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Does training beget training over the life course? Cumulative advantage in work-related non-formal training participation in Germany and the UK

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Does training beget training over the life course?

Cumulative advantage in work-related non-formal training participation in Germany and the UK.

Abstract: Continuous training participation over the career becomes ever more important. However, most existing research mainly analysed training at single points in time. This paper investigates training dynamics and hence asks the question whether training begets training. We provide two contributions to the literature: First we analyse if previous training participation has an effect on later participation, leading to strict cumulative advantages. Second, by comparing Germany and the UK, we aim to explore whether these processes differ between countries with divergent skill formation systems. Using dynamic random effects probit models, which control for time-constant unobserved factors, and panel data (NEPS and UKHLS) we find that the accumulation of training experiences is mainly determined by initial education as well as job and firm characteristics. Still, previous participation plays a secondary yet noteworthy role, signifying dynamic growth in both countries, with higher effects for the UK. Thus, we show that only considering worker, job, and firm characteristics when analysing inequality in training participation neglects a significant further mechanism that is rooted in previous training participation. We come to three main conclusions: (1.) There is a potential amplification of early inequalities over time. Individuals who are initially on career paths that promote regular training participation are likely to keep and even enhance their advantage over time. (2.) On the other hand, our results also suggest the potential for individuals to break free from non-participation patterns. (3.) The inequality generating pathways can be influenced by institutions.

1. Introduction

Rapid technological innovation requires constant adaptation to workplace and occupational skill requirements. Many policy analysts and scholars expect that initial 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). Moreover, the pace of current technological developments suggests that workers need to continuously engage in training over their careers to stay up-to-date. Failure to engage in regular skill adaptation can result in skill obsolescence and labour market marginalization (e.g. de Grip, 2006). Accordingly, various studies show that training participation is associated with employment stability in many countries (Ebner and Ehlert, 2018; McMullin and Kilpi-Jakonen, 2014; Parent, 1999). Therefore, regular training participation is a crucial resource for workers. At the same time, training participation is highly unequally distributed, and especially those most in need of retraining, such as less-educated and older workers, are least likely to participate (Cedefop, 2015).

Despite the large existing literature on further training participation, we know little about the dynamics of training participation over workers' careers. Many studies found that participation in further training over the life course is higher among those who already have high educational attainment (Kramer and Tamm, 2018; Wolbers, 2005; Kilpi-Jakonen *et al.*, 2015). This is often interpreted as a "Matthew effect" (Blossfeld *et al.*, 2020; Merton, 1968), one form of manifestation of cumulative advantage (DiPrete and Eirich, 2006). However, considering training dynamics more closely reveals that the accumulation of training participation experiences can be due to a "two-fold path-dependency" (Offerhaus, 2014: 81). The first path is the standard explanation for observed inequalities in training participation of workers and goes through educational attainment and subsequent positioning in the labour market (Hornberg *et al.*, 2023). There is broad consensus regarding the influence of previous educational attainment (e.g. Kramer and Tamm, 2018), and corresponding workplace characteristics and task profiles on training participation probability (e.g. Görlitz and Tamm, 2016; Schindler, Weiss, and Hubert, 2011). Thus, the first explanation for differences in training dynamics is that some workers are channelled into jobs with higher continuous training demands and opportunities. In the following, we will refer to this path as the *labour market allocation path*.

The second pathway generating training dynamics runs through prior participation in further training. In this case, training may be caused by the individual's training history itself (Offerhaus, 2014). This pathway can be described as *strict cumulative advantage* (DiPrete and Eirich, 2006): Strict cumulative advantage refers to a phenomenon where individuals or groups accumulate increasing advantages or benefits over time. It is characterised by dynamic growth, where the existing advantages determine the accumulation of further advantages. In strict cumulative advantage, initial differences between individuals or groups are amplified and continue to widen as time progresses.

The two paths may create different patterns of inequality between workers, depending on which one dominates. When training inequalities are primarily influenced by differences in initial education and job placement, those with higher initial education are more likely to accumulate further

training. In this labour market allocation pathway, individual training trajectories would tend to remain comparatively stable over the career. On the other hand, if training inequalities between workers are mainly driven by prior participation in further training, they are expected to increase over time. The disparities between workers would therefore primarily hinge on the development of the individual training participation trajectory in preceding years. In such scenarios, accumulation is rooted in *dynamic growth*, wherein the likelihood of participating in training undergoes changes throughout one's career. While social inequalities are likely to increase because workers who initially embark on training trajectories with regular participation are more inclined to increase their probability of participation over time (Sousounis and Bladen-Hovell, 2010), the notion of dynamic growth also suggests that individual training trajectories possess some degree of flexibility. Through short-term shifts in training behaviour, workers who have previously shown patterns of non-participation may be directed towards alternative trajectories that involve more consistent participation, regardless of their specific job positions. Consequently, if the accumulation of training experiences is based on strict cumulative advantage, individuals who are disadvantaged or possess lower levels of education may be afforded a genuine opportunity for a fresh start in career trajectories featuring more regular training participation.

Only a few studies have attempted to disentangle the effects of previous training participation from those of initial education and training. This is also because of the methodological difficulties that arise when separating the two processes that generate path dependence. The raw correlation between previous 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. 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 compare the extent of path dependency between countries and find lower path dependency in countries with higher expenditures on education or a more advanced knowledge economy. Sousounis and Bladen-Hovell (2010) use a more sophisticated method, helping to analyse the underlying pathways behind such findings. Using dynamic random effects models based on the BHPS, they show that previous training has a sizable

effect on further training participation in the United Kingdom during the 1990s - the effect being comparable in magnitude to that associated with formal educational qualifications. Furthermore, they show that this effect is stronger among higher-educated workers.

Educational systems and the labour market context presumably influence the dynamics of training participation trajectories, leading to differences between countries. In this study, we compare two countries that represent strongly different institutional settings: Germany and the UK. Germany has a strong focus on occupation-specific skills; therefore, further training mainly occurs later in life to adapt to technological and structural changes. In contrast, in the UK, more individuals enter the labour market with general skills and immediately require further training to learn job-specific skills. Thus, they require further training at the beginning of a job as well as later in response to changes in skill requirements. This should not only lead to differences in the volume of training participation, as shown by earlier research (Brunello, 2001; Vogtenhuber, 2015), but also to different dynamics over the life course because of differences in the importance of the two pathways for training accumulation outlined above. We assume that in the UK, strict cumulative advantage plays a significant role in the accumulation of training experiences (Sousounis and Bladen-Hovell, 2010), whereas in Germany, its influence is relatively less pronounced due to the strong occupational labour markets.

In this paper, we focus on work-related non-formal further training after initial education - like computer, language and soft skills courses - that do not lead to recognized certificates such as college or vocational training degrees. We aim to add to this literature first by re-investigating the major drivers of training accumulation and testing whether the link between previous training participation and future participation can be found also in more recent data for Germany and the UK. Second, we investigate whether institutions influence the effect of training on future training participation. For this purpose, we analyse panel data from the German National Educational Panel Study (NEPS) from 2010 to 2021 and the United Kingdom Household Longitudinal Study (UKHLS) for the same time window. 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

General pathways

Chains of further training participation over time can be caused by two broad types of pathways. First, they may be the consequence of individual and job-specific stable risk/success factors. 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 describes the first path 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 pathway has "true state dependence", as the states at the two points in time are 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."

"Figure 1: True state dependence in training participation"

***** Figure 1 here *****

The empirical literature on inequalities in training participation identifies several factors that may explain "spurious state dependence" of training participation. Many studies show that training probabilities are strongly determined by placement in jobs and firms (Anger *et al.*, 2023; Ehlert, 2020; Görlitz and Tamm, 2016; Hornberg *et al.*, 2023; Schindler *et al.*, 2011). The main reason for these findings, presumably, is that firms, as the main provider of further training, invest mainly in workers with tasks that require constant updating because this yields the largest returns. Furthermore, firms also differ in terms of human resource policies with some focusing more on training provision than others (Wotschack, 2020). Finally, individual traits such as education, personality, and motivation are

related to training participation (Gorges *et al.*, 2016; Laible *et al.*, 2020). Thus, repeated training participation may be due to the workplace and mostly stable individual characteristics.

Cunha and Heckman (2007) provide a theoretical justification for 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” (ibid.: 35); they describe this effect as “self-productivity” (ibid.). Skills might be “self-reinforcing” and “cross fertilizing” (ibid.). The latter means that skills in one area can foster skills in another area. 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. (2) “Skills produced at one stage may raise the productivity of investment at subsequent stages” (ibid.:35). Cunha and Heckman describe skill investments as synergistic, as “levels of skill investments at different ages may bolster each other” (ibid.). 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” (ibid.: 35). Dynamic complementarity implies that a basic computer course would make it possible to attend a course on a specific computer program.

From a human capital perspective, both mechanisms (self-productivity and dynamic complementarity) lead to higher incentives to invest in training because they reduce costs and increase benefits. Moreover, dynamic complementarity, together with self-productivity, produces “multiplier effects, which are the mechanisms through which skills beget skills and abilities beget abilities” (Cunha and Heckman, 2007: 35). Consequently, both employers and employees have greater incentives to invest in training if another relevant spell of training has previously taken place, thereby fostering cumulative advantages.

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, who are by far the most important providers of further training (Wotschack and Solga, 2014; Cedefop, 2015), presumably use signals of productivity to make decisions, as formulated in signaling theory (Spence, 1973). Assuming rational, efficiency-oriented companies (Williamson, 1985), 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 since it may signal higher returns to subsequent training courses.

We expect similar outcomes in the much smaller segment of further training initiated by individuals. Employees themselves may not be directly aware of the potential payoffs of further training. However, previous non-formal training experiences and participants' impressions of them might influence the motivation to train in the future through changing the expectations of success and the value of non-formal training participation (Gorges and Kandler, 2012). This prediction is based on Eccles' (2005) expectancy-value theory. It argues that the determinants for educational choices are mainly based on individuals' 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.

Based on these considerations from both the employer and the employee perspective, we expect to find an effect of previous training on future training net of individual characteristics and context factors: *Participation in job-related non-formal training in one year increases the probability of training participation in the following year* (Hypothesis 1).

Furthermore, it may be that the effect of previous training participation differs by levels of initial education. Research shows that skill levels are strongly associated with educational attainment (Heisig and Solga, 2015), and according to the technology of skill formation, skills beget skills. Therefore, we argue that higher education boosts the effects of previous training participation on future training participation. On the firm level, this may be because employers perceive higher

educated individuals as more trainable in general (Di Stasio, 2014). This may further increase the belief that previous training participation in this group eases future skill acquisition. In other words, employers believe that training falls on a more fertile soil among the highly educated. On the individual level, higher education may boost the effect of previous training on success expectancy and the value attached to future training decisions. This may be due to the importance of autobiographical memories and socio-cultural influences in the decision to participate in a training course (Gorges, 2015). Highly educated individuals already have more experience with learning in the past and thus more positive memories and high appreciation of learning (Gorges and Kandler, 2012). Therefore, previous courses may have even larger effects on success expectancy and the value of learning for future courses. Consequently, 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: *People with higher education levels exhibit a stronger effect of previous training participation on future training participation* (Hypothesis 2).

Institutional moderation

We expect Hypothesis 1 and Hypothesis 2 to apply in both countries. However, the strength of each of the two pathways that lead to cumulative advantages might be moderated by institutional contexts.

In that regard, differences in skill-formation systems may take on a key role. A well-known dichotomy used in 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 labour markets (OLMs) are characterised by high levels of occupational specificity and highly developed and standardized vocational training systems. In OLMs, (vocational) educational diplomas signal that the employee possesses occupation-specific skills that are in demand in the labour market (Arum and Shavit, 1995). The high level of standardization results in a high level of skill transferability, allowing employees to move between companies within the same occupation

during their careers. Furthermore, it enables employers to fill job vacancies by external workers (Marsden, 1990). Therefore, an employee in an OLM can be described as a “specialized craftsman” (Rözer and van de Werfhorst, 2020). It is well known that the German educational system provides most labour market entrants with such occupation-specific skills, especially in the vocational education sector, resulting in early skill matches for many workers.

General skill regimes found in internal labour markets (ILMs) are more strongly focused on the development of general skills, with vocational training at career entry being much less developed and standardized (Estevez-Abe *et al.*, 2001). In ILMs, like the UK, employers generally aim to fill vacancies at higher levels in the organization “from among its existing employees” (Marsden, 1990: 415). An employee in an ILM can be seen as a “broad craftsman” (Rözer and van de Werfhorst, 2020) who possesses general skills upon entry into the labour market, but attains firm-specific occupational skills in the context of enterprise-related training (Wolbers, 2003: 134) and experience. Accordingly, boundaries in entry requirements are 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).

As a consequence of these differences, occupational outcomes and attainment are much more “amenable to career contingencies and discretionary employer behaviour” (Gangl, 2003:110) in ILMs. This is likely to lead to an increasing divergence in occupational attainment within skill groups over time in ILM contexts (*ibid.*: 111). In OLMs, by contrast, occupational outcomes are mainly determined by educational and vocational certificates. Therefore, the accumulation of training participation experiences is likely to follow a rather stable pattern in Germany and a comparatively more dynamic pattern in the UK.

Following these considerations, it is plausible to assume that the signaling function of further training for employers differs between Germany and the UK. In Germany, there is a greater similarity in workers' skills within the same occupation. In contrast, in the UK, there is a significant divergence in skills among workers within the same occupation. Thus, compared to Germany, employers in the

UK may rely more heavily on previous training participation as a signal for further trainability.

Furthermore, UK employees, with their rather general skill profiles, are more likely to benefit from the cross-fertilizing aspect of skills than in Germany.

Differences in labour market institutions between the UK and Germany may also influence training dynamics. The German labour market represents a setting with incentives for training even if it is unrelated to the standardized occupation-specific task profile because of high levels of employment protection. This means that employees can safely invest time and effort into further training, even if the skills acquired are firm-specific (Estevez-Abe *et al.*, 2001). Moreover, high levels of employment protection make it less expensive for employers to upgrade or convert the skills of their existing workforce than to fire them and hire new workers with the relevant skills from the external labour market (Dieckhoff, 2013: 94). Therefore, high employment protection decreases strict cumulative advantage at the individual level because employers have an incentive to train their entire workforce, not just those with prior training experience. In contrast, the UK, characterized by relatively lower employment protection levels, allows firms to exercise greater selectivity in choosing which individuals to provide training to. The cost-effectiveness of replacing employees who signal low productivity or trainability with external workers is amplified due to these lower levels of employment protection. Consequently, previous training within the firm may serve as a crucial signal when making decisions about further training for workers in this context.

Based on the institutional differences outlined above, there are reasons to expect that strict cumulative advantages and disadvantages in further training would be more frequently promoted in the UK labour market than in Germany: *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* (Hypothesis 3).

We furthermore anticipate a more pronounced cross-national difference in outcomes for groups with less than higher education. This is because the skill profiles of lower- and intermediate educated workers vary more across countries than those of highly educated workers. The skill regime

differences outlined above are rooted in combinations of educational levels and fields (e.g. health, social science) and occupations, as demonstrated by DiPrete *et al.* (2017), and DiPrete and Chae (2023), with these studies also highlighting the significant heterogeneity in the occupational specificity of educational programs within countries. Not only do educational programmes in Germany tend to be more closely associated with occupational positions than in the UK, but Germany also tends to sort more individuals into educational programmes that are more closely associated with specific occupations than other educational programmes (DiPrete and Chae, 2023). Country variations in the linkage between most educational fields and occupations are less marked for workers with tertiary education compared to those with non-tertiary education (DiPrete and Chae, 2023, Supplementary Material). Thus, it might be the case that higher educated workers have a more similar skill profile across both countries in regard to their occupational specificity compared to non-tertiary workers. Therefore, we hypothesize that the patterns of training participation dynamics are more consistent between countries for individuals with tertiary education than those without.

Against this backdrop, we formulate our final hypothesis: *The differences between countries in the effect of previous training participation on later training participation are highest for individuals less than tertiary education* (Hypothesis 4).

3. Data and method

Data

We utilize two longitudinal datasets to test our hypotheses. The UK Household Longitudinal Study *UKHLS* (Understanding Society) is employed for the UK, comprising roughly 40,000 households in the United Kingdom (University of Essex, Institute for Social and Economic Research 2020). We analyse data from 2010 (wave 2) to 2021 (wave 12). For Germany, we use the starting cohort 6 (SUF 13.0.0) of the National Educational Panel Study (NEPS) (Blossfeld *et al.*, 2019), which gathers comprehensive information on educational trajectories, competencies, and returns to education

for individuals born between 1944 and 1986. We examine waves 2 to 13, which provide detailed data on non-formal training participation for the same time period as the UKHLS.

Since our goal is to disentangle the different pathways of training participation accumulation, specifically strict cumulative advantage and factors related to job positioning, we focus on (dependent) employees. Including unemployed individuals would introduce additional mechanisms which would divert us from our research objective. Thus, we restrict our sample to continuously employed (employed at each interview) workers, aged 25–55 without missing data on our covariates. Focusing on prime-age workers allows us to have more certainty that our cross-country results are not affected by differences in school-to-work (Brzinsky-Fay, 2007) and retirement transitions (Fasang, 2012).

Dependent variable: further training

Our primary focus lies on job-related non-formal training, which stands out as the prevailing form of adult education and training, as indicated by Cedefop (2015). Job-related non-formal training encompasses training activities directly linked to one's occupation, commonly delivered through classroom instruction, lectures, theoretical and practical courses, seminars, or workshops. It does not result in qualifications acknowledged by national or sub-national education authorities. In our analysis, we use the UKHLS variable indicating training since the previous interview and its purpose. The UKHLS provides data for up to three training spells between interviews. Formal training spells were disregarded, as was training for leisure and hobbies. Youth training schemes, key skills, and basic skills training were classified as non-formal. Hence, respondents were assigned a value of 1 if one of the three spells was non-formal and job-related, and 0 otherwise. In the NEPS, respondents were asked about training course participation since the last interview, with detailed data collected for two randomly selected courses. We focus on job-related training courses, and assign a value of 1 if at least one of the two courses was non-formal and job-related.

Moderator: education

Hypotheses 2 and 4 suggest differences in the estimates between workers with higher education and the other educational groups. Therefore, we need an operationalization that distinguishes tertiary education from other degrees. In Germany, we distinguish three levels of education using the International Standard Classification of Education (ISCED-97): low (ISCED 0–2), intermediate (ISCED 3–4), and high (ISCED 5–6). The UKHLS uses its own classification for educational levels, but we define low education as those with less than an upper secondary degree, medium education as those with at least an upper secondary degree but less than a tertiary degree, and high education as those with some kind of tertiary degree. This makes the UK classification comparable to the German classification based on ISCED. Our harmonization is based on the approach of Turek (2020) in the Comparative Panel File.¹ We thereby ensure that our coding fits to our theoretical arguments describing educational (cross-country) differences in occupational specificity outlined above.

Control variables

In our models, we incorporate control variables for various confounding factors that may influence training participation in both the previous year ($t-1$) and the following year (t).

Education as described above is controlled for because lower levels of education are associated with lower participation in further training (Bassanini *et al.*, 2005; OECD, 2019). We control for *gender* as some studies suggest that women are less likely to participate in training (Boll and Bublitz, 2018; Dämmrich *et al.*, 2015). *Age* may also affect training participation, so we include linear and squared age controls. We further control for the *number of children* (with a slight difference in the data, as in the UK information is supplied for children under the age of 16 while in Germany for children up to 18 years of age) since family formation reduces the probability to train for women (Zoch, 2023) and we control for whether workers are *cohabiting* (coded 0/1) or *married* (coded 0/1). *Part-time employment* is associated with lower training participation rates (Boll and Bublitz, 2018), so

¹Detailed coding of the educational variable can be found in the *online appendix* (Figure A1).

we control for whether workers are employed on a part-time contract (coded 0/1). Employers may be hesitant to offer training to workers with *fixed-term contracts* because the limited time may not justify the investment. Thus, we also control for whether workers have a fixed-term contract (coded 0/1). *Company size* may also influence training participation rates (Grund and Martin, 2012), so we include the number of employees as a control variable (number of employees: operationalisations are presented in Table A1 in the *online appendix*). Tasks are important determinants of training participation (Görlitz and Tamm, 2016). As we do not have information on the tasks performed, we control for *occupations* (ISCO-88 2-digit) and *changes of occupation* between waves (coded 0/1) as well as *sectors* (Klassifikation der Wirtschaftszweige 2008 (DE) and Standard Industrial Classification 2007 (UK)).

Descriptive information for both datasets can be found in Table A1 (in the *online appendix*). Our German sample includes 5,760 individuals and 30,616 person-years, with a training participation rate of 34 percent. Over half of the sample (52 percent) holds a high level of education, while 46 percent hold a medium level of education, and the remaining 2 percent have a low level of education. The UK sample, includes 13,748 individuals and 65,333 person-years, with a slightly lower training participation rate of 29 percent. The majority of individuals hold a high educational credential (52 percent), followed by those with medium educational credentials (30 percent) and less-educated respondents (18 percent).

Method

The concept of true state dependence (or strict cumulative advantage) is straightforward in theory, but poses methodological challenges. The primary challenge is how to address the initial condition and endogenous covariate problem, as well as how to handle unobserved heterogeneity (Skrondal and Rabe-Hesketh, 2014). To address these issues, we use *dynamic random-effects probit*

models proposed by Rabe-Hesketh and Skrondal (2013)², utilizing the Stata ado *xtpdyn* developed by Grotti and Cutuli (2018) with standard errors clustered on the individual level. Dynamic random-effects probit models are mainly used to calculate outcome inertia caused by previous states of a binary outcome variable.

We attempt to measure true state dependence in the following way³:

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

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 .

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 and Rabe-Hesketh, 2014). We therefore condition on the response at y_{i0} , as proposed by Wooldridge (2005) and Rabe-Hesketh and Skrondal (2013).

A second challenge to address is the problem of endogenous covariates. In addition to the strict exogeneity assumption regarding the idiosyncratic error term (u_{it}), consistent estimation of RE panel models also requires exogeneity in relation to the person-specific time-constant error term (c_i). This means that we assume no correlation between c_i and Z_{it} at any time $E(c_i | Z_{it})=0$, 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) suggests the inclusion of

² In contrast to Sousounis and Bladen-Hovell (2010) this method controls for the initial conditions of the time-varying confounders.

³ The explanation of the formula is adapted from Grotti and Cutuli (2018).

values of time-varying confounders at each period (except the initial period). This approach requires balanced data sets. We follow a more parsimonious approach which allows analysing unbalanced data by modelling unobserved heterogeneity by including within-unit averages of the independent time-varying variables (Biewen, 2009; Stewart, 2007; Rabe-Hesketh and Skrondal, 2013) and the initial values of the explanatory variables (Rabe-Hesketh and Skrondal, 2013).

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 represents the within-unit averages of the explanatory variables, based on all periods. a_i stands for the residual unit-specific time-constant error term. If c_i captures unobserved heterogeneity, then y_{it-1} can be interpreted as true state dependence. As explained above, we additionally control for the initial training condition, the initial condition of the time-varying confounders, 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 try 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. These models aim to be “almost consistent,” meaning that the “estimator is sufficiently close to the parameters of interest for practical purposes” (ibid.: 217). To facilitate the interpretation of our results, we calculate average marginal effects in all our models.

4. Results

Table 1 provides descriptive statistics on the transition rates for job-related non-formal training within both countries. In Germany, workers who participated in training in the previous year have a 52 percent probability of engaging in training again in the following year, compared to a 23

percent likelihood for those who did not participate in training previously. In the UK, individuals who participated in training during the previous year have a 50 percent chance of doing so again in the following year, whereas this likelihood is 20 percent for those who did not train in the previous year.

Both countries display a pronounced inertia in training participation, as demonstrated by the estimates of total state dependence derived from the raw data—29 percentage points in Germany and 30 percentage points in the UK. Total state dependence quantifies the difference in the probability of training participation in the current year between those who did and did not participate in training the previous year. Given that these estimates are based on raw data, they encapsulate both true state dependence and spurious state dependence pathways. In our further analysis, we aim to precisely identify the factors contributing to the observed inertia in training participation. This involves disentangling true state dependence from spurious state dependence. By doing so, we aim to gain deeper insights into the accumulation processes of training participation and the underlying pathways driving it.

**** Table 1 here ****

Figure 2 shows the results of our full dynamic random effects probit models (see Table A2 and A3 in the *online appendix*) testing Hypotheses 1 and 3 by plotting the respective average marginal effects with 95% confidence intervals. It shows for both countries a substantive and statistically significant association between previous training participation and later training participation. In the UK, workers who received training in the previous year are, on average, about 13 percentage points (pp.) more likely to receive training in the following year, compared to approximately 8 pp. in Germany.

Our analysis supports Hypothesis 1, which posits that training participation in one year increases the probability to train in the following year in both countries, reinforcing the idea that “training begets training.” Similarly, Hypothesis 3 is confirmed, indicating that true state dependence in training participation is higher in the UK than in Germany.

“Figure 2: Average marginal effects of job-related training participation at time point (t-1) on participation at time point (t) in Germany and the UK.”

“* Figure 2 here ***”**

“Note: 95% Confidence Intervals, Source: NEPS SC6 SUF 13.0.0, Wave 2 – Wave 13 (2010 – 2021), and UKHLS, Wave 2 – Wave 12 (2010 – 2021), authors' calculations”

Having established this, another interesting question is the relative relevance of true versus spurious state dependence. Following Sousounis and Bladen-Hovell (2010), we use our estimates to calculate the share of total state dependence attributable to true state dependence (see Table 2).

“* Table 2 here ***”**

Table 2 shows the predicted probabilities of training participation at time t for both Germany and the UK. Specifically, it shows the predicted probabilities for workers who participated in training at time $t-1$ ($P(1|1)$), as well as the predicted probabilities for workers who did not participate at time $t-1$ ($P(1|0)$). Comparing true state dependence with the total state dependence (based on raw data)⁴ shows that in the UK true state dependence accounts for 43 percent (13/30) of the raw state dependence while in Germany it is only 28 percent (8/29). This emphasizes that, although both countries exhibit similar levels of total state dependence, the extent to which total state dependence is based on true state dependence differs. The analysis indicates that previous training participation is a more substantial factor in the accumulation of training experiences in the UK compared to Germany.

“Figure 3: Average marginal effects of job-related training participation at time point (t-1) on participation at time point (t) by educational groups in Germany and the UK.”

⁴ The total state dependence includes both pathways described in the theory section (spurious and true state dependence).

“* Figure 3 here ***”**

“Note: 95% Confidence Intervals, Source: NEPS SC6 SUF 13.0.0, Wave 2 – Wave 13 (2010 – 2021), and UKHLS, Wave 2 – Wave 12 (2010 – 2021), authors' calculations”

Figure 3 illustrates the outcomes obtained from the analysis carried out to examine the influence of education on true state dependence in training participation (Hypotheses 2 and 4) by plotting the respective average marginal effects for each educational group with 95% confidence intervals. Concerning Hypothesis 2, stating that people with higher education levels exhibit a stronger effect of previous training participation on future training participation, no substantial evidence is discovered. Our analysis reveals only marginal disparities between educational groups, with confidence intervals overlapping in both countries. Unfortunately, the limited sample size constrains our ability to make definitive conclusions about less-educated workers in Germany. No differences in strict cumulative advantage are found for other educational groups. In the UK, highly educated workers who participated in training in the previous year show an approximate increase of 13 pp. in future participation, compared to 9 pp. in Germany. For workers with intermediate education levels, the increase is about 12 pp. in the UK and 7 pp. in Germany. For less-educated workers, it is about 12 pp. in the UK and 2 pp. in Germany.

Thus, findings indicate comparable levels of true state dependence in job-related training for highly and intermediate educated employees in Germany and for all educational levels in the UK, contrary to Hypothesis 2. Along the same lines, the extent country differences in true state dependence in further training are similar for high- and intermediate-educated workers. We therefore cannot confirm Hypothesis 4, which stated that the largest difference between the countries would be found for the group of workers with low or intermediate levels of education.

“* Table 3 here ***”**

Table 3 illustrates that in Germany, true state dependence accounts for 28 percent (43 percent in the UK) of the total state dependence for highly educated, 24 percent (41 percent in the UK) for intermediate educated and 7 percent (42 percent in the UK) for less educated. Therefore, our results indicate that true state dependence plays a more significant role in the accumulation of training experiences across all educational groups in the UK compared to Germany.

Robustness Checks

To assess the stability of our results under various conditions, this section provides a concise summary of our series of robustness checks. Detailed results and descriptions are available in the *online appendix*.

The data collection procedures employed in the NEPS and UKHLS differ slightly. The UKHLS collects information on up to three training spells between interviews, while the NEPS asks respondents about training course participation since the last interview, with detailed data obtained for two randomly selected courses. Grüttgen et al. (2023) have developed a logical imputation approach that allows for the analysis of all courses occurring between two waves. We employ this measure to examine whether the observed differences between countries in our main analysis may be attributable to variations in data collection procedures. Using the non-formal job-related training variable based on logical imputation does not alter the results of our analysis in Germany. Results and details can be found in the *online appendix* (Figure A3 and corresponding Table A6).

In our main analysis, we estimated the mean effect for each country. However, there may be significant heterogeneity within each country across different sectors. We assumed that differences between countries would be smaller in sectors with a high proportion of highly educated workers and more pronounced in sectors with a very low proportion of highly educated workers due to convergence within the European higher education area. Examining sectors with a high share of highly educated workers showed no substantial changes compared to our main analysis (refer to *online*

appendix Figure A4 and Tables A7 & A8). We also examined sectors with a low share of highly educated workers in both Germany and the UK, finding relatively stable coefficients without substantial changes compared to our main analysis (refer to *online appendix* Figure A5 and Tables A9 & A10). These findings suggest that our main analysis, which estimated the mean effect for each country, is robust across sectors with different proportions of highly educated workers.

We also explore the potential impact of the public sector on our findings by conducting an additional analysis excluding the public sector from our sample. This was done to investigate whether the inclusion of public sector workers may have influenced the observed relationship between training participation and subsequent participation. Upon conducting this analysis, we found that the coefficients remained robust and did not show substantial changes compared to our main analysis that included the public sector. Results and details can be found in the *online appendix* (Figure A6 and corresponding Tables A11 and A12).

5 Discussion and conclusions

In a rapidly changing labour market, continuous training participation becomes ever more important. Yet, previous research shows a highly unequal distribution of training participation (Blossfeld *et al.*, 2020: 5). This paper adds to the literature about the causes of inequalities in training participation by applying a longitudinal perspective on recent data and considering the dynamics of training participation within careers in a country-comparative perspective. We conceptualize the accumulation of training within careers as a “two-fold path-dependency” (Offerhaus, 2014: 81). The first path relates to educational attainment and subsequent labour market positioning (Hornberg *et al.*, 2023; Kramer and Tamm, 2018; Görlitz and Tamm, 2016; Schindler, Weiss, and Hubert, 2011), i.e. training participation is due to initial education and placement on the labour market. The second pathway involves individual training histories, representing a case of strict cumulative advantage (DiPrete and Eirich, 2006) in which training in one year leads to training in the following year. We argue that differentiating between true and spurious state dependence enhances our understanding of

the observed inequality in training participation and its broader implications for social inequality in the labour market.

Our results reveal that strict cumulative advantage plays a sizeable, but not the predominant role in training participation accumulation over the life course. Many previous studies focus on Matthew effects in training participation without differentiating between the impact of initial education and placement on the labour market and the impact of prior participation (e.g. Blossfeld *et al.*, 2020). Yet, most studies implicitly assume that social inequalities in the accumulation of training experiences stem from relatively stable worker, job, and firm characteristics. Indeed, our results confirm that the primary determinants of training participation are initial education, job characteristics, and firm characteristics, reflecting the process of labour market allocation. They account for more than half of the observed raw correlation between training participation in the previous year and the current year in the UK, and even two-thirds in Germany. However, our findings also reveal that “training begets training”, providing evidence for an additional growth dimension in the accumulation of training participation: Previous participation plays a secondary yet noteworthy role, signifying dynamic growth albeit at a lower level. Thus, only considering worker, job, and firm characteristics when analysing inequality in training participation neglects a significant further pathway that is rooted in previous training participation.

Furthermore, in line with our expectations, the effect of job-related training on future training is more pronounced in the UK than in Germany, indicating the significance of institutional factors. This difference is sizeable: the direct impact of previous participation accounts for 43 percent of the raw state dependence in the UK compared to only 28 percent in Germany. Evidently, the emphasis on general education and internal labour markets combined with a liberal labour market regime in the UK fosters a scenario where skills beget skills. Consequently, training participation trajectories appear to be more dynamic in the UK compared to Germany and inequality increases over the course of careers much more strongly than in Germany.

Additionally, we only find limited evidence for variation in strict cumulative advantage across educational groups in both countries. We initially anticipated that highly educated workers would exhibit stronger true state dependence, while those with intermediate and low education levels would display weaker true state dependence. However, our findings do not support this hypothesis. In the UK we find no differences in true state dependence between educational groups. In Germany, high and intermediate educated workers exhibit similar participation dynamics, while individuals with low education levels seem to derive fewer benefits from previous training participation. However, it is important to acknowledge that the small sample size seriously constrains our ability to make definitive assertions about less-educated workers in Germany.

Our findings largely confirm, update, and contextualize earlier findings about state dependence of training participation from the UK. Relying on data from the BHPS, the UKHLS's precursor, and a similar methodology Sousounis and Bladen-Hovell (2010) find sizeable effects of previous training participation.⁵ Our results also indicate that training begets training when analysing a more recent period in the UK. However, we find comparatively lower levels of true state dependence. Furthermore, they found larger effects among the highly educated. The latter finding could not be replicated by our analyses suggesting that the importance of true state dependence increased in the UK for less-educated workers. Yet, our analyses show that state dependence is strongly context dependent. In Germany the direct effect of previous training participation is substantially lower. Vice versa, the impact of stable worker, job, and firm characteristics on continuous training participation is much higher in Germany. These disparities between countries, specifically in terms of how structural aspects and previous participation ($t-1$) affect the probability of training participation (t), lead us to the conclusion that factors related to the Matthew effect and labour market allocation are more crucial in Germany compared to the UK. This is due to the fact that the relative impact of spurious and true state dependence is more similar in the UK than in Germany.

⁵ Sousounis and Bladen-Hovell (2010) find effect sizes between 16 pp. (women) and 22 pp. (men)

There are several limitations that should be acknowledged in our study. Firstly, our empirical models rely on strong assumptions. According to Skrondal and Rabe-Hesketh (2014), dynamic random effect probit models should be considered as working models aiming for 'almost consistent' results. While we make efforts to control for relevant confounders, there remains uncertainty about how effectively the initial training condition captures time-constant unobserved factors. Additionally, it is likely that there are still idiosyncratic errors present due to time-varying unobserved factors. For example, we cannot rule out the possibility that training participation may occur in 'package deals,' where training participation over several years is based on the same decision to invest in one's employee's human capital (or in one's own capital) for consecutive years (for example to prepare for a certain position in the organization). Further, we are not able to account for employer agency. These factors may contribute to an overestimation of true state dependence. Yet, even if this is the case, our analyses still show that structural conditions such as placement on the labour market are more important in both countries. Also, assuming that the biases are similar in the two countries, the cross-national differences we show are not affected. Yet, it could be that our focus on training participation in adjacent years without considering longer lags might also lead to an underestimation of true state dependence. Here, we argue that given the short duration of most training courses of less than one week on average the mechanisms leading to true state dependence are less plausible for longer gaps.

Our findings carry three significant implications regarding social inequalities in the accumulation of training experiences: (1.) There is a potential amplification of early inequalities over time. Individuals who are initially on career paths that promote regular training participation are likely to keep and even enhance their advantage over time. Consequently, the gap in participation probability widens between individuals with otherwise similar characteristics, but differing patterns of participation in preceding years. (2.) On the other hand, it also suggests the potential for individuals to break free from non-participation patterns and transition into pathways characterized by more regular training participation. Changing to more training intensive jobs and firms has greater potential for this than participation in single training courses. Yet, training participation itself may also set off chains of participation. (3.) The inequality generating pathways can be influenced by institutions. These insights

have implications for policies directed at reducing inequalities in training participation. Our findings show that training participation can offer second chances for individuals who have initially entered the labour market in a disadvantaged position or who enter the labour market after longer interruptions (due to e.g. unemployment or parental leave). Since most of the training course we study are employer-organised and employer-funded, we do not know whether our findings can also be extrapolated to any publicly funded training initiatives or offers. However, our findings suggest that policy measures that encourage firms to invest also into the training of the lower-skilled and less privileged workforce could have the potential of reducing social inequalities in the labour market.

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Figure 1: True state dependence in training participation

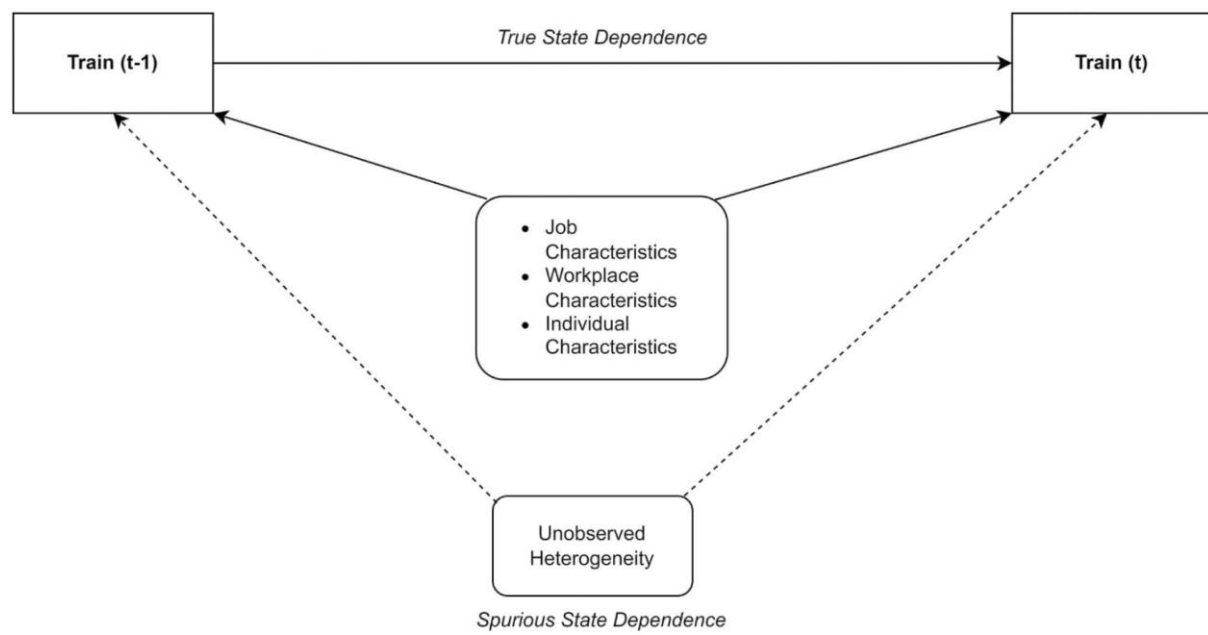


Figure 2: Average marginal effects of job-related training participation at time point (t-1) on participation at time point (t) in Germany and the UK.

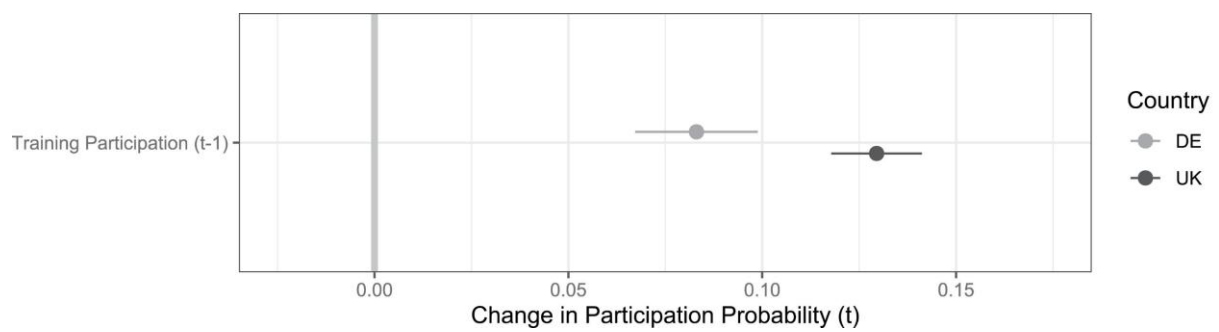


Figure 3: Average marginal effects of job-related training participation at time point (t-1) on participation at time point (t) by educational groups in Germany and the UK.

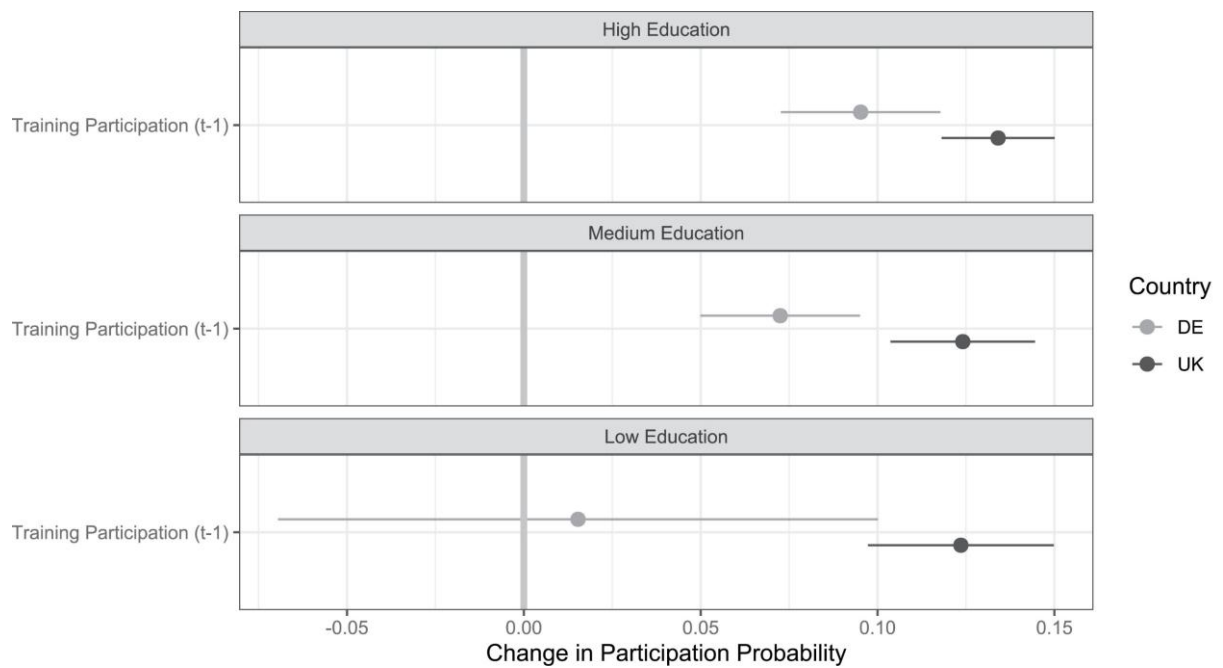


Table 1: Descriptive transition rates in job-related non-formal training (in row %)

	Training participation t	No training participation t	Total
Germany			
Train. Part. $T - I$	52	48	100
No train. Part. $T - I$	23	77	100
	33	67	100
United Kingdom			
Train. Part. $T - I$	50	50	100
No train. Part. $T - I$	20	80	100
	29	71	100

Source: NEPS SC6 SUF 13.0.0, Wave 2 – Wave 13 (2010 – 2021), and UKHLS, Wave 2 – Wave 12 (2010 – 2021), authors' calculations.
Sample sizes: DE 5,760 persons (30,616 person-years) / UK 13,748 persons (65,333 person-years).

Table 2: Raw-data probabilities and predicted probabilities in Germany and the UK.

	DE	UK
Raw data probabilities		
(1) Training <i>t-1</i>	0.52	0.50
(2) No training <i>t-1</i>	0.23	0.20
(3) (1)-(2)	0.29	0.30
Predicted Probabilities holding characteristics constant		
(4) Training <i>t-1</i>	0.36	0.34
(5) No training <i>t-1</i>	0.28	0.21
(6) State dependence	0.08	0.13
As % of (3)	27.59	43.33

Source: NEPS SC6 SUF 13.0.0, Wave 2 – Wave 13 (2010 – 2021), and UKHLS, Wave 2 – Wave 12 (2010 – 2021), authors' calculations.
Sample sizes: DE 5,760 persons (30,616 person-years) / UK 13,748 persons (65,333 person-years).

Table 3: Raw-data probabilities and predicted probabilities for educational groups in Germany and the UK

	DE			UK		
Raw data probabilities	<i>High edu</i>	<i>Medium edu</i>	<i>Low edu</i>	<i>High edu</i>	<i>Medium edu</i>	<i>Low edu</i>
(1) Training t-1	0.56	0.48	0.44	0.53	0.45	0.48
(2) No training t-1	0.28	0.19	0.17	0.23	0.16	0.17
(3) (1)-(2)	0.28	0.29	0.27	0.30	0.29	0.31
Predicted Probabilities holding characteristics constant						
(4) Training t-1	0.43	0.29	0.23	0.39	0.30	0.32
(5) No training t-1	0.34	0.22	0.21	0.26	0.18	0.19
(6) State dependence	0.09	0.07	0.02	0.13	0.12	0.13
As % of (3)	27.59	24.14	7.41	43.33	41.38	41.94

Source: NEPS SC6 SUF 13.0.0, Wave 2 – Wave 13 (2010 – 2021), and UKHLS, Wave 2 – Wave 12 (2010 – 2021), authors' calculations.
Sample sizes: DE 5,760 persons (30,616 person-years) / UK 13,748 persons (65,333 person-years).