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Accessibility of Training in Older Age: A European Perspective on Path Dependency in Lifecourse Trajectories

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Abstract

Investments in lifelong learning often create unsatisfactory results and contribute to reproduction of inequalities. A lifecourse approach allows the study of accumulation mechanisms and discovering how path dependency in behaviours relates to macrostructural mechanisms. Using data from the Survey of Health, Ageing, and Retirement in Europe (SHARE), we trace individual training trajectories in the population of 50+ in twelve European countries between 2010 and 2015 (27 370 respondents). We use a hierarchical Bayesian logit model to assess the probability of training during the sixth wave, with a lagged dependent variable as a predictor. Results suggest that training participation is path-dependent and access to training is limited for people who have not trained previously. We find a relationship between a macrostructural context and path dependency during training. An interaction between macro-predictors and the lagged dependent variable shows that access to training is greater in countries with stronger knowledge economies, stronger emphasis on education, and a proactive ageing climate. The size of the welfare system plays no role. These results have implications for policies that address problems of cohesion, active ageing and, adult learning. We argue that lifecourse perspective must be considered to recognise path dependency and address measures to improve accessibility.

Keywords

lifelong learning, training, path dependency, older workers, population aging, Bayesian

Introduction

In a rapidly changing and unpredictable socioeconomic context, skill obsolescence and an upward shift in demand for human capital particularly influence older workers who simultaneously must deal with the prospect of working longer (De Grip and Van Loo 2002). Continuous acquisition and adjustment of skills are necessary to extend working lives, postpone retirement, and increase employability in older age (Evans et al. 2013; Groot and Van den Brink 2000; Picchio and van Ours 2013). Lifelong learning (LLL) is also important to stimulate active ageing, enhance social capital, and empower political inclusion (Cedefop 2012). From a broader policy perspective, LLL addresses rising socioeconomic inequalities and disparities in health, quality of life, and others (EC 2010; Green 2006). These arguments have long been discussed, and in the last two decades, nearly all strategic policy documents in the European Union refer to LLL as a priority (Holford and Mleczko 2013). Despite large budgets, investments in LLL in the European Cohesion Policy 2007–2013 were inefficient and did not reach expected targets, especially concerning poor results for older groups. Instead of social and economic cohesion, they often contributed to existing disparities through accumulation of advantages and disadvantages based on unequal access to education and selective approaches to training in companies (Cedefop 2015; EC 2010 2013; Formosa 2012).

In this article, we focus on training accessibility—the probability of attending training for people who have not participated before. Broadly, accessibility is part of path dependency, or a tendency to continue with an activity or state (Bernardi et al. 2018; Liebowitz and Margolis 1995). Low participation in LLL derives primarily from possibilities for engagement rather than personal motivation to participate (Kilpi-Jakonen et al. 2015; Leuven and Oosterbeek 1999; Picchio and van Ours 2013; Roosmaa and Saar 2010; Rubenson and Desjardins 2009). As a measure of barriers to enter training, accessibility plays a vital role in the efficiency of LLL policies. Opportunities to learn will always be distributed unevenly, but institutional arrangements and policies help overcome external and individual barriers to participation, creating more equitable conditions. Reduction of social inequalities through LLL policies is impossible unless LLL is more accessible to groups that are less likely to participate. Accessibility is also essential to increasing overall training participation; only easy access enables more people to enter training.

We assess whether participation in training is path-dependent, analysing how previous attendance affects the probability of further attendance. We then shift to a comparative perspective, assessing disparities in accessibility of training between countries and the factors that explain them. Using data from the Survey of Health, Ageing, and Retirement in Europe (SHARE), we observe individuals in twelve countries over five years. A multilevel data structure allowed us to study the role of macro-level predictors related to demand for human capital, a welfare state, public support for education, and active ageing climate.

With this study, we contribute to the literature in three ways. First, using a novel, longitudinal perspective on training participation that allows measurement of accessibility, we add to growing literature on analysis of lifecourses (Piccarreta and Studer 2018). Empirical application of the lifecourse approach and evidence based on panel data remain limited regarding LLL. Extant research commonly focuses on cross-sectional views, analysing supply and demand factors that drive educational attainment in old age (Roosmaa and Saar 2010; Saar and Räis 2017). This perspective is unable to show temporal dynamics in participation at the individual level, contrary to panel data, which allows tracing individual learning trajectories and viewing them in terms of continuity or accessibility. To our knowledge, this study is first to empirically assess path dependency in training participation. We argue that path dependency is an important causal pathway in analysing lifelong learning. The “shadow of the past” can lock individuals in progressing chains of risks and accumulation of advantages and disadvantages, limiting their potential and opportunities for switching into more beneficial pathways (Ben-Schlomo and Kuh 2002; Bernardi et al. 2018; Kuh et al. 2003).

Second, this article also adds to evidence regarding LLL in older age by combining a lifecourse approach with a comparative perspective. Longitudinal patterns of behaviours reveal essential aspects of broader structures or macro-level mechanisms. As we demonstrate, training accessibility differs across countries and relates to macro-characteristics. The results suggest how contextual factors can foster potential for breaking down path dependency (Roosmaa and Saar 2010; Rubenson and Desjardins 2009). The study's design required complex, multilevel modelling with random slopes for a lagged dependent variable (LDV) and cross-level interactions that could be assessed only in a Bayesian framework (Gelman and Hill 2007).

Third, the results have implications for policies that address problems of cohesion, active ageing, and improvement of adult-learning attendance. We argue that the lifecourse perspective must be considered to recognise path dependency trajectories and address measures to improve accessibility. Limited access to training for disadvantaged groups, such as older and less-skilled people who are overlooked in market-based systems, might further drive accumulation of inequalities. Path dependency hampers policies that address cohesion and potentially lead to their failure. Although emphasised in some articles (Kilpi-Jakonen et al. 2015; Leuven and Oosterbeek 1999; Roosmaa and Saar 2010; Rubenson and Desjardins 2009), these arguments do not have sufficient empirical evidence.

Accessibility of Training: Possible Underlying Mechanisms

Lifecourse perspective and path dependency

Recent interest in the lifecourse paradigm contributes to better understanding of late-life outcomes as an effect of long-term processes. The lifecourse perspective suggests that intracohort inequalities result not only from period-specific influences, but long-lasting processes of differentiation. Such processes might include a form of accumulation of advantages and disadvantages (Crystal and Shea 1990; O'Rand 1996), or accumulation of inequalities (Ferraro et al. 2009), according to which initial intracohort inequalities grow stronger as an effect of disparate exposure to risks and differential access to opportunity structures over a lifetime. This accumulation has a structural character, and individual agency must be viewed in a framework of external opportunities (Dannefer 2003).

The idea of accumulation is increasingly popular in studies of LLL participation (Blossfeld et al. 2014; Bukodi 2016; Kilpi-Jakonen et al. 2015), though empirical evidence based on longitudinal data is limited. Lifecourse studies commonly characterize LLL as a tool for stratification that can stimulate the growth or decrease of inequalities. In one of only a few longitudinal studies, Bukodi (2016) argues that LLL contributes to development of inequalities over the lifecourse. The author traces individuals from the UK from their teenage years to age 38, finding that training is more beneficial to individuals with high initial socioeconomic positions than for those less-advantaged. Blossfeld et al. (2014) and Kilpi-Jakonen et al. (2015) use comparative evidence, suggesting that participation in training in adult age depends on socioeconomic positions, which reflects the accumulation hypothesis.

Mechanism of accumulation is closely related to path dependency in behavioural trajectories which is observed in various areas of life (Bernardi et al. 2018; Kuh et al. 2003). Path dependency characterises a process in which the probability of biographical event in time *t* depends on the longer life history reaching back to at least a few time units (Bernardi et al. 2018). Following Ben-Schlomo and Kuh (2002) and Kuh et al. (2003), we can refer to two lifecourse mechanisms that should lead to path dependency in training participation. The first one is *accumulation with risk clustering* in which exposures are clustered due to a common underlying factor. In case of training, education and learning abilities – if assumed to be time-constant – affect the likelihood of participation similarly at time *t* and *t+1*, and result in accumulation at the individual level. The second mechanism is a *chain of risks with additive effect* where exposures (beneficial or adverse) are linked to each other in a sequence, and one tends to lead to another. Participation in training can increase skills that improve learning abilities, awareness of benefits of learning, and motivation for further participation (Froehlich et al. 2015; Hansson 2008; Pak et al. 2018; Zwick 2012). Previous training attendance might also ease further access by signalling a worker's potential for development to employers and affecting their training-related decisions (Lazazzara et al. 2013; Spence 1973; van der Heijden et al. 2016). Thus:

> (H1) Training participation is path-dependent: the probability of training is greater for individuals who participated previously.

Comparative perspective

The next question is how and why path dependency and accessibility differ across countries. Comparative analyses of training in older age are nearly exclusively limited to a cross-sectional perspective, and no study compares countries regarding path-dependency or accessibility of training. Most studies do not focus on old age but on general training attendance. Nevertheless, cross-sectional evidence can frame hypotheses regarding disparities of accessibility of training between countries. In Europe, training in older age is most common in the Nordic states, the U.K., the Netherlands, and Switzerland, and low participation occurs in Southern and Central Europe and the Baltic states (Brunello et al. 2007; Beblavy et al. 2014; Dämmrich et al. 2014). Research suggests a negative correlation between general participation and inequality of participation; differences between low-and high-skilled adults are greater in countries with low general participation (southern Europe and the Baltic countries), and lower in countries with high participation (Nordic countries) (Roosmaa and Saar 2010). Such differences are usually explained using four contexts—economic, welfare, education, and sociocultural (Boeren et al. 2010).

The economic mechanism refers to the degree of development and competitiveness of an economy that shapes the relationship between demand for human capital and its supply among older generations (Beblavy et al. 2014; Dämmrich et al. 2014; Saar and Räis 2017). Innovation, development, and high competition between companies drive demand for qualifications and knowledge (Coulombe and Tremblay 2007). Investment in human capital exhibits a countercyclical pattern, which is lower during downturns versus booms (Brunello et al. 2007). During difficult periods, employers, the primary drivers of learning, focus on short-term stabilisation, reducing unnecessary expenditures, including training. The financial crisis of 2007–2008 was identified as one reason for low increases to LLL participation, especially among older groups, and low efficiency of investments in the EU Cohesion Policy 2007–2013 (EC 2013; Munnell and Rutledge 2013). Other economic studies consider the role of compressed wage structures (Bassanini and Brunello 2008), minimum wage (Hansson 2008), degree of market regulations (Coulombe and Tremblay 2007; Bassanini and Brunello 2011), and unemployment rate (Wolbers 2005). To verify the role of economic factors, we limit our discussion to the knowledge economy as a general factor:

> (H2) Access to training is greater in countries with more developed knowledge economies.

Another research topic focuses on structural factors, such as welfare state and institutional contexts. In studies of ageing, this perspective has roots in political economy of ageing (Phillipson 2006) that studied structural dependencies of older people (Townsend 1981) and the ageing enterprise that controls and limits people's activities (Estes 1979). A structural approach confronts people's interests in training (resulting from capabilities, consciousness, and motivation) with various external barriers and opportunities for participation. Institutional arrangements, welfare regimes, and public policy can improve a person's capability of overcoming a variety of barriers to training participation. By supporting disadvantaged groups, they create fairer conditions and reshape unequal distributions of opportunities to participation (Roosmaa and Saar 2010; Rubenson and Desjardins 2009). An institutional framework also influences employers' investment in staff training. Elements such as retirement regulations, taxes, and incentives affect calculation of costs, benefits, and the expected period of return on investment (Lazazzara et al. 2013). For these reasons, welfare regimes frame explanations of disparate activity rates and intracohort inequalities in old-age training (Beblavy et al. 2014; Green 2006; Rubenson 2006). The Scandinavian welfare model (Riddell and Weedon 2012) and universal LLL regimes (Verdier 2013) emphasise social integration, individual aspirations, and empowerment more strongly. Participation in adult education is thus less market-driven and relies more on public support, and consequently, rates are higher and inequalities lower. In contrast, the Mediterranean welfare model favours active cohesion policies less (Riddell and Weedon 2012) and is thus less supportive, which results in lower and more unequally distributed LLL participation. The same applies to liberal (Green 2006 2011) and market-oriented LLL regimes (Verdier 2013), such as in the United States and United Kingdom where the determinant of training is labour market demand for human capital. To account for the structural approach, we offer two hypotheses. First, we refer to the size of the welfare state instead of comparing welfare models:

(H3) Access to training is greater in larger welfare states.

Another aspect of the structural framework is the education system. Dämmrich et al. (2014) connect participation with stratification of educational systems, arguing that Nordic and liberal countries, with less stratified systems, have lower barriers to participation in adult learning than Central European countries in which the systems are highly stratified. Wolbers (2005) suggests that adult learning is more frequent in countries in which the education system emphasises vocational training more strongly. Considering education:

(H4) Access to training is greater in countries with stronger public support for education.

The third general perspective on training refers to sociocultural factors. A culture of learning influences attitudes and motivations toward learning, and the rich, adult-learning culture in Nordic countries fosters participation (Rubenson and Desjardins 2009; Wolbers 2005). Education in older age is additionally affected by age culture and norms. Old-age stereotypes, though similar in their content, differ in magnitude across countries, creating lower or greater barriers to employer-sponsored training (Harper et al. 2006; Van Dalen et al. 2009). Continuous learning and intellectual activities also constitute a core element of the active ageing paradigm. In this perspective, LLL enables maintenance and improvement of quality of life, health, and wellbeing, fostering social activity and employment (Cedefop 2012; Narushima et al. 2018). Thus:

(H5) Access to training is greater in countries with a more proactive culture of ageing.

Methods

Data

Data came from the Survey of Health, Ageing, and Retirement in Europe (SHARE, Release 6.0). SHARE is a cross-national, longitudinal research program that collects data on nationally representative samples of adults aged 50 and older from 27 countries (Börsch-Supan et al. 2013). The present study is restricted to 12 counties that participated during waves 4 (2010/11), 5 (2013), and 6 (2015). We include only those respondents who were 50 years or older during wave 4 and who were interviewed during all three waves, resulting in a sample of 28 899 individuals (Table 1). There were no missing values for the control variables. In the final analysis, we included cases with a full information on training participation in all waves (95% of the sample = 27 370 observations).

Variables

For a dependent variable, we use a question that indicated attendance in educational or training courses during the last 12 months (0=no, 1=yes). The question was asked in the same form during waves 4 through 6 (a different question was used during waves 1 and 2, and wave 3 did not include a similar item).

Table 1. Descriptive statistics of control variables (for wave 6)

	Austria	Germany	Sweden	Spain	Italy	France	Denmark	Switzerland	Belgium	Czech Rep.	Slovenia	Estonia	Total
Female (%)	57.8	52.9	56.1	56.1	55.6	57.3	54.0	54.6	55.8	60.5	58.2	62.3	57.5
Age (at wave 4)	65.3	66.4	68.8	67.1	66.0	65.3	63.6	64.6	64.5	65.0	65.0	65.6	65.4
Education (%)													
Primary	24.4	11.1	41.5	83.1	70.8	41.8	15.6	19.2	40.2	45.7	33.6	29.1	39.1
Secondary	49.7	54.2	29.0	9.0	23.3	35.2	40.7	64.6	26.9	41.3	48.6	48.9	39.3
Tertiary	25.9	34.7	29.6	7.9	5.9	22.9	43.7	16.2	32.9	13.0	17.8	22.1	21.6
Employment pattern (%)													
Not working	74.1	67.9	67.0	69.1	73.4	68.5	46.0	51.1	64.1	73.8	78.1	56.5	65.5
Employed	12.7	14.2	14.5	10.3	11.7	15.5	31.2	28.3	17.8	12.0	10.8	20.4	16.7
Deactivation	8.7	11.4	13.2	7.5	5.7	9.4	11.8	11.2	8.5	8.5	5.7	11.1	9.3
Reactivation	0.6	0.8	0.7	1.1	1.0	0.8	1.3	2.4	0.5	1.1	0.4	2.4	1.2
Other	3.9	5.8	4.5	12.1	8.3	5.9	9.7	7.1	9.1	4.6	5.0	9.7	7.4
Total N	2,829	968	1,261	2,398	2,172	2,835	1,645	2,459	3,146	3,224	1,606	4,356	28,899

Note: Unweighted.
Source: SHARE data 2010-2015 (own estimates).

Control variables (Table 1) include gender, age, education (grouped into 3 categories according to ISCED levels: 0–2=primary, 3–4=secondary, and 5–6=tertiary), and employment pattern. The last variable was created based on employment during three waves and included five categories—not working (i.e., unemployed, retired, or inactive during all waves), continuously employed (i.e., employed or self-employed during each wave), deactivation (i.e., first working then retired/unemployed/inactive), reactivation (i.e., first retired/unemployed/inactive and then working), and other.

Analytical approach

We build a model from wave 6 with information regarding training trajectory included as a lagged dependent variable (LDV). This approach allows us to omit potential problems related to application of fully dynamic panel models with LDV (Keele and Kelly 2006; Wilkins 2017). To analyse path dependency and training accessibility, we estimate Hierarchical Bayes Logit Models (HBLM). HBLM is the Bayesian equivalent of multilevel or mixed-effects models. The general form of the model appears in Eq. 1. The dependent variable is the probability of participation in training during wave 6. Models include random intercepts (u_{0j}). Lags 1 (i.e., participation in training one wave before) and 2 (i.e., two waves before) of the dependent variable are included as predictors, with coefficient β_1 and a random slope u_{1j}, allowing it to vary across countries (in practice, LDV is included as a dummy variable but is not shown in Eq. 1). Random intercept and random slope were allowed to correlate (σ_{u01}). Models that estimated the effect of macro-level predictors (β_2) included a cross-level interaction of the macro-predictor and LDV (β_3), including a random slope for LDV simultaneously, as Heisig and Schaeffer (2019) recommend.

$$\text{logit}\{\Pr(\text{train}_{ij} = 1 | x_{ij}, u_{0j}, u_{1j})\} = \beta_0 + \beta_1 \text{lag}_{\text{train}_{ij}} + \beta_2 \text{macro}_j + \beta_3 \text{lag}_{\text{train}_{ij}} \times \text{macro}_j + \beta_n \text{contr}_{ij} + \\ + \left(u_{0j} + u_{1j}\text{lag}_{\text{train}_j}\right), \text{ for } i = 1, \ldots, \text{n};\ j = 1, \ldots, k \qquad \text{(Eq. 1)}$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim \text{N}(0, \Omega_u), \quad \Omega_u = \begin{bmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{bmatrix}$$

We use a Bayesian framework to fit this model for two reasons. First, a sample of k=12 countries is too small for modelling based on maximum likelihood (ML) and might lead to biased results (Bryan and Jenkins 2016; Maas and Hox 2005). In such cases, HBLM is recommended (Gelman and Hill 2007) due to use of priors and Markov Chain Monte Carlo (MCMC) sampling, which improve the reliability of estimates and allow for more in-depth diagnostics. MCMC iteratively samples parameter estimates, compares them to observed data, and updates the estimates. At the convergence point, an *a posteriori* distribution of all model parameters is given, meaning that each β has its own distribution with an average that corresponds to the standard logit model's coefficient. HBLM shrinks varying coefficients toward the grand mean, borrowing information from other clusters and providing more conservative and reliable estimates. Second, the non-linear model has a complex design with a multilevel structure, LDV with a random slope, and cross-level interaction. Contrary to HBLM, ML cannot handle this degree of complexity. Bayesian modelling is also superior versus the frequentist approaches regarding other aspects, such as validation of the model and flexibility during postestimation (McElreath 2016).

In the model, we use weakly informative, regularizing priors. For intercepts and coefficients, we use weekly informative normal (0, 10) priors that imply no strong expectations for the parameters' values but conservatively guard against overestimating associations between variables (Bürkner 2017; McElreath 2016). For the variance part, we use half-Cauchy priors (0, 1), which is a special case of t family priors that is most suitable for hierarchical models with a small number of groups (Bürkner 2017; Gelman 2006; McElreath 2016). With a broad peak in distribution at zero, Cauchy prior shifts group-level parameters towards the grand mean to reduced influence of outliers but allows for larger deviations in areas of high likelihood. This shrinkage ability supports more stable estimates for the true population parameter that we are most interested in this study. Simplified versions of models (e.g., without random slopes) produced nearly the same results both with ML and Bayesian frameworks (Supplementary Table A4). Estimation was conducted using MCMC sampling with the Hamiltonian Monte Carlo algorithm (4 chains with 4 000 iterations, 1 000 for warmup, and total post-warmup sample=12 000) using the brms package (Bürkner 2017) based on Stan computational framework (http://mc-stan.org/) in R ver. 3.5.1. All models converged with large effective posteriori sample sizes. Trace plots were inspected visually showing no signs of nonconvergence, and the $\hat{R}$ values equal to 1 suggesting proper chains convergence (Bürkner 2017)

In the results section, we present the mean and 95 percent credible intervals (CI) of the posterior distribution (a range in which the true parameter lies with a 95% probability). For interpretation and visualisation of the effects of predictors, especially in the case of interactions, we use predicted mean values of the response distribution (i.e., predicted probabilities). Assessment of model fit was conducted using WAIC and a median of Bayesian R^2 (Gelman et al. 2019; Vehtari et al. 2016). Lower values of WAIC indicate better fit. Bayesian R^2 is a posterior ratio of predicted variance and variance plus error variance, showing a data-based estimate of the proportion of variance explained by new data. To compare slopes of the interaction term, we use Cohen's (1988) measure of effect size and a corresponding Cohen's U_3 nonoverlap measure. The effect size, computed as $(\mu_1 - \mu_2)/\sqrt{(\sigma_1^2 + \sigma_2^2)/2}$ and adapted to the Bayesian framework (Kruschke 2012), measures the difference between mean values of two coefficients relative to the pooled variability of these coefficients. A greater value indicates a greater effect, with values higher than 1.6 corresponding to a nonoverlap value higher than 0.95. The nonoverlap measure informs about credibility of a difference between slopes (computed based on *a posteriori* samples of coefficients) as a share of scenarios in which slope A is larger than slope B.

Table 2. Categories of the lagged dependent variable

wave 4	wave 5	LDV category
No	No	LagA
Yes	No	LagB
No	Yes	LagC
Yes	Yes	LagD

Given three waves, there are four possible combinations of LDV (Table 2). The point of interest is the category LagA, which shows the probability of training during wave 6 after non-participation and represents the accessibility of training for new participants. Due to the random slope, the effect is country-specific.

Country-level predictors

To test hypotheses related to a macro-context, we selected four macro-predictors (Table 3). Degree of knowledge economy (H2) is represented by the Knowledge Economy Index (KEI), which indicates a country's overall degree of development regarding a knowledge economy. KEI was computed based on the World Bank's method (Chen and Dahlman 2006), which uses the degree of economic and institutional incentives for efficient use of human capital, education and human resources, innovation potential, and the quality of information and communication technologies infrastructure. The size of the welfare state (H3) is indicated by total social welfare expenditures as a percentage of GDP (SWE), comprising total social spending toward old age, survivors, incapacity-related benefits, health, family, active labour market programmes, unemployment, housing, and other social policies. Public support for education (H4) is represented by government expenditures on education as a percentage of GDP (EDU). As a measure of the culture of active ageing (H5), we use the Active Ageing Index (AAI), which measures the degree to which older people live independent lives and participate in paid employment and social activities, and their capacity to remain active into old age. It is calculated using 22 indicators grouped into four domains—employment, participation in society, independent living, and capacity for active ageing (AAI 2013). Detailed statistics for countries appear in Supplementary Table A1. Values for the macro-predictors are provided for years 2014-2015, to which the training question refers, or the closes possible time. Values of these indicators do not vary significantly over time, thus using alternative reference years provides similar results.

Table 3. Macro-level predictors

Hypothesis	Predictor	Code	Ref. year	Source	Values: min (L), average (M), max (H)
H2: Knowledge Economy	Knowledge Economy Index	KEI	2012	World Bank methodology (Chen and Dahlman, 2006); Retrieved from DICE database[1].	L=7.9 M=8.6 H=9.4
H3: Size of welfare state	Social welfare expenditure as a % of GDP	SWE	2015	OECD (2015) online database[2]	L =15.9 M=24.8 H =32.0
H4: Public support for education	Expenditure on education as a % of GDP	EDU	2014	World Bank online database (WB, 2014) [3]	L =5.1 M =5.5 H =7.7
H5: Culture of active ageing	Active Ageing Index	AAI	2014	DG EMPL & UNECE methodology (AAI, 2013). For UE countries retrieved from Active Ageing Index Portal[4]. For Switzerland calculated by the Swiss Federal Statistical Office (FSO, 2018).	L =29.8 M =36.6 H =44.9

[1] DICE Database "Knowledge Economy Index, 1995 - 2012". ifo Institute, Munich, 2013. Available online: www.cesifo-group.de/DICE/fb/ziuXgj7S.

[2] OECD (2015). The OECD Social Expenditure Database. Available online: www.stats.oecd.org.

[3] World Bank Open Database. Available online: www.data.worldbank.org.

[4] Active Ageing Index Portal. Available online: www.statswiki.unece.org/display/AAI/Active+Ageing+Index+Home

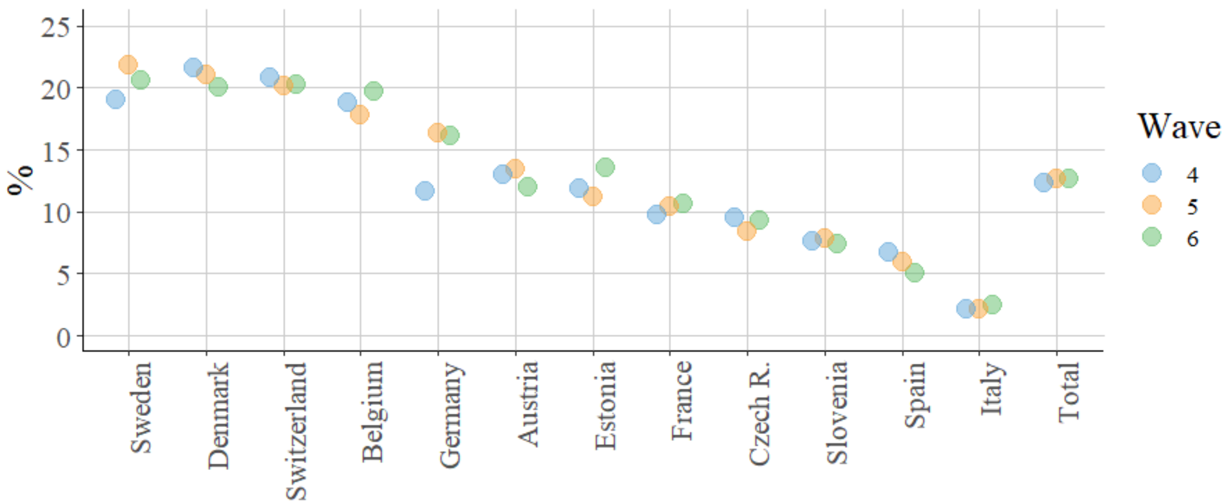
KEI correlates strongly with EDU and AAI at almost 0.8 (Supplementary Table A2). The correlation between EDU and AAI had a medium weight of 0.55, and correlations between SWE and other predictors were weak or close to zero. For comparisons between models, all macro-predictors were z-standardized (mean=0, SD=1).

Results

Descriptive overview

Average participation in training differed greatly among countries, ranging from ca. 20% in Sweden, Denmark, Switzerland, and Belgium to 2% in Italy (Figure 1), but participation across waves was stable within countries.

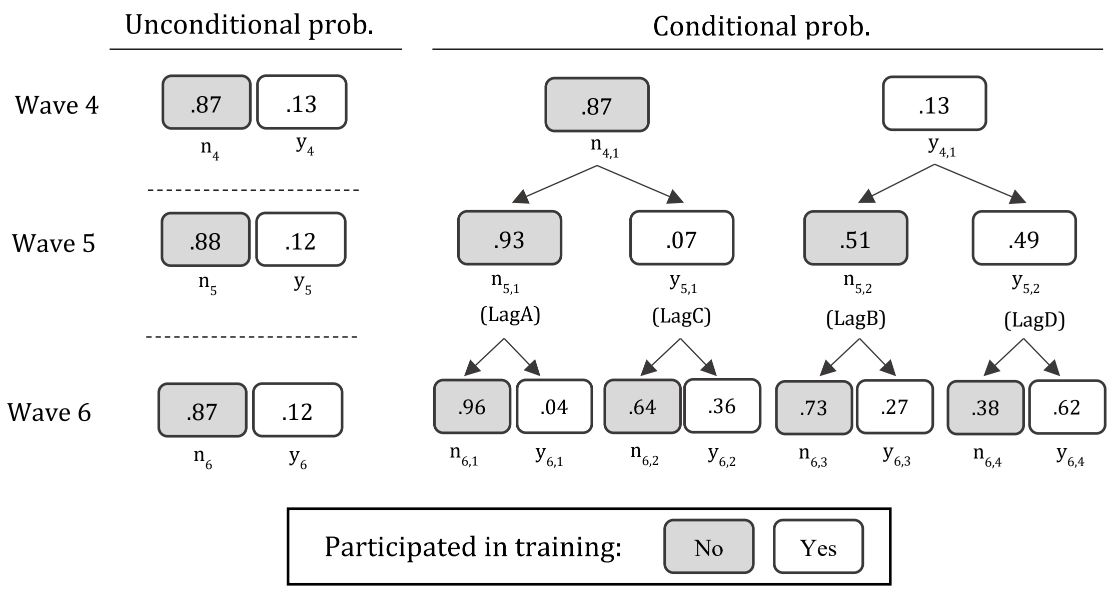
Figure 1. Participation in training by country and wave



Source: SHARE data 2010-2015 (own estimates).

General participation in the pooled sample was 12.5% during each wave. This unconditional probability of training can be compared with probabilities conditional on previous participation. Figure 2 shows the flow of individuals through categories of participation and non-participation during three waves. Unconditional and conditional probabilities of participation during wave 4 (y_4 and $y_{4,1}$) are the same, but those for wave 5 are different. Some who trained during wave 4 ($y_{4,1}$) also did so during wave 5 ($y_{5,2}$), but others did not ($n_{5,2}$). Diversification of patterns continued into wave 6, resulting in four conditional probabilities of training along four paths (LagA, LagB, LagC, and LagD), which ranged from 0.04 to 0.62.

Figure 2. Probability of training unconditional and conditional on previous participation



Notes: Based on frequencies calculated for individuals who participated in all three waves.
Source: SHARE data 2010-2015 (own estimates).

The scheme depicts expected path dependencies in the form of an increasing probability to remain on non-training (0.87 → 0.93→0.96) and training paths (0.13→0.49→0.62). Paths with training incidences in the past had a greater probability of further participation. For example, the conditional probability of training during wave 6 for those who did not train during wave 5 but did so during wave 4 was higher than the unconditional probability (0.27 versus 0.12). The probability of starting training (accessibility: $y_{6,1}$) was lower than the unconditional probability during wave 6 (0.04 against 0.12).

Path dependency

To obtain reliable estimates of control variables at the general and country levels, and predict conditional probabilities during wave 6, we estimate BHLM using Eq. 1, but without macro-predictors. Table 4 shows results for two models—M1 with LDV only and M2 with additional controls.

Table 4. Bayesian hierarchical logit models for the probability of training during wave 6

	Log-odds	CI [Q2.5; Q97.5]	OR	Log-odds	CI [Q2.5; Q97.5]	OR
Intercept	-1.07	[-1.26; -0.89]	0.34	-1.69	[-1.97; -1.41]	0.18
Lags of training (*Ref.: LagB*)						
LagA (accessibility)	-2.01	[-2.33; -1.71]	0.13	-1.58	[-1.85; -1.33]	0.21
LagC	0.41	[0.23; 0.58]	1.50	0.42	[0.24; 0.60]	1.53
LagD	1.42	[1.21; 1.60]	4.13	1.30	[1.09; 1.48]	3.67
Female	-	-	-	0.26	[0.17; 0.35]	1.29
Age (0=50 y.o.)	-	-	-	-0.32	[-0.40; -0.24]	0.73
Education (*Ref.: Primary*)	-	-	-			
Secondary	-	-	-	0.58	[0.45; 0.72]	1.79
Tertiary	-	-	-	1.11	[0.97; 1.24]	3.03
Employment pattern (*Ref=Not working*)	-	-	-			
Employed continuously	-	-	-	0.53	[0.39; 0.68]	1.70
Deactivation	-	-	-	0.04	[-0.12; 0.19]	1.04
Reactivation	-	-	-	0.25	[-0.11; 0.59]	1.28
Other	-	-	-	0.14	[-0.06; 0.34]	1.15
Variance part						
sd(Interecept)	0.24	[0.08; 0.46]	-	0.22	[0.07; 0.44]	-
sd(LagA)	0.47	[0.26; 0.78]	-	0.37	[0.18; 0.65]	-
sd(LagC)	0.11	[0.00; 0.32]	-	0.13	[0.01; 0.36]	-
sd(LagD)	0.18	[0.01; 0.43]	-	0.17	[0.01; 0.42]	-
cor(Intercept, LagA)	0.33	[-0.32; 0.85]	-	0.24	[-0.43; 0.82]	-
cor(Intercept, LagC)	0.08	[-0.76; 0.84]	-	0.17	[-0.70; 0.86]	-
cor(Intercept, LagD)	0.25	[-0.59; 0.88]	-	0.15	[-0.65; 0.84]	-
cor(LagA, LagC)	0.10	[-0.75; 0.84]	-	0.11	[-0.73; 0.83]	-
cor(LagA, LagD)	0.25	[-0.60; 0.85]	-	0.29	[-0.60; 0.88]	-
cor(LagC, LagD)	0.11	[-0.76; 0.86]	-	0.12	[-0.74; 0.85]	-
N	27370			27370		
WAIC	14646.3			13914.5		
Bayes R2 (median)	0.252			0.285		

Notes: OR – odds ratio. Effective sample sizes between: (M1) 4694—13214, (M2) 3926—25620.
Source: SHARE data 2010-2015 (own estimates).

Adding control variables to model M2 improved fit (WAIC decreased by 732, se=57.2). Females, on average, had a greater probability of training (OR=1.29), and the probability of training decreased with age (OR=0.73) and increased with education level ($OR_{secondary}$=1.79, $OR_{tertiary}$=3.03). Higher coefficients were also found for the employed group (OR=1.79) in comparison to the not-working group. Both models suggest path dependency in training participation (H1) since CI for LDV did not overlap with zero. Slopes for LDV from M2 (with control set to zero) in log-odds scale were: LagA=-3.27 [-3.62; -2.92], LagB=-1.69 [-1.97; -1.41], LagC=-1.27 [-1.57; -0.96], LagD= -0.39 [-0.70; -0.08]. All slopes differed with probability equal to 1. Effect sizes were large, between $\Delta_{LagA,LagB}$= 9.7 and

$\Delta_{LagA,LagD}$= 17.0. Interpretation of the effects of LDV is, however, easier when presented as probabilities (last row of Table 5). Probabilities conditional on LDV (estimated for observed values) differed from the unconditional probability of training during wave 6 (0.12). Accessibility of training for new participants (LagA) was only 0.05 [0.04;0.06]. People who trained before had higher chances of participating again (LagB=0.27 [0.23;0.32], LagC=0.36 [0.30;0.42]), with particularly high predicted probability for those who trained during waves 4 and 5 (LagD=0.62 [0.56;0.67]).

Table 5. Probability of training during wave 6 conditional on training during waves 4 and 5 by country

	LagA		LagB		LagC		LagD	
Austria	0.04	[0.04;0.05]	0.27	[0.23;0.31]	0.34	[0.28;0.40]	0.60	[0.55;0.66]
Belgium	0.07	[0.06;0.08]	0.30	[0.26;0.35]	0.42	[0.36;0.48]	0.68	[0.63;0.73]
Czech R.	0.04	[0.03;0.05]	0.24	[0.20;0.28]	0.34	[0.28;0.40]	0.57	[0.50;0.63]
Denmark	0.07	[0.06;0.09]	0.27	[0.23;0.32]	0.35	[0.28;0.41]	0.64	[0.59;0.70]
Estonia	0.04	[0.03;0.04]	0.27	[0.23;0.31]	0.35	[0.30;0.41]	0.63	[0.57;0.68]
France	0.05	[0.04;0.06]	0.27	[0.22;0.31]	0.33	[0.27;0.39]	0.56	[0.50;0.62]
Germany	0.05	[0.04;0.07]	0.28	[0.23;0.34]	0.40	[0.33;0.49]	0.63	[0.55;0.70]
Italy	0.02	[0.01;0.03]	0.18	[0.13;0.24]	0.27	[0.19;0.36]	0.47	[0.34;0.58]
Slovenia	0.04	[0.03;0.05]	0.22	[0.17;0.27]	0.30	[0.23;0.37]	0.55	[0.47;0.63]
Spain	0.02	[0.01;0.02]	0.19	[0.14;0.23]	0.24	[0.18;0.30]	0.48	[0.38;0.57]
Sweden	0.08	[0.06;0.10]	0.26	[0.22;0.31]	0.34	[0.28;0.41]	0.55	[0.48;0.62]
Switzerland	0.08	[0.06;0.09]	0.30	[0.26;0.35]	0.41	[0.35;0.47]	0.65	[0.60;0.70]
Total	0.05	[0.04;0.06]	0.27	[0.23;0.32]	0.36	[0.30;0.42]	0.62	[0.56;0.67]

Note: Prediction for the observed values based on Model 2 (Table 2). 95% CI in brackets.
Source: SHARE data 2010-2015 (own estimates).

Accessibility: differences between countries

Coefficients for LDV varied at the group level (i.e., SD for LDV differed from zero). In all countries, the pattern of conditional probabilities similarly increased from LagA to LagD (Table 5). Although the probability of LagA was low, it had the largest variance at the country level. For example, accessibility predicted for the observed values was highest in Sweden (0.08 [0.06;0.10]) and Switzerland (0.08 [0.06;0.09]), and lowest in Italy (0.02 [0.01;0.03]) and Spain (0.02 [0.01;0.02]). Since this is a probability model, predictions differ based on specification of controls. For example, when predicted for high-training groups, such as employed women, aged 50, and with tertiary education, differences in accessibility rose, ranging from 0.11 [0.08;0.15] in Italy to 0.34 [0.28;0.40] in Sweden.

To explain differences and test hypotheses H2–H5, we fit models with macro-level predictors included one at a time and their interaction with the LDV (allowing for random slopes of LDV). Selected results from four Bayesian hierarchical logit models appear in Table 6. Results are limited only to the interaction term (interpretation of control variables does not change in comparison to M2). Full model estimates appear in Supplementary Table A3.

Table 6. Bayesian hierarchical logit models for the probability of training during wave 6, including macro-level predictors. Only cross-level interaction-term shown: effects of macro-predictor at the levels of LDV

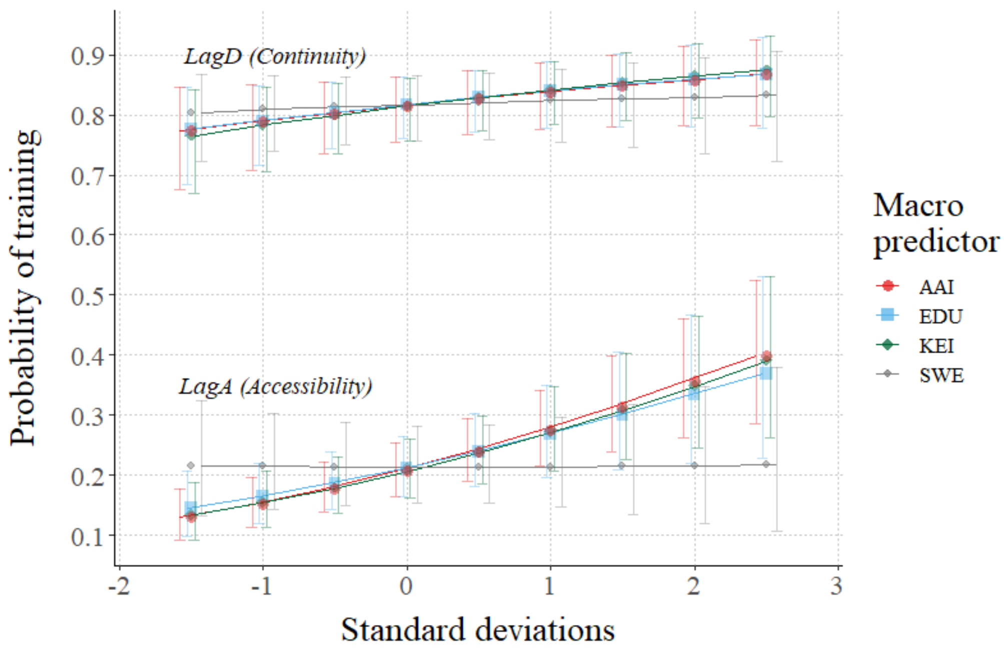
	(M3) **KEI**		(M4) **SWE**		(M5) **EDU**		(M6) **AAI**	
(A) Regression results (log-odds and 95% CI)								
Intercept for macro-predictor								
LagA	-3.24	[-3.52;-2.95]	-3.26	[-3.63;-2.90]	-3.25	[-3.56;-2.95]	-3.25	[-3.56;-2.95]
LagB	-1.67	[-1.94; -1.40]	-1.69	[-1.98; -1.41]	-1.68	[-1.96; -1.40]	-1.67	[-1.96; -1.40]
LagC	-1.26	[-1.55;-0.96]	-1.27	[-1.58;-0.97]	-1.25	[-1.56;-0.95]	-1.25	[-1.56;-0.95]
LagD	-0.38	[-0.69;-0.09]	-0.37	[-0.69;-0.07]	-0.39	[-0.71;-0.09]	-0.39	[-0.71;-0.09]
Slopes for macro-predictor								
LagA	0.36	[0.15;0.57]	0.00	[-0.33;0.33]	0.31	[0.07;0.56]	0.38	[020.;0.56]
LagB	0.07	[-0.12; 0.26]	-0.04	[-0.24; 0.14]	0.03	[-0.17; 0.23]	0.07	[-0.10; 0.25]
LagC	0.15	[-0.07;0.38]	-0.09	[-0.31;0.13]	0.01	[-0.22;0.25]	0.19	[-0.02;0.40]
LagD	0.20	[-0.01;0.42]	-0.05	[-0.17;0.27]	0.17	[-0.06;0.39]	0.17	[-0.05;0.39]
(B) Effects for slopes of LDV								
Probability of the difference between slopes (nonoverlap)								
$\Delta_{AB}>0$	0.99		0.63		1.00		1.00	
$\Delta_{AC}>0$	0.96		0.75		0.99		0.96	
$\Delta_{AD}>0$	0.92		0.67		0.90		0.98	
Effect size of the difference between slopes								
Δ_{AB}	2.92		0.31		2.54		3.48	
Δ_{AC}	1.93		0.63		2.50		1.92	
Δ_{AD}	1.51		0.40		1.23		2.07	
N	27370		27370		27370		27370	
WAIC	13917.8		13915.6		13914.0		13914.7	
Bayes R2 (median)	0.29		0.29		0.29		0.29	

Note: All models additionally control for gender, age, education and employment pattern and are clustered by country with a random slope for LDV. Effective sample sizes for presented coefficients between: (M3) 5505—9398, (M4) 5428— 12614, (M5) 5821— 10149, (M6) 4715— 8506. Estimated in part B based on posteriori samples of coefficients (n=12.000).
Source: SHARE data 2010-2015 (own estimates).

Part A of Table 6 shows intercepts (i.e., main effects) and slopes (i.e., interaction effects) of macro-predictors for the four categories of LDV (with control set to zero). The intercepts of the macro-predictors were similar in all models and represent the difference in the average probability of training (as shown before in Table 5)—the lowest for LagA and highest for LagD. The slopes of the macro-predictors serve to verify H2–H5. To test the hypothesis that accessibility is greater in countries with a higher value for the macro-variable, the slope should be steeper for LagA than for other lags. LagA increases with KEI, EDU, and AAI, with a similar strength between 0.31 and 0.38. These values were higher than for other lags, with the largest difference for LagB. Values for LagD were between 0.17 and 0.20. In the case of SWE, all slopes close to zero.

Part B of Table 6 shows the probability that a slope for LagA is steeper than for other lags (nonoverlap measure, values close to 1 indicate credible results) and corresponding effect sizes (a higher value indicates a higher effect, with values > 1.6 corresponding with a nonoverlap value >0.95). The slope for LagA was steeper than those for other lags in M6 (where all differences were statistically robust at the level >0.95), and for M3 and M5 (where the differences were slightly smaller and the probability that LagA is larger than LagD is only 0.92 and 0.90, respectively). In the case of M4, the probability that the slopes differed was too low to be credible at the level of 0.90. Effect sizes were strongest for AAI and slightly lower for KEI and EDU. However, the differences in corresponding estimates between models are small and it is impossible to conclude whether any of the macro-predictors had a stronger effect (e.g., the probability that the effect size for Δ_{AD} was higher for AAI=2.07 than EDU=1.23 is only 0.74).

Figure 3. Predicted accessibility of training for different levels of macro-level predictors



Note: For readability, lines for LagB and LagC are not shown. They would be located between LagD and LagA. Predicted probability for employed females with higher education, aged 50.

Source: SHARE data 2010-2015 (own estimates).

Results are shown in Figure 3 as a predicted probability of training. The cross-level interaction is visualised by the difference in the gradient of change between the lower set of lines that represents accessibility (LagA) and the upper set that represents the probability of continued training (LagD). The probability of training increased, on average, with values for KEI, EDU, and AAI both for LagA and LagD, but the increase was credibly higher for slopes of LagA. Consequently, these macro-predictors related positively to training accessibility, supporting H2, H4, and H5. No such relationship was observed for SWE, for which both lines were nearly parallel and the entire interaction term was invalid, thus not supporting H3.

As a robustness check, we tested alternative specifications of HBLM models. Results were stable across specifications of priors (e.g., cauchy [0, 5] and half-student-t [4, 0, 1] for the variance part). Adding random slopes for control variables produced nearly the same results. Following other studies (Green and Janmaat 2011; Riddell and Weedon 2012), we used alternative macro-predictors, such as employment rate of people aged 50–74, socioeconomic inequalities, expenditures on education as a portion of public expenditures, GDP per capita, and GDP growth 2010–2015 (Supplementary Table A5). KEI, SWE, EDU, and AAI were chosen because they were reliable, were grounded in the theoretical framework, and provided clearest interpretation.

Conclusions

Low training attendance of older people is a prominent challenge for EU policies, and many countries have dedicated strategic programs to improve it, though efficiency of the measures is disputable. We assess path-dependency and accessibility of training to provide a new perspective on LLL in older age. The literature offers some insights into factors that shape differences in training attendance across countries, such as demand for human capital and characteristics of welfare regimes (Riddell and Weedon 2012; Roosmaa and Saar 2010; Saar and Räis 2017). Cross-sectional data cannot reveal, however, dynamics at the individual level and how LLL-related inequalities are shaped over time. This study takes a lifecourse approach, treating lifelong learning literally as a process that occurs longitudinally. Based on three waves of SHARE panel data for a population 50+ in twelve European countries, we trace individual trajectories of training and analyse them in terms of conditionality on previous attendance, continuity, and accessibility.

We start by analysing patterns of training from a longitudinal perspective. During each wave, about 12.5% of the population declared participation in training during the previous 12 months. Although differences across countries were large, the attendance rate was stable across waves for each country. When we switch from a cross-sectional to longitudinal perspective, we find that dynamics at the individual level are considerable. Results support the hypothesis that training participation is path-dependent. On the one hand, previous participation strongly improves the chances of further participation, which means that once they start learning, people are much more inclined to continue. On the other hand, the probability of starting training after non-participation (accessibility) is much lower than the average unconditional probability. Generally, the average probability that a person who did not attend training during waves 4 and 5 will train during wave 6 was only 5%, less than half of the average probability of training (12%). The likelihood of training was much higher for people who trained during a previous wave (between 27% and 36%), especially for those who trained during both waves (62%).

As expected (H1), we observe path dependency in training participation, which suggests that previous biography and decisions have a causal impact on future events (Bernardi et al. 2018; Liebowitz and Margolis 1995). Dependency develops primarily through accumulation with risk clustering and chains of risks with additive effect (Ben-Schlomo and Kuh 2002; Kuh et al. 2003). Both these mechanisms are established on factors that shape propensity and opportunities for training participation (Hansson 2008; Lazazzara et al. 2013; Pak et al. 2018; Zwick 2012), which might be stable over time (e.g., education, learning abilities, and company training policy) or can be reinforced by previous participation (e.g., motivation, specific human capital, employers' recognition of learning potential). What is surprising, and what provides an original contribution to LLL research is that the strength of path dependency differs across countries. In Spain and Italy, participation is selective, is strongly conditioned by past activity, and its barriers are stronger than in Sweden, Switzerland, and Belgium. We test whether these differences relate to the degree of macro-characteristics, such as development of knowledge economy, size of the welfare state, public support for education, and active ageing culture. We test cross-level interactions between each of the macro-level predictors and LDV using Bayesian hierarchical modelling. The most important was the interaction with the category of people who have not trained before (i.e., accessibility), which suggests that the macro-context correlates with the openness of a training system. Path dependency can be responsible for "locking-in" the pathway making it difficult for an individual to escape from the progressing chain of risks (Liebowitz and Margolis 1995). Such a lifecourse stagnation (Bernardi et al. 2018) can affect individual development by limiting opportunities and individual potential for participation in training. Accessibility, in this perspective, indicates the potential for breaking down the path dependency. As we have found, the level of accessibility is related to contextual factors. An interaction in cases of Knowledge Economy Index, Expenditure on education, and Active Ageing Index shows that with an increase of the macro-predictors, path dependency is lower and access to training is higher. In the case of SEW, there were no interactions, and the predictor did not correlate with path dependency.

Results support H2, that training accessibility is greater in countries with a stronger knowledge economy. European economies are increasingly based on human capital, and LLL is a necessary tool to increase economic progress and competitiveness (Descy and Tessaring 2005). Combined with a progressive economy, technological changes, and increasing competitiveness, both employers and employees are increasingly encouraged to invest in skills and knowledge (Hanushek and Kimko 2000). Results from the current study suggest that stronger and more innovative economies provide greater opportunities to train in older age. Access to training is, however, only one side to the challenge of efficient investment in human capital. Any such attempts must be accompanied by proper conditions that ensure not only the possibility and comfort of training, but a realistic perspective to use acquired skills and knowledge at work (Armstrong-Stassen and Schlosser 2008; Zwick 2012). Equilibrium between opportunities to both improve human capital and use it is crucial to development of a knowledge economy.

Another perspective that frames the hypothesis is a structural approach oriented toward a welfare state and public policies, and their ability to remove barriers to participation (Rubenson and Desjardins 2009). One recommendation for future research is that the size of a welfare state is unrelated to training accessibility, as H3 suggests. A measure that combines expenditures in very disparate areas, such as social protection and pro-active policies, is too general to account for mechanisms that drive educational attainment. This might also be true in cases of general typologies of welfare regimes used in many studies of LLL (Green 2006; Rubenson 2006; Rubenson and Desjardins 2009; Verdier 2013). Only part of a welfare state—the weight ascribed to education—appears to be a relevant indicator of training behaviours that correlates positively with access to training (H4). This result should be considered in relation to policies that address socioeconomic inequalities. Larger investments in education indicate that a state is increasing emphasis on social cohesion (Putnam 2004), but cohesion cannot be achieved if a training system is closed. Availability of opportunities for education, especially for people who did not attend it previously, constitutes the fundament of an efficient cohesion approach. Low accessibility and strong accumulation of training may be one reason LLL policies fail, since they do not reach the target population. This conclusion corroborates other studies that suggest that a reduction of social inequalities through LLL policies is impossible unless LLL is more accessible to groups that are less likely to participate (Kilpi-Jakonen et al. 2015; Picchio and van Ours 2013; Roosmaa and Saar 2010). LLL is a tool of stratification; it shapes individual life trajectories and affects socioeconomic structure, stimulating growth if there is a strong path dependency and decreasing inequalities if participation is more accessible. Additionally, improvements to accessibility relate directly to average participation rates. Countries with high training attendance, such as Sweden, Denmark, Belgium, and Switzerland, are characterised by greater accessibility and lower conditionality of participation. Countries with low training attendance, such as Italy and Spain, have lower accessibility. Policy programmes related to LLL often use average training rates as target indicators to measure efficiency of public interventions. This study supports the argument that the way to increase participation leads through increasing access to training (Roosmaa and Saar 2010).

Training accessibility is greater in countries with proactive ageing cultures, supporting H5. Cultures of old age, age roles, norms, and stereotypes affect attitudes toward learning in older age (Rubenson and Desjardins 2009; Wolbers 2005). Countries such as Sweden and Switzerland have excessively proactive cultures of old age, with strong emphasis on education. Recognition of LLL's role in successful ageing creates a foundation for active attitudes of individuals (Withnall 2010). Employers' decisions regarding training are also affected by old-age norms and culture-based expectations (Posthuma and Campion 2009). Results from the current study corroborate the argument that access to training in older age is a necessary condition for active ageing.

This study has a few limitations. Effects of macro-predictors should not be interpreted causally. As contextual factors, they reflect economic, structural, and socio-cultural mechanisms, and interpretation should be embedded in a theoretical framework. Due to model complexity, we cannot include all macro-factors in a single model, separating effects. Data from 12 countries is also insufficient for drawing causal conclusions but contrary to the frequentist approach, Bayesian modelling provides reliable estimates of models with one macro-predictor. This study is based on three panel waves, and thus we cannot control for earlier training behaviours. Similarly, we cannot control for what individuals anticipate in the future, e.g. expected retirement age, what could affect their current training behaviours (Bernardi et al. 2018). SHARE data is only for the population of 50+, and since this is the first study of path dependency in training, we can hypothesise only whether similar patterns would occur for younger groups. The analysis of access to training are limited to the structural barriers, omitting individual dispositions for participation (Froehlich et al. 2015; Zwick 2012) and organisation-level factors, such as organisational culture or age management policies (Armstrong-Stassen and Schlosser 2008; Pak et al. 2018). Analyses covered the period 2010–2015, when most European countries were experiencing economic slowdowns that likely resulted in reduction to investment in human capital, especially among older generations (EC 2013; Munnell and Rutledge 2013).

Despite these limitations, this study provides novel insights into the nature of LLL in older age. Accumulation of advantages and disadvantages shapes development of socio-economic structures and stimulates divergence in which initial differences enlarge over time (Crystal and Shea 1990; O'Rand 1996; Ferraro et al. 2009; Dannefer 2003). The roles of these mechanisms are magnified by an ageing population; increasing lifespans and longer working careers provide more time for accumulation-driven inequalities to develop, both within older generations and between younger and older cohorts. Consequently, the role of investments in adult education increases. LLL is not merely an effect of accumulated lifecourse inequalities, but a tool for their further development. Strong path dependency and low access to training might only petrify or reinforce socioeconomic disparities, having a more profound influence on the lives of older people. If we want active, productive, and more equal societies, LLL policies must be efficient at encouraging participation of disadvantaged individuals, especially those in older age. We argue that policies that address lifecourse developments should include a lifecourse perspective. Only then can potential path dependencies be broken by adequate measures.

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[to be placed here – deleted for the review process]

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Appendix

Table A1. Statistics of macro-predictors for countries

	KEI[1]	SWE[2]	EDU[3]	AAI[4]
Austria	8.6	27.7	5.4	34.1
Germany	8.9	24.9	4.9	37.4
Sweden	9.4	26.3	7.7	44.9
Spain	8.4	24.7	4.3	32.6
Italy	7.9	28.5	4.1	34.0
France	8.2	32.0	5.5	35.8
Denmark	9.2	29.0	7.6	40.3
Switzerland	8.9	15.9	5.1	44.0
Belgium	8.7	29.2	6.6	37.7
Czech Republic	8.1	19.4	4.0	34.4
Slovenia	8.0	22.6	5.3	29.8
Estonia	8.4	17.7	5.5	34.6
Avarage	8.6	24.8	5.5	36.6
SD	0.5	4.8	1.2	4.4

Source:

[1] DICE Database "Knowledge Economy Index, 1995 - 2012". ifo Institute, Munich, 2013. Available online: www.cesifo-group.de/DICE/fb/ziuXgj7S.

[2] OECD (2015). The OECD Social Expenditure Database. Available online: www.stats.oecd.org.

[3] World Bank Open Database. Available online: www.data.worldbank.org.

[4] Active Ageing Index Portal. Available online: www.statswiki.unece.org/display/AAI/Active+Ageing+Index+Home

Table A2. Correlation between macro-predictors

	KEI	SWE	EDU	AAI
		correlation		
KEI	1			
SWE	0.06	1		
EDU	0.77	0.35	1	
AAI	0.84	-0.06	0.61	1

Source: own estimates.

Table A3. Bayesian hierarchical logit models for the probability of training during wave 6, including macro-level predictors. Full model (log-odds and 95% CI in brackets)

	(M3) **KEI**		(M4) **SWE**		(M5) **EDU**		(M6) **AAI**	
Intercept	-1.67	[-1.94; -1.40]	-1.69	[-1.98; -1.41]	-1.68	[-1.96; -1.9]	-1.67	[-1.95; -1.40]
Lags of training (main ef.) (*Ref.: LagB*)								
LagA	-1.57	[-1.77;-1.38]	-1.57	[-1.85; -1.31]	-1.58	[-1.79;-1.38]	-1.58	[-1.76;-1.41]
LagC	0.41	[0.22; 0.60]	0.42	[0.24; 0.60]	0.42	[0.24; 0.60]	0.41	[0.22; 0.60]
LagD	1.29	[1.09; 1.47]	1.32	[1.12; 1.50]	1.28	[1.09; 1.46]	1.28	[1.08; 1.47]
Macro (main ef.)	0.07	[-0.12; 0.26]	-0.04	[-0.24; 0.14]	0.03	[-0.17; 0.23]	0.07	[-0.10; 0.25]
Macro#Lag (interact.)								
Macro#LagA	0.29	[0.08; 0.51]	0.04	[-0.24; 0.32]	0.28	[0.07; 0.51]	0.31	[0.13; 0.49]
Macro#LagC	0.08	[-0.13; 0.30]	-0.05	[-0.21; 0.12]	-0.02	[-0.21; 0.19]	0.12	[-0.07; 0.32]
Macro#LagD	0.13	[-0.09; 0.35]	0.1	[-0.08; 0.26]	0.14	[-0.06; 0.34]	0.10	[-0.10; 0.31]
Female	0.26	[0.17; 0.35]	0.26	[0.17; 0.35]	0.26	[0.17; 0.35]	0.26	[0.17; 0.35]
Age (0=50 y.o.)	-0.33	[-0.41; -0.25]	-0.32	[-0.4; -0.25]	-0.32	[-0.40; -0.25]	-0.33	[-0.40; -0.25]
Education (*Ref.: Primary*)								
Secondary	0.58	[0.45; 0.72]	0.58	[0.45; 0.72]	0.58	[0.45; 0.71]	0.59	[0.46; 0.72]
Tertiary	1.10	[0.97; 1.25]	1.11	[0.97; 1.25]	1.1	[0.97; 1.24]	1.11	[0.98; 1.25]
Employment pattern (*Ref=Not working*)								
Employed continuously	0.52	[0.38; 0.67]	0.53	[0.38; 0.67]	0.53	[0.39; 0.67]	0.52	[0.38; 0.66]
Deactivation	0.03	[-0.12; 0.19]	0.04	[-0.12; 0.19]	0.04	[-0.12; 0.19]	0.03	[-0.12; 0.19]
Reactivation	0.24	[-0.12; 0.57]	0.24	[-0.11; 0.59]	0.25	[-0.10; 0.59]	0.23	[-0.13; 0.57]
Other	0.13	[-0.07; 0.33]	0.14	[-0.05; 0.34]	0.14	[-0.06; 0.33]	0.13	[-0.07; 0.33]
Variance part								
sd(Interecept)	0.19	[0.05; 0.38]	0.25	[0.08; 0.48]	0.23	[0.08; 0.46]	0.19	[0.05; 0.39]
sd(LagA)	0.22	[0.04; 0.47]	0.39	[0.18; 0.71]	0.24	[0.08; 0.47]	0.16	[0.01; 0.39]
sd(LagC)	0.14	[0.01; 0.39]	0.13	[0.01; 0.36]	0.13	[0.01; 0.36]	0.15	[0.01; 0.40]
sd(LagD)	0.16	[0.01; 0.41]	0.14	[0.01; 0.40]	0.14	[0.01; 0.39]	0.17	[0.01; 0.43]
N	27370		27370		27370		27370	
WAIC	13917.8		13915.6		13914.0		13914.7	
Bayes R^2 (median)	0.29		0.29		0.29		0.29	

Note: Correlations in the variance part not shown. Effective sample sizes between: (M3) 3176—17829, (M4) 4458—23132, (M5) 4327—19849, (M6) 2352—17581.

Source: SHARE data 2010-2015 (own estimates).

Table A4. Comparison of Bayesian models presented in the article with simplified versions estimated with Maximum Likelihood.

	Model with lags and controls			Model with lags, controls and macro-predictor (AAI)		
	B1	ML1a	ML1b	B2	ML2a	ML2b
Specification:	B; RS+	ML; RS–	ML; RS+ ; Unreliable	B; RS+; Inter +	ML; RS–; Inter–	ML; RS+; Inter+; Unreliable
Intercept	-1.69 ***	-1.76 ***	-1.67 ***	-1.67 ***	-1.74 ***	-1.66 ***
Lags of training (*Ref.: LagB*)						
LagA	-1.58 ***	-1.51 ***	-1.59 ***	-1.58 ***	-1.51 ***	-1.58 ***
LagC	0.42 ***	0.44 ***	0.40 ***	0.41 ***	0.44 ***	0.41 ***
LagD	1.30 ***	1.32 ***	1.27 ***	1.29 ***	1.32 ***	1.26 ***
Female	0.26 ***	0.26 ***	0.26 ***	0.26 ***	0.26 ***	0.26 ***
Age (0=50 y.o.)	-0.32 ***	-0.32 ***	-0.32 ***	-0.33 ***	-0.32 ***	-0.33 ***
Education (*Ref.: Primary*)						
Secondary	0.58 ***	0.60 ***	0.58 ***	0.58 ***	0.60 ***	0.59 ***
Tertiary	1.11 ***	1.13 ***	1.10 ***	1.11 ***	1.13 ***	1.11 ***
Employment pattern (*Ref=Not working*)						
Employed continuously	0.53 ***	0.54 ***	0.53 ***	0.52 ***	0.53 ***	0.52 ***
Deactivation	0.04 ***	0.05	0.04	0.03 ***	0.04	0.03
Reactivation	0.25 ***	0.26	0.25	0.23 ***	0.24	0.23
Other	0.14 ***	0.15	0.14	0.13 ***	0.14	0.13
Macro (main ef.) [AAI]	-	-	-	0.06 ***	0.24 ***	0.23 ***
Macro#LagA	-	-	-	0.31 ***	-	-
Macro#LagC	-	-	-	0.12 ***	-	-
Macro#LagD	-	-	-	0.10 ***	-	-
Variance part						
sd(Interecept)	0.22	0.30	0.41	0.23	0.24	0.14
sd(LagA)	0.37	-	0.35	0.24	-	0.33
sd(LagC)	0.13	-	0.27	0.13	-	0.16
sd(LagD)	0.17	-	0.22	0.14	-	0.16
N	27370	27370	27370	27370	27370	27370

Notes: Only model with AAI presented as an example. * p<0.05 ** p<0.01 *** p<0.001

Specification of the model: Estimation method: Bayesian (*B*), Maximum Likelihood (*ML*). Random slopes for lags: included (*RS*+), not included (*RS*–). Cross-level interaction between macro-predictor and LDV: included (*Inter*+), not included (*Inter*–).

Unreliable - model does not converge. Results shown for a model estimated with a simpler method of optimization (lme4 option "nAGQ"=0), which does not guarantee correct results.

Table A5. Alternative macro variables: Bayesian hierarchical logit models for the probability of training during wave 6, including macro-level predictors. Only cross-level interaction-term shown: effects of macro-predictor at the levels of LDV

	MA1		MA2		MA3		MA4		MA5		MA6	
	Empl.rate 50-74		**Gini**		**EDU_publ**		**GDPpcap**		**GDP 10-15**		**AAI 2016**	
(A) Regression results (log-odds and 95% CI)												
Intercept for macro-predictor												
LagA	-3.25	[-3.58; -2.92]	-3.27	[-3.61; -2.93]	-3.26	[-3.57; -2.95]	-3.26	[-3.58; -2.95]	-3.26	[-3.61; -2.9]	-3.32	[-3.6; -3.04]
LagB	-1.67	[-1.96; -1.40]	-1.70	[-1.98; -1.42]	-1.67	[-1.95; -1.40]	-1.68	[-1.97; -1.40]	-1.68	[-1.97; -1.41]	-1.71	[-2,0; -1.41]
LagC	-1.26	[-1.56; -0.96]	-1.27	[-1.58; -0.96]	-1.26	[-1.56; -0.96]	-1.27	[-1.57; -0.96]	-1.26	[-1.58; -0.97]	-1.32	[-1.64; -1,0]
LagD	-0.37	[-0.68; -0.07]	-0.39	[-0.70; -0.09]	-0.38	[-0.69; -0.07]	-0.39	[-0.70; -0.09]	-0.37	[-0.70; -0.06]	-0.43	[-0.76; -0.1]
Slopes for macro-predictor												
LagA	0.25	[-0.03; 0.53]	-0.24	[-0.53; 0.05]	0.33	[0.10; 0.57]	0.31	[0.06; 0.55]	0.20	[-0.10; 0.51]	0.37	[0.18; 0.56]
LagB	0.07	[-0.11; 0.27]	-0.01	[-0.21; 0.19]	0.08	[-0.10; 0.27]	0.05	[-0.12; 0.23]	0.09	[-0.10; 0.30]	0.03	[-0.17; 0.24]
LagC	0.15	[-0.08; 0.38]	-0.06	[-0.30; 0.18]	0.12	[-0.09; 0.35]	0.15	[-0.06; 0.36]	0.11	[-0.12; 0.36]	0.09	[-0.14; 0.33]
LagD	0.07	[-0.15; 0.32]	-0.18	[-0.41; 0.05]	0.12	[-0.10; 0.37]	0.17	[-0.03; 0.39]	0.07	[-0.16; 0.33]	0.14	[-0.10; 0.40]
(B) Effects for slopes of LDV												
Probability of the difference between slopes (nonoverlap)												
$\Delta_{AB}>0$	0.93		0.97		0.99		0.99		0.79		1.00	
$\Delta_{AC}>0$	0.79		0.91		0.95		0.93		0.72		0.99	
$\Delta_{AD}>0$	0.93		0.69		0.96		0.90		0.83		0.98	
Effect size of the difference between slopes												
Δ_{AB}	1.57		1.84		2.30		2.41		0.83		3.43	
Δ_{AC}	0.83		1.33		1.75		1.41		0.61		2.60	
Δ_{AD}	1.44		0.47		1.70		1.19		0.93		2.08	
N	27370		27370		27370		27370		27370		24964	

Note: All models additionally control for gender, age, education and employment pattern and are clustered by country with a random slope for LDV. For interpretation see description of Table 6 in the article.
Empl. rate 50-74 - Employment rate for group aged 50-74 (2015). Gini – Gini coefficient, measure of socioeconomic inequalities (2015). EDU_publ – Expenditures on education as a portion of public expenditures (2014). GDPpcap - GDP per capita (2015). GDP 10-15 - GDP growth 2010–2015. AAI 2016 – Active Ageing Index 2016 (without Switzerland).
Source: SHARE data 2010-2015 (own estimates).