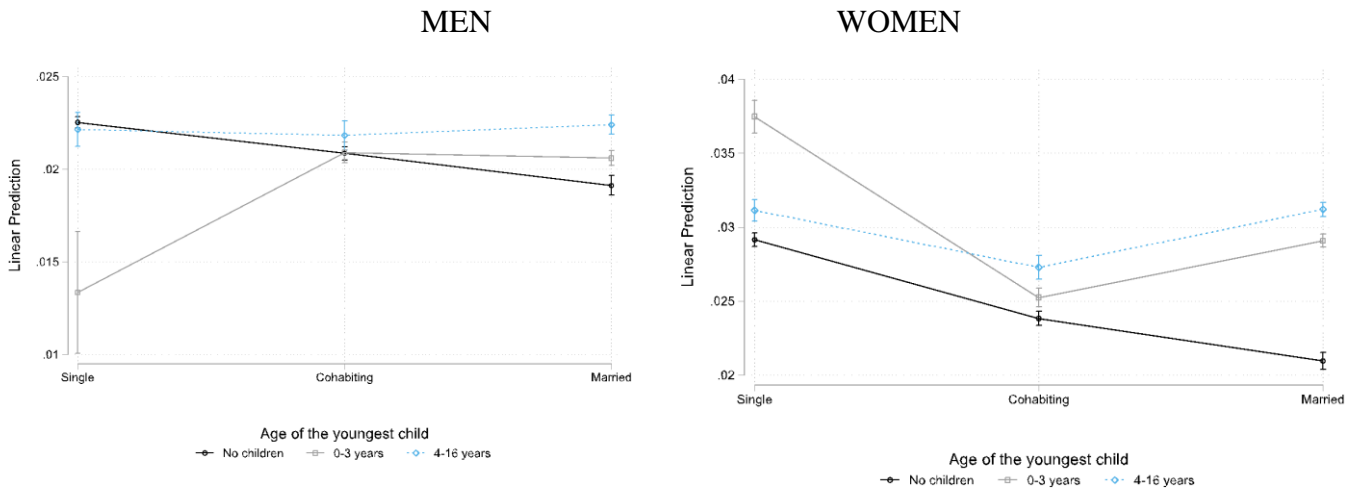


Figure 6 Income differences in the influence of having children (age and number) on enrolment in formal AE (predictive margins of multilevel fixed-effects linear regression models), Finland

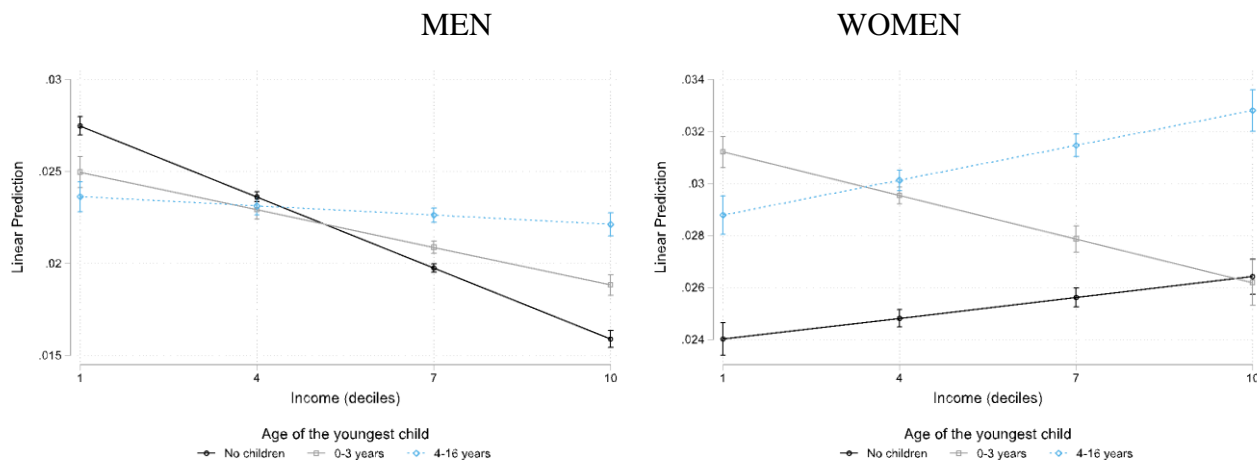
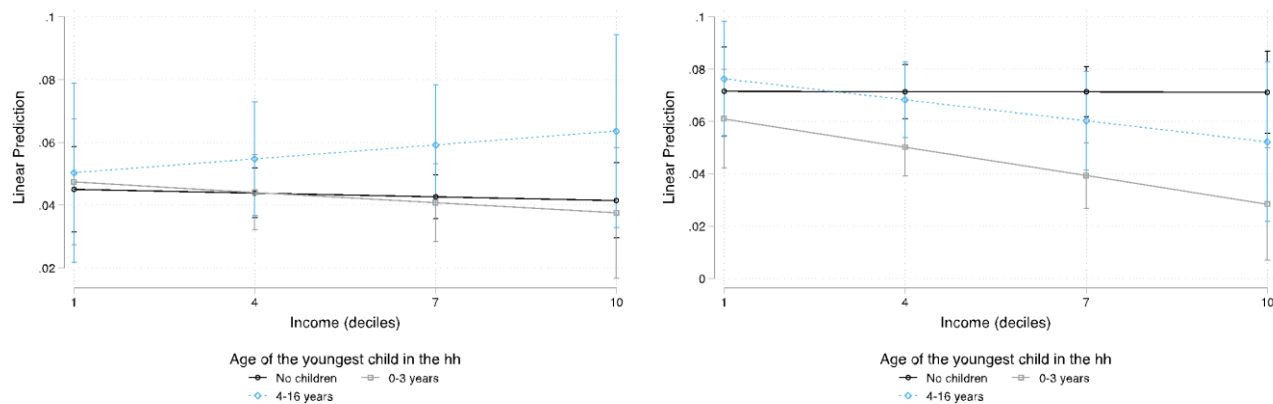


Figure 7: Income differences in the influence of having children (age and number) on enrolment in formal AE (predictive margins of multilevel fixed-effects linear regression models), the United Kingdom



Figures 4 and 5 demonstrate how the influence of children on AE enrolment varies by marital status, showing bigger differences among women than men, in both countries. In Finland, single fathers with young children (although they are very few), have a much lower chance to participate in formal AE, whereas among single mothers with young children the probability is higher than any other (single) women. Cohabiting men and women do not seem to differ in relation to the age of the child (if any) in AE enrolment, whereas among married individuals, childless couples have the lowest probability to enrol. For both married men and women,

the likelihood to enrol in formal AE is highest if the children are already school-aged. In the United Kingdom, there seem to be no differences by marital status among men, and among women the differences follow a similar pattern between the categories; Women with young children in the household are least likely to enrol in formal AE, regardless of marital status, and the highest likelihood if they are childless. These results may indicate that marital status not only represent the resources at hand (having a partner) but grasps the strong gender differences in UK society where the influence of family life (i.e. having children) is so divided between women and men (i.e. gendered roles and responsibilities within the family) that marital status is a less influential factor.

The income differences in the impact of family life on AE enrolment seem to vary between men and women in Finland (see Figure 6). Among men, the probability for AE decreases the higher their income is, the biggest income difference being among childless men and the smallest among those with older children. Among women on the other hand, the likelihood for formal AE increases towards the higher income levels if they have older children or none. Interestingly, if they have young children in the household, mothers with higher incomes are less likely to enrol (a similar trend to men). This is a contrasting result to other women with similar income levels. However, the levels of change between income deciles are very small (range within 0.01 among women and within 0.015 among men).

Income differences in the United Kingdom (Figure 7) show, again, almost opposite results to Finland. Among men with higher income levels the enrollment increases among fathers with older children, for others the impact does not differ by income level. This is opposite to Finland with a negative income association for all men. Among women, mothers (with children of any age) have a negative association with income and AE enrolment, similar to mothers with young children in Finland. Childless women in the UK seem to have no income differences in relation to formal AE enrolment. Although the volume of the income differences is higher in the UK than in Finland, surprisingly the income-family nexus seems to be an issue mainly among women, and particularly mothers in the UK.

DISCUSSION AND CONCLUSIONS

This paper studies how family life influences participation in formal adult education in Finland and the United Kingdom. The main components that often form the need and motivation for further educational qualifications arise from educational attainment, labour market (in)activity and family life. Particularly, we argue that these factors provide gendered motivations and opportunities for formal adult education due to resource constraints, i.e. financial and time resources, being weighed unequally between women and men in various family and labour market situations. Therefore, this paper studies how the relationship between family life and



resource constraints creates gender differences in formal adult education participation, and how these vary between different institutional contexts.

Overall, women have been gaining an advantage in obtaining higher levels of educational attainment, on average, which is also seen in the higher uptake of formal adult education across the individual life course. Despite the higher volume of women attaining formal adult education, the impact of family life is more depriving for women than men. Our results indicate there are significant gender differences in how family life and labour market attainment influence enrolment in formal adult education. While men are less affected by these factors, women seem to be more constrained in taking up further educational qualifications if they have children in the household. This is in line with Pont (2004) who found that mothers are less likely to take up on any training due to family responsibilities.

In the United Kingdom the picture of gender differences is a clearer one: there are no marital status or income differences found in relation to having children in the household among men. This, combined with the overall result of low impact of children in general, indicates that men are not deprived for AE enrolment due to family life factors in the UK. A high income level actually increases the likelihood of enrolment among fathers. This result is found also among Finnish men - higher income levels increasing and lower levels decreasing the enrolment chances for fathers. We also find marital status differences: fathers in a stable union (marriage or equivalent) are more likely to attend formal AE compared to childless married men. Overall, the results among men suggest that having children promotes AE for men, but they require stability in terms of partnership and labour market attainment to participate in formal adult education.

The positive impact of having children found among married and high-income men is also visible among Finnish women. However, this extends outside marriage and is found among women with any marital status. While single fathers with small children in Finland had lower likelihood for AE, for single mothers, surprisingly, the enrolment is higher. Additionally, women with small children and lower incomes are found to have a higher likelihood to enrol in formal AE. These results suggest that the deprived situations (finances, relationship) raise a higher need for formal adult education than the barriers induced by family responsibilities (Massing & Gaulty 2017; Pont 2004). However, mothers in these situations enrol in formal AE while the child is young, and in this context, eligible for universal childcare. The results in the UK, however, are almost the opposite. Mothers with all relationship statuses have a lower likelihood to enrol in AE, particularly if their children are small, compared to childless women. Furthermore, if mothers with small children have higher income levels, the likelihood is even lower. This is a somewhat positive result, as among those who have low income, having children does not deprive their chances any more than low-income childless women.



Outside of men and women having different constraints from family life, men being deprived to a lesser extent than women, the results between Finland and the United Kingdom require further elaboration. While enrolment in formal adult education in the UK is less affected by family life or labour market position among men, mothers, particularly those with young children, bear the burden of family responsibilities preventing formal AE enrolment. In Finland on the other hand, both men and women with children have a higher likelihood to enrol, but among women even more so if they have low resources such as single parenthood or low income. However, these results cannot directly entail whether the constraints on participation in formal AE arise from time or financial resource constraints, or from something else related to family life and responsibilities. Hence, further research should focus on examining these in more detail, using survey data on time use, financial spending and feelings of financial inadequacy, and how these are related to different family situations and further in labour market trajectories and career paths in/discluding adult education.

From an institutional aspect, the Finnish adult education system provides opportunities that do not have high financial or timely constraints, and may promote the livelihoods of individuals from more disadvantaged situations. The labour market protections and universal family policies may support this, providing more equal chances for mothers and fathers to enrol in formal adult education programmes. In the UK, formal AE requires high financial and time resources, and thus enrolment opportunities for those with lower attainment of these resources are limited. The gendered roles of mothers, spending more resources on family responsibilities, are more clear in the UK as mothers are in weaker positions to enrol in formal adult education.

Considering that those with higher initial education are more likely to enrol in formal AE, and that opportunities are gendered due to unequal distribution of family responsibilities, the policies do not promote better livelihoods through adult education in the United Kingdom. Weak labour market protection may boost this as individuals are not able to take up formal (full-time) education due to fear of losing labour market standing. This, added to the lack of family support, means the influence of having children reduces the chances even further. This all suggests that there is a Matthew effect in the UK (Bukodi 2017); the middle classes or those with already high resources benefit from formal adult education by being able to update and upgrade their skills and qualifications in the capitalist labour market that is changing due to technological innovations. To be able to provide opportunities for those in unstable or risky situations, not the least imposed by technology, labour market protection should be stronger in relation to enrolling in AE, family support should compensate for the increased costs of having children and the adult education system should provide opportunities despite income level or educational attainment. These policy recommendations would reduce the negative impact of individual resource constraints and provide more equal opportunities in terms of gender



and family situations, but also in terms of being able to benefit from the formal adult education system at times of insecurity and instability in the technology-driven labour markets where automation and robotization has imposed the need for new skills and tasks or increased the risk of job loss. Thus, the formal adult education system operates as a vital institution in providing ways for individuals and families to keep up with the labour market requirements and maintain their economic standing, but also in sustaining skilled workers for changing labour markets.

In light of our results and previous studies, research should focus on the way adult education systems work in various country contexts. This paper finds two possible types of systems of formal adult education; the results for Finland suggest a system that promotes opportunities for individuals in vulnerable life situations and adult education is used as an intervention, whereas the results for UK suggest that formal adult education system emphasises the updating of skills for those with high human capital, financial resources and with well-off situations. Thus further research should look in-detail on whether there are other types of formal AE systems, and if the aims of these systems are actually met in relation to who is enrolled or whether the system fails in its aims.



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Table A1. Descriptive statistics of the variables

Variable	Finland	The United Kingdom
Enrol in formal adult education	0.02 (0.2)	0.05 (0.2)
Age of the youngest child in the hh		
No children	52.6	57.5
Age 0-3 years	24.4	26.5
Age 4-16 years	23.0	16.0
Number of children in the hh		0.81 (1.0)
Marital status		
Single	34.3	32.2
Cohabiting	26.1	40.2
Married	39.6	27.6
Main activity		
Employed	83.3	84.2
Unemployed	7.2	4.1
Outside the labour force	9.5	11.7
Educational level FIN/UK		
Basic / None	11.7	5.3
General Sec. / A-levels	29.7	16.1
Vocational Sec. / O-levels	13.6	19.4
Opisto / Other secondary	3.6	7.3
Bachelor (poly) / other higher qf	18.9	31.5
Bachelor University / higher degree	1.6	2.5
Master (poly) / teaching qf	0.1	0.9
Academic tertiary / First degree	19.1	16.4
Doctorate / Other	1.7	0.7
Age	32.8 (7.2)	13.7 (5.5) (from 16)
Country (UK only)		
England		86.3
Wales		5.2
Scotland		8.5
Sample		
Female	51	51.9
Birth cohort	1965-1985	1966-1984
Nr of persons	631 628	3 938
N (person-years)	11 070 456	23 372

Note: The means (percentages) of variables refer to person-years. Statistics for continuous variables show also standard deviation in brackets



