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Empirical Article

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Gender and Educational Inequalities in Extending Working Lives: Late-Life Employment Trajectories Across Three Decades in Seven Countries

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Abstract

Public policies encourage later retirement, but they often do not account for discrepancies in the capacity for extending working lives. This paper studies trends and inequalities in extending working lives between 1990 and 2019 from gender and education perspectives in seven countries (Australia, Germany, Russia, South Korea, Switzerland, United Kingdom, and United States). The three-decade-long data provide insights into the societal transition toward extended employment that began in the mid-1990s. Using latent class growth analysis, we identify five universal trajectories representing late-life employment in all countries: Early, Standard and Late Exit patterns, and stable Nonemployment and Late Employment patterns. Regression analyses show that Non-Employment dominated the 1990s, but it significantly declined, giving space to Late Employment as one of the major employment pathways. Gender and educational differences are considerable and stable and constitute important stratification markers of late careers. Progress toward later employment affects all analyzed countries but in different ways, suggesting the simple generalizations of one-country findings can be risky. We discuss the risks of universal progress toward extending employment that can bring unequal results and negative consequences for vulnerable groups. This study also contributes methodologically by exploring the trajectory-oriented perspective on late careers.

Keywords: comparative study, employment trajectories, growth model, older workers, retirement

INTRODUCTION

The last 30 years have brought unprecedented changes to how older people work and retire. Since the 1990s, the dominant paradigm in aging policies began to evolve from an early-exit orientation toward later retirement (Han & Moen, 1999; Ebbinghaus & Hofäcker, 2013). Extending working lives, that is, remaining in the workforce until or beyond the official pension age, became the major response to the challenges of population aging, diminishing labor supplies, and increasing costs of pension systems. Restricting early retirement options and increasing retirement ages strongly contributed to extending working lives (Boissonneault et al., 2020). For example, between 1995 and 2018, the OECD-average labor force participation for the group aged 55–64 increased from 48.7 to 63.9, and the average exit age increased from 62.4 to 64.6 (OECD, 2019). The progress toward extending working lives appears inevitable for all developed countries but carries a risk of deepening existing socioeconomic inequalities (Carr, 2019; Fasang, 2012). Recent reforms fail to provide sufficient and equal opportunities to reach later retirement ages (Krekula & Vickerstaff, 2020; Ní Léime & Street, 2016). They mostly have a "one size fits all" character and pay little attention to discrepancies in the potential to extend working lives, e.g., between low- and high-educated or men and women. People who are unable to work longer can be drawn into states of poverty and exclusion, others can be forced to work longer than they envisaged or preferred. To understand the consequences of the transition towards "actively aging" societies, we must recognize the heterogeneity of older peoples' situations and consider inequalities caused by these developments.

In this research, we study trends in extending working lives over the last three decades in a comparative perspective and ask three general research questions. First, which late-life employment trajectories can be found in contemporary societies, and what are the differences and similarities across countries? Second, does the prevalence of trajectories change over time; in particular, what trends contributed most to the increase in average exit ages? Third, to what extent are late-life employment trajectories stratified by gender and education, and have such differentials changed over time? To answer these questions, we apply latent class growth analysis to identify employment trajectories between ages 60 and 69 in the period from 1990 to 2019. In particular, we focus on people who continue work until later ages and compare them with those who exit early and remain inactive through their 60s. We use latent class regression models to analyze time trends and differences by gender and education in the prevalence of late-life employment trajectories. Finally, using a multiple group analysis, we compare the developments between countries to assess if trends are universal or country-specific. This research requires panel data covering long life spans of late careers for several cohorts and a comparative perspective. Such a unique dataset is provided by the Comparative Panel File (CPF), an initiative that harmonizes the world's largest and longest-running household panel studies from seven countries (Turek et al., 2021): Australia, Germany, the United Kingdom, South Korea (henceforth Korea), Russia, and the United States.

This paper contributes to the literature in three ways. First, we add to the long tradition of sociological research on stratification and inequality (Carr, 2019; Rothman, 2016) by applying the "inequality lens" to study recent developments in late-life employment. A large body of research suggests that later careers and retirement processes become more dynamic, diverse, and unpredictable (Brückner & Mayer, 2005; Calvo et al., 2018; Henretta, 1992; Shultz & Olson, 2012). However, the mixed and limited empirical evidence does not permit evaluating how strong and unequal these trends are (Fasang, 2012; Macmillan, 2005; Maestas, 2010; Riekhoff, 2016). To address a concern that the progress toward extended employment can drive the development of inequalities, this study considers the mechanics and societal consequences of these changes. Drawing upon the life course perspective, we look at older people's employment patterns as structured in ways that reproduce life course advantages and disadvantages (Dannefer, 1987; Ferraro et al., 2009; O'Rand & Henretta, 1999). We focus on two central dimensions that stratify life-course developments and occupational careers from young until older ages, i.e., education and gender (Fisher et al., 2016; Visser et al., 2016; Radl, 2013). Education has emerged as the key source of inequality in a wide range of domains, including fertility, health and mortality, employment and income, political and cultural values, lifestyles, and networks and relationships (Lutz & Samir, 2011; Rothman, 2016). Gender strongly differentiates late-life employment and exit transitions, despite older women's increasing presence in the workforce in the last decades (Moen et al., 2016; Noone et al., 2010).We argue that discrepancies in life-course pathways can produce unequal potentials and opportunities to extend working lives that are fundamental to understanding the changing situation of older generations.

As the second principal contribution, the historical perspective offers original descriptive and practical insights into the societal transition toward extended employment. The historical strength of our design comes from the three-decade-long data that capture the entire transition towards extending working lives from its onset in the mid-1990s. This transition marks an essential divergence from the trends that dominated the second half of the 20th century, such as the continuous decline in average retirement ages and old-age employment rates (Boissonneault et al., 2020), standardization of late-life employment trajectories (Atchley, 1982; Han & Moen, 1999), and consolidation of predictable retirement patters (Laslett, 1991; Moen et al., 2005). The recent three decades belong to a new chapter in the social history of the developed countries characterized by the progressing population aging and increasing activity of older generations (Carr, 2019). By tracing the trends and inequalities in extending working lives, we can better understand the evolution and diversity of late-life careers. For example, this study considers whether increases in average retirement ages observed since mid-1990 were driven by a reduction of early exit or popularization of work until the late 60s, and whether this differed between education levels and genders. Such knowledge is essential for designing policy measures that are both efficient and inclusive. An efficient increase of retirement ages at the aggregated level does not necessarily imply that all groups similarly experience this process. Therefore, inclusive policies must recognize and address the heterogeneity among older generations to avoid reinforcing existing discrepancies at older ages.

Third, the major methodological novelty is the study's longitudinal and multicountry design applied to an extensive dataset. Unlike cross-sectional evidence, the longitudinal design covers a broad observation window to study how careers develop over older ages. Using a trajectory-based method of latent class growth analysis (Laursen & Hoff, 2006; Muthén & Muthén, 2000), we can distinguish groups that follow specific employment patterns. This approach fits our longitudinal and comparative perspective better than alternative methods, such as transition models, event history analysis, and sequence analysis. Transition and event-oriented methods focus primarily on retirement and exit ages; thus, they do not distinguish employment trajectories and can overlook some of the dynamics and complexity of late careers (e.g., as discussed by Calvo et al., 2018, and Fasang, 2012). Sequence analysis, although successfully applied to study late careers (Calvo et al., 2018; McMunn et al., 2015; Worts et al., 2016; van der Horst et al., 2017), is more challenging for multicountry research like ours. Latent class growth analysis allows us to compare trajectories across time, groups, and countries, adding an important contribution to previous research. Moreover, our models enable multiple imputations of missing data in employment statuses based on longer employment trajectories, which is particularly useful for panel surveys with data missing by design (such as the US data where recent waves were conducted every second year). The ability of latent class models to identify employment pathways has been used before for young and middle-aged individuals (Damaske & Frech, 2016; Garcia-Manglano, 2015; Huang et al., 2011; Hynes & Clarkberg, 2005; Lallukka et al., 2019; Serra et al., 2017), but not for older adults. Additionally, the multiple-group approach to latent growth analyses enables comparing different institutional and social country contexts that set the baseline framework for developing life course patterns (Bernardi et al., 2019; Townsend, 1981; Van Winkle & Fasang, 2021).

BACKGROUND

Toward extending working lives

Since the late 1970s, late-life employment trajectories began to evolve due to several processes (Fasang, 2012; Hofäcker & Radl, 2016). First, retirement has transformed from a single, age-based event into a more complex and lengthy process, varying considerably across individuals (Henretta, 1992; Moen et al., 2005; Mutchler et al., 1997). For example, new career patterns emerged, such as bridge jobs undertaken by employees eligible for retirement who continue working in different positions, organizations, or fields (Beehr & Bennett, 2014; Cahill et al., 2006). Second, the regulatory impact of social, legal, and organizational norms on the exit sequence has weakened (Brückner & Mayer, 2005). For example, pension reforms such as abolishing mandatory retirement in some countries (e.g., the United States between 1978 and 1986) profoundly changed the retirement landscape (Costa, 1998). Older age becomes more flexible but also less predictable and secure due to the reduced protective role of welfare systems. These developments provide more space for individual preferences and aspirations yet enforce greater individual responsibility for work and retirement decisions (Ekerdt et al., 2000). Third, the decreasing demand for physical work in modern economies and improving health and workability of older people opened more possibilities to work until and beyond retirement (Mermin et al., 2007; Moen et al., 2016). Finally, changes in late-life employment trajectories were stimulated by the vivid paradigmatic shift in aging policies. Extensive early retirement opportunities and generous pension benefits have been limited since the mid-1990s when governments faced challenges of population aging and reoriented their policies towards active aging and later retirement (Hofäcker & Radl, 2016). These reforms contributed to higher labor force participation at older ages (Boissonneault et al., 2020).

It is often assumed that late-life careers and retirement patterns have destandardized as a result of these processes. Destandardization suggests that employment trajectories in this period of life are more diverse in terms of order and composition of occupational sequences, and retirement exit is more blurred, extended over a longer time, unpredictable, and varying across individuals (Cahill et al., 2006; Kohli, 2007; Mutchler et al., 1997; Shultz & Olson, 2012). However, previous research offers mixed and limited empirical evidence in this regard. Although some studies suggest an increasing with in differentiation of late careers, that is, rising complexity in terms of the number of distinct states and transitions, mainly related to the popularization of bridge jobs and re-employment (Maestas, 2010; Tang & Burr, 2014), others argue that the variability in retirement patterns is not progressing that quickly (Han & Moen, 1999; Macmillan, 2005; Riekhoff, 2016; Riekhoff & Järnefelt, 2018). It appears that the most explicit and significant dimension in which late-life employment patterns evolve and diversify over time is the timing of exit. Retirement has stretched over a much broader age range, with some groups exiting early and others extending their employment until older ages (Han & Moen, 1999; Henretta, 1992). A literature review by Fisher et al. (2016) shows considerable heterogeneity in retirement timing in the United States, Europe, and other countries, linked to various individual, family, work, and macroeconomic factors. Calvo et al. (2018) suggest that retirement patterns in the United States differ primarily between early, standard, or late exit, and early and standard exit account for more than half of the sample. In Belgium, Sanderson and Burnay (2016) found a rising diversification of exit timing for some groups since the late 1990s.

Concluding, late-life employment and retirement patterns appear to be evolving, particularly regarding the timing of exit and the rising pressure and opportunities to work longer, yet we still cannot be sure how significant and permanent these changes are. There are also concerns about whether the high levels of life course destandardization found in some studies result from specific conceptualizations and methodological choices (Fasang, 2012; Mayer, 2009). This is because the assessments of life course complexity may differ due to applied modeling techniques (Pelletier et al., 2020; Warren et al., 2015). In particular, approaches focusing only on exit events (e.g., transition models, event history analysis) or cross-sectional or short-term panel data cannot present us with a complete picture of life course complexity. Recent literature suggests instead investigating late careers using trajectory-oriented methods, such as sequence analysis or longitudinal growth models (Calvo et al., 2018; Van Winkle & Fasang, 2021). Furthermore, much less is known if there are uniform transformations of the timing and patterns of exit across different countries. We use a long, historical, and comparative perspective to fill this gap and study heterogeneity of late-life careers with particular attention to the timing of labor market exit. We expect to identify several major trajectories, such as nonemployed at all, standard exit (around the age of 65), early and late exit (before and after the standard retirement age), and late employment (until the late 60s). Based on the literature and data suggesting a trend toward later exit ages and rising old-age employment rates, we hypothesize that at the general level, the patterns of late employment and later exit become more popular (Hypothesis H1a), while patterns of nonemployment and early exit become less popular over time (Hypothesis H1b).

Social stratification of late-life trajectories

Education is one of the major stratification markers at older ages, as it structures later-life courses, careers, and retirement patterns. The effect of education is primarily mediated by the type of work (e.g., manual or non-manual) and working conditions. Workers in low-skill or labor-intensive occupations show stronger intentions to retire earlier (Radl, 2013; Wahrendorf et al., 2013). Favorable work environment, interesting work, and supportive organizational policies stimulate attitudes to continue employment until later ages (Robroek et al., 2015; van Solinge & Henkens, 2007), whereas jobs with high physical or psychological demands and limited control motivate earlier retirement (Blekesaune & Solem, 2016; Carr et al., 2016). Higher education also correlates with a healthy lifestyle, higher standard of living, and better access to the health system, contributing to a longer life expectancy, less disability, and longer working lives (Backes-Gellner et al., 2011; Visser et al., 2016). For example, health-related exit is one of the most common exit patterns among low-educated older workers (van den Berg et al., 2010; van Rijn et al., 2014; Vanajan et al., 2020).

We expect that educational stratification of late careers and retirement will lead to inequalities in the abilities and opportunities to extend working lives (Carr, 2019; Fasang, 2012; Krekula & Vickerstaff, 2020). Such inequalities may rise over time if the probability of late and early exit develop differently for low and high-educated groups. Previous research provides solid ground to expect that higher educated are more likely to extend their working lives than lower educated due to better workability and opportunities and that this trend will continue. The situation of lower educated appears more complex. They tend to exit work earlier, forced by limited working opportunities, work-related health problems, and reduced workability. At the same time, their options for early retirement with a secure income have been strongly reduced in recent decades. Additionally, lower educated workers may have accumulated less wealth, forcing them to continue working (Fisher et al., 2016; Radl, 2013). Overall, we hypothesize a trend toward later exit (i.e., increase in patterns of late employment and later exit and decrease in non-employment and early exit) among all educational groups (Hypothesis H2a), but assume it will be slower for lower educated than for higher educated workers (Hypothesis H2b). As a result, we expect that educational differences in extending working lives will grow over time. The gap between these two groups can be related to macro-level contextual factors that affect the vulnerability of retirement decisions among lower educated, such as the social security system. A comparative context may shed light on this issue (see below).

Gendered patterns of late-life employment

The social stratification of late-life employment and retirement has a strong gender dimension (Moen et al., 2016; Noone et al., 2010). Although many countries introduced reforms to equalize retirement criteria, women's retirement age and pension benefits are mostly lower than men's. Traditionally gendered social roles also expect women to focus their activities around the household, family and care (Dentinger & Clarkberg, 2016). Pensions reforms, the evolution of social norms, and increasing labor force participation in recent decades affected the late careers of women more strongly than those of men and made them less predictable than before (Widmer & Ritschard, 2009). As studies show, women tend to be less financially prepared for retirement due to lower incomes during their working lives. They are also less likely to have private pension incomes and receive lower benefits from state and private pensions (Hardy & Shuey, 2000; Madero-Cabib & Fasang, 2016; Noone et al., 2010). Women also exit the labor market at younger ages than men due to their disadvantaged occupational position (Radl, 2013). Riekhoff (2016) observed that retirement patterns of Dutch women are more heterogeneous than men's, mainly due to their rising labor market participation. Riekhoff and Järnefelt (2017) found gender differences in retirement trajectories even in Finland, a country with strong support for women's employment and high female labor market participation. Public policies toward postponing retirement largely ignore these gender differences (Ní Léime & Street, 2016).

We expect different opportunities and constraints during men's and women's late careers will diversify the likelihood of extending working lives. On the one hand, women are more likely to have restricted working opportunities, for example, due to family and care obligations. On the other hand, retirement systems and low pension benefits put intense pressure on women to work longer (often leading to forced and stressful work trajectories). The situation of women is also evolving more dynamically due to the quickly increasing level of education and continuously increasing labor force participation of subsequent cohorts (Samir & Lutz, 2017). Consequently, although late-life employment trajectories should still differ by gender, for example, with women following early exit trajectories more often and late employment trajectories less often than men, we expect that the situation of women has changed more quickly over the last three decades. Specifically, we hypothesize that both men and women have experienced the trend toward later exit (i.e., increase in patterns of late employment and later exit and decrease in nonemployment and early exit; Hypothesis H3a), but the increase in late-life employment trajectories consistent with extended employment has been faster for women (Hypothesis H3b).

Country context

This study analyses developments in seven countries that highly differ due to the situation of older people and the aging context (information below is based on the OECD data, 2016–2020). On one side of the spectrum, we include Germany with a stable retirement context. It strongly incentivizes postponement of retirement and has the lowest income inequalities among people aged 65+ (Gini coefficient = 0.269, OECD data, 2018). The extensive corporatist welfare regime provides high social and pension expenditures and an efficient pension system with high replacement rates. On the other side of the scale, we analyze Korea and Russia, which have undergone intensive yet very different social, political, and economic transitions during the last three decades. These developments produced unstable situations for older people, high gender inequalities, and limited welfare protection. Korea has an underdeveloped and largely inefficient welfare system, the OECD-highest poverty rate among the elderly adults (Kim, 2017; OECD, 2018). Russia's post-communist regime reports a low poverty rate among older generations, yet it suffers from other problems that constrain extending working lives, such as low life expectancy, low employment rates, and low average exit ages (OECD, 2019).

Between these two relatively clear profiles, we have four countries with a more nuanced context for extending working lives: the neo-liberal regimes of Australia and the United States and the liberal-corporatist of Switzerland and the United Kingdom. They all report moderate social and pension expenditures and low (United Kingdom) or moderate (Australia, United Kingdom, United States) income poverty among the elderly. The United States stands out with one of the highest income inequalities among the population 65+ in the OECD (Gini = 0.41 for 2017). Australia, the United Kingdom, and the United States have similar characteristics of labor market activity, for example, moderate employment rates and exit ages. Switzerland shows stable high employment of older men and women corresponding to high average exit ages. Furthermore, the United Kingdom's pension replacement rate is among the lowest of all developed countries, yet private pensions help to increase the value close to the OECD average (OECD, 2019).

These country profiles do not account for various relevant factors (e.g., changes in policies, pension arrangements, and retirement ages); however, detailed case studies are beyond the scope of this article. We also cannot examine the effects of country-level characteristics in a multivariate framework (this requires a multilevel design with many countries). Nevertheless, employment rates and exit ages cannot tell us the whole story of trends in late careers, and by comparing seven countries, we want to shed more light on this area. We do not intend to hypothesize country-specific developments, but we expect the major trends to be similar across the countries. Specifically, we expect that the hypothesized developments represent common, universal trends, namely increasing late employment and later exit (i.e., H1a) and decreasing nonemployment and early exit (H1b), increasing educational differences (H2b), and quickly changing women's situation (H3b). The underlying processes are considered universal for all developed countries, including demographic aging, policy reforms stimulating later retirement, improving employability and opportunities to work longer (especially for the higher educated), and changing labor market situation of women (OECD, 2019). Variation in the strength and size of these effects is inevitable, as the country context can moderate the hypothesized developments, but we assume they do not alternate the direction. For example, we can expect relatively low gender and educational differences in employment patterns in Germany, larger educational discrepancies in Korea (due to the poverty pushing to work longer), and larger gender differences in Russia (due to the significantly lower retirement age and employment rates for women). For other countries, the expected developments are uncertain.

DATA AND METHODS

Data

The data come from seven countries and were integrated using Comparative Panel File (CPF; for details, see Turek et al., 2021 or www.cpfdata.com). The CPF is a new and first fully open harmonization initiative in the social sciences. CPF's goal is to support comparative life course research. The harmonized data allow studying life trajectories of several generations across countries and against a changing historical background. CPF provides an open-source code to combine data from the largest and longest-running household panel surveys (with regular, mostly yearly, interviews of households members) from Australia (The Household, Income and Labor Dynamics in Australia Survey, HILDA), Germany (The German Socio-Economic Panel, SOEP), the United Kingdom (The British Household Panel Survey, BHPS, and Understanding Society—The UK Household Longitudinal Study, UKHLS), South Korea (The Korean Labor and Income Panel Study, KLIPS), Russia (The Russian Longitudinal Monitoring Survey, RLMS), Switzerland (The Swiss Household Panel, SHP), and the United States (The Panel Study of Income Dynamics, PSID). Some of the surveys served for comparative analysis, for example, for income inequalities (Musick et al., 2020), but not for studying late-life employment. The CPF ver.1.4 creates a harmonized dataset with 2.84 million observations from 377,000 respondents interviewed between 1968 and 2020. The oldest survey, PSID, started in 1968 (41 waves), and the youngest, HILDA, in 2001 (19 waves; see Table 1).

Variables

Descriptive statistics of the variables used in the analysis are presented in Table 1. Precise information on harmonization and original questions for all countries can be found in the CPF Codebook (Turek, 2021). The dependent variable is based on *employment status*, measured by self-categorizing the primary labor market status each year (harmonized across countries based on multiple input variables), with 1 indicating paid employment and 0 for other situations (e.g., unemployed, retired, disabled, or not active).

The main predictors are gender, education, and time trend. *Gender* is measured as a binary variable. *Education level* is harmonized across countries according to the International Standard Classification of Education (ISCED) 2011. We used a three-level classification of education: low (ISCED 0–2), medium (3–4), and higher (5–8). Missing values were filled in, and inconsistencies were adjusted based on information from other waves (excluding 47 respondents with all missing values). To analyze the *time trend* in employment trajectories, we used the year effect when the respondent reached 60. It indicates the beginning of the observation window for employment trajectories. The variable was centered at 2000 = 0. Respondents entered the observation window earliest in 1990 (United States, Germany, United Kingdom, and Russia), 1995 (Korea and Switzerland), and 1998 (Australia). The latest cohort reached the age of 60 in 2012.

We use the *interview year* to define the sample and trajectories. We also use self-rated health and household income as additional control variables. *Self-rated health at 60* indicates a person's self-assessment of health status at the age of 60 measured on a 5-point scale (1 = very good/excellent health; 5 = very poor/bad health; labels slightly differ by country, see Turek, 2021). We used the value measured at the beginning of the observation window (i.e., age 60). If it was not available, we used values reported at age 59, 58, 61, or 62. Korea reports many missing values because the question has been asked only since the KLIPS's sixth wave in 2003.

Household income at 60 indicates monthly net adjusted household disposable income after taxes and transfers at respondent's age of 60. Some data sets (United States since 1994, Australia, United Kingdom) provide a negative household income indicating a loss or debit—these were recoded into zero for consistency with other countries. Income is measured in local currencies. Before applying sampling criteria (i.e., for the entire CPF sample), the highest 1% per country was removed as outliers, and values were *z*-standardized within countries (with 0 as average and 1 as standard deviation). The *z*-standardized variable is used in analysis to provide comparability and correct the skewed distribution (descriptive statistics in Table 1 present original values). We used the value measured at the beginning of the observation window (i.e., age 60). If it was not available, we used values reported at age 59, 58, 61, or 62.

Sample selection

The analysis covers lifespan between the age of 60 and 69 and the period from 1990 to 2019. In practice, the sample includes individuals who reached 60 in 1990 or later. We restricted the sample to individuals whose employment trajectory could be reliably identified. The initial sample included 66,317 individuals aged 60-plus with at least one observation; however, for many respondents, the information was partial (e.g., 43% had not more than three observations within the observation window). To assure that the observation window encloses the entire age range of interest, we required a minimum of four measurements between ages 60 and 69 and at least one measurement in each of the three age ranges: 60–63, 64–66, and 67–69. This results in an analytical sample of n = 22,314.

Handling missing data in employment trajectory

Out of the 22,314 individuals selected for the analysis, 35% had measurements on all 10 employment statutes between 60 and 69 (Appendix A). The remaining 65% has missing values related to item- and wave-nonresponses (yet 85% of the analytical sample has maximum 3 missing values, Appendix A). The selection criteria described above already assured that respondent's data stretch over the entire observation window. The remaining missing data were imputed relying on the available employment information between 57 and 72. For example, a person employed at the age of 60, 61,

Table 1. Descriptive statistics of the variables used in the analysis

	[1] Australia	[2] South Korea	[3] United States	[4] Russia	[5] Switzerland	[6] Germany	[7] United Kingdom	Total
Male	46.8	45.2	46.5	33.7	43.5	48.4	46.0	45.2
Female	53.2	54.8	53.5	66.3	56.5	51.6	54.0	54.9
Education								
Low	42.0	68.9	17.6	32.4	9.5	14.6	38.9	31.9
Medium	28.5	23.8	55.3	46.8	61.2	58.3	30.1	42.6
High	29.5	7.2	27.1	20.8	29.3	27.1	31.0	25.5
Share of employed by age								
60	58.3	55.2	64.4	36.8	69.7	49.2	51.9	53.2
61	52.6	52.9	60.7	31.8	65.9	39.1	46.3	47.1
62	48.6	50.9	54.8	27.2	59.8	33.5	40.8	42.1
63	44.7	48.1	48.9	23.4	51.6	28.5	36.5	37.4
64	41.0	47.1	43.2	21.7	41.5	22.3	32.4	32.8
65	34.6	45.8	40.7	17.1	31.3	18.6	23.7	27.4
66	29.6	44.5	35.1	15.8	25.4	11.9	18.8	22.6
67	25.6	42.8	32.4	12.5	24.8	11.0	16.4	20.6
68	22.1	40.5	28.6	12.1	22.8	9.7	13.9	18.5
69	19.2	37.7	28.8	9.7	21.0	8.5	11.6	16.8
Time trend covered—beginning of the observation window for employment trajectory (year of reaching age 60)								
Min	1998	1995	1990	1991	1996	1990	1990	1990
Max	2012	2012	2012	2013	2012	2012	2013	2013
Interview period								
Min	2001	1998	1990	1994	1999	1990	1991	1990
Max	2019	2019	2019	2019	2019	2019	2018	2019
Self-rated health at age 60 (scale 1–5)								
Mean (*SD*)	2.8 (1.0)	2.9 (0.9)	2.5 (1.1)	3.1 (0.6)	2.0 (0.7)	2.8 (0.9)	2.4 (1.1)	2.7 (1.0)
N	2,119	1,820	2,461	2,107	1,355	4,624	4,826	19,312
Houshold income at age 60 (original values in local currencies)								
Mean (*SD*)	62,113 (46,245)	2,650 (2,376)	63,070 (46,980)	92,050 (225,624)	86,125 (50,607)	33,335 (20,796)	2,478 (1,894)	38,044 (83,767)
N	2,239	2,456	2,427	2,102	1,286	4,971	5,051	20,532
N respondents (analytical sample)	2,391	2,624	2,476	2,352	1,509	5,335	5,627	22,314

Notes: Statistics are based on the analytical sample. Gender, education and age have no missing values (*N* = the analytical sample). For self-rated health and household income, the sample size is provided in the table.

63, and 64 was most probably employed at 62, and a person who reported non-employment at several consecutive waves most likely remained unemployed. This predictability allows us to recover the employment trajectory based on partial information. However, to account for the uncertainty, we applied multiple imputations of missing values based on the full variance-covariance matrix of employment measurements (between 57 and 72). Using Mplus's multiple imputations procedure with the MCMC simulation and Bayesian estimation, we created 50 datasets with imputed values. Analyses are initially performed on each dataset separately and later integrated using the Rubin theorem to obtain a single set of estimates (Asparouhov & Muthén, 2010). Out of the total 223,140 measurement points (*n* multiplied by ten age points), 16.2% were imputed. The number ranged between 7.8% in Germany and 18.8% in Russia, except the United States, with a higher number of 46.5% missing values related to PSID's design (from 1997 onwards, the survey was conducted every second year). The results have been tested for the sensitivity to the treatment of missing values: consistent results are provided by analyses based on samples restricted to a higher minimum number of measurements, as well as with an alternative approach using Full Information Maximum Likelihood based on the available information (Muthén & Muthén, 1998–2017; results available online at OSF: https://osf.io/hakg6). For other variables, we used no imputation. Education and gender have no missing values. Due to many missing values in self-rated health and household income (up to 31% of the analytical sample per country), models with these variables are presented separately (additionally, we do not include self-rated health for Korea).

Analytical approach

To identify employment trajectories, we applied multiple groups latent class growth analysis (LCGA, also known as group-based trajectory analysis). LCGA belongs to the group of longitudinal growth mixture models (GMM) that analyze the heterogeneity in growth processes. LCGA detects latent classes of individuals with similar growth trajectories over time (Herle et al., 2020; Muthén & Muthén, 2000). The latent trajectories and membership are inferred from the data and can be confronted with theoretical assumptions. This strategy has several advantages over the purely theoretical a priori-defined trajectories (Warren et al., 2015). Most of all, we can compare the quality of classification across models and within various groups and select the solution that fits both the theoretical assumptions and statistical criteria. As an outcome, each individual obtains a probability of membership in each of the identified classes. Based on this, we can select the most-probable class and verify the classification uncertainty. An essential quality of the LCGA is its precision in identifying the main trajectories based on binary indicators (e.g., Damaske & Frech, 2016; Garcia-Manglano, 2015; Serra et al., 2017).

To include predictors in LCGA and verify their predictive effects for latent trajectories, we run a three-step LCGA (multinomial) logistic regression that accounts for measurement error in the class assignment (Nylund-Gibson et al., 2014). For this, we apply the manual R3STEP procedure in Mplus (Asparouhov & Muthén, 2014). In addition, the three-step LCGA was adjusted to the multiple group analysis with countries as groups to account for the clustered structure of the data. This solution allows for a direct country comparison while providing flexibility with adjusting the model constraints. Additionally, the three-step approach was adjusted to account for the multiple imputations of missing values.

In the first step, we determine the number of latent classes based on unconditional LCGA models. They provide a more stable and transparent approach to classifying observations than a conditional model with covariates. To find the optimal solution, we first performed a series of LCGA models with different numbers of clusters and different polynomials of the growth parameter (i.e., linear, quadratic, cubic, and quartic effects of age) on the pooled sample with country-clustered standard errors. To decide on the number of latent classes, we relied on several fit statistics and considered substantive interpretation and stability of the results across the models (Nylund et al., 2007; Tofighi & Enders, 2008). We run several best LCGA models separately by country and gender to investigate stability of the results (Appendix C). Separate models clearly identified the main trajectories of interest in all countries and for both genders, with only minor differences in the trajectory shapes. This consistency allowed us to fix the growth parameters equal across countries (as in a pooled-sample model) to provide equivalent measurement, while estimating class sizes and covariates' effects (in the third step) independently for each country (as in separate country models). The final LCGA solution is built on the multiple datasets with imputed missing values for employment trajectory and later extracted to be used with covariates from the not-imputed data in the third stage.

In the second step, we predicted class probabilities and class membership based on the selected LCGA model. For each individual, the class probability informs us about the probability of belonging to each class, creating a fuzzy classification that accounts for uncertainty in class membership. Based on this, a single categorical variable of the most likely class membership identifies the class with the highest probability. The predicted classification was extracted to be used for graphical illustration. Additionally, the probability-based membership facilitates assessing quality of classification using entropy measures (low posterior probabilities for all classes indicate high uncertainty; Collins & Lanza, 2010).

In the third step, we run latent class regressions separate by country to capture the effect of gender, education, and time. Covariates are added through the manual R3STEP regression (Asparouhov & Muthén, 2014). In this procedure, we fix all the model parameters to values from the final LCGA solution without covariates and based on multiple imputed datasets. This approach accounts for measurement errors in class assignment by adjusting for the fuzzy classification and assures that adding covariates does not affect the class structure. Thus, we advance previous research by using a more reliable analytical strategy. The main results of the LCGA regression are presented in the form of a series of logistic regressions with binary dependent variables representing each class contrasted against all other classes. The results are equivalent to a multinomial model but provide a more straightforward interpretation (independent of reference categories) and better serve as formal tests for the hypotheses, especially for assessing time trends. For the graphical illustration of the results, we predicted marginal effects of covariates for the probability of class membership based on simplified multinomial models (i.e., without the R3STEP procedure).

Given the high classification precision (entropy higher than 0.95), this approach provides matching results to the R3STEP procedure and is more useful for visualizations. In models M1-M3, we include only the basic predictors of gender and education as the key stratification markers. Although many other predictors can affect employment, these models present the "total" effect of gender and education on employment trajectories. The coefficients and interpretation change when self-rated health and household income are added to Model M4 because the new (intervening) variables mediate part of the gender and education effect (Bartman, 2021).

Missing value imputation and the LCGA analyses with R3STEP were conducted using Mplus 8.4 software (Muthén & Muthén, 1998–2017). Part of the analysis, including graphical illustration, was performed in Stata 16. The analytical code and additional information are available online at the OSF: https://osf.io/hakg6.

RESULTS

Trajectories of employment

To identify employment trajectories, we estimated unconditional LCGA models. Table 2 presents fit statistics for models with up to eight latent classes and growth slopes that include intercept, linear, and quadratic terms. To select the optimal solution, we used statistical and theoretical criteria. Values of the Bayesian information criterion (BIC) decrease with each additional class suggesting an improvement in model fit (Tofighi & Enders, 2008), yet the decrease slows down at the six-class solution. Entropy (0–1) is calculated based on posterior membership probabilities, with larger values suggesting better latent class separation (Collins & Lanza, 2010). All models demonstrated a high level of entropy (above 0.94 for data with imputed missing values and 0.85 for the nonimputed data), indicating a reliable classification performance. The average predicted probability (APP) of group membership in each class is between 0.82 and 0.96, higher than the recommended minimum of 0.7 (Nagin, 2005).

From a theoretical perspective, the goal of the LCGA was not to maximize the precision in identifying all existing trajectories but to identify the main trajectories of interest where we expected most change over time, that is, Non-Employment, Late Employment, Early Exit, and Late Exit (description of classes is provided later). These four trajectories are clearly recognized and show stable sizes in models with six and more classes. We also considered the number of difficult to interpret classes, that is, unusual employment patterns (residual classes) or classes combining more than one specific pattern. Based on fit criteria, parsimony, and interpretability, and given the stability of the results across different models, we decided to focus on the six-class solution. Models with seven and more classes only add residual trajectories and small classes (less than 5%). Models with up to five classes merge two of the more common trajectories. Adding cubic growth term did not improve model characteristics (see Table B2 in Appendix B).

Employment trajectories identified by the six-class LCGA model for the total sample are visualized in Figure 1. For each age point, the y-axis presents the average probability of employment for a given class. Due to the lack of clear re-entry patterns, all trajectories refer to exit transitions (Early, Standard, and Late Exit) and stable employment patterns

Table 2. Model fit evaluation information for different LCGA models of employment trajectory between the age of 60 and 70

Number of classes	AIC	BIC	Number of parameters	Entropy: MI data (raw data)	Classes (%)					
					Number of classes ≤ 5%	Complex classes: % (number)	Nonemployed	Late employment	Early exit	Late exit
1	348,757	348,805	10	—	0	100.0 (1)	NA	NA	NA	NA
2	252,053	252,121	14	0.986 (0.932)	0	100.0 (2)	NA	NA	NA	NA
3	229,700	229,787	18	0.977 (0.919)	0	24.6 (1)	53.9	21.5	NA	NA
4	225,158	225,265	22	0.968 (0.916)	0	NA	50.3	21.4	14.0	NA
5	220,347	220,472	26	0.964 (0.880)	0	7.4 (1)	48.2	17.0	14.7	NA
6	218,838	218,983	30	0.955 (0.859)	0	6.7 (1)	48.5	15.1	9.7	9.1
7	217,826	217,991	34	0.951 (0.869)	2	9.2 (2)	47.4	15.1	10.2	6.1
8	217,255	217,439	38	0.940 (0.850)	2	11.4 (3)	46.1	14.4	12.0	6.0

Notes: Total n = 22,314. All models are based on 50 multiple imputations and include a linear and quadratic term for trajectories (with fixed values across the countries). The table shows the mean values of the parameters across all imputed datasets. For the AIC (Akaike information criterion) and BIC (Bayesian information criterion, sample-size adjusted values shown), low values indicate a better fit. Entropy (0–1) is calculated based on posterior probabilities of membership; larger values suggest better class separation. Entropy calculated for the datasets with imputed missing values (MI) differs from the one estimated for the raw data. Classes indicate the number of clusters with estimated size in the pooled sample (definition of classes is provided further in the text). NA indicates that a class is not available (not clearly identified). Complex classes are clusters with difficult for interpretation employment patterns—they represent small and unusual trajectories (residual classes) or combine more than one specific pattern.

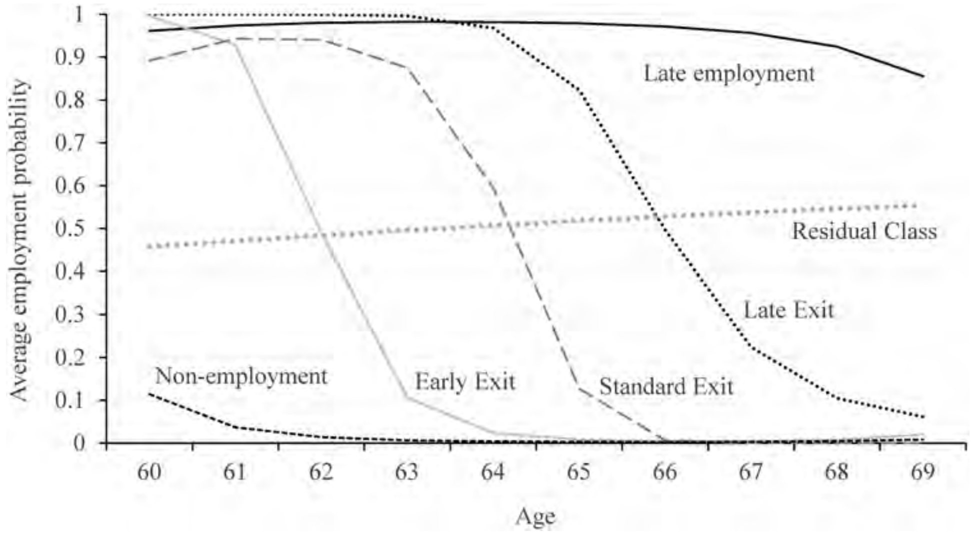

Figure 1. Profiles of employment trajectories estimated from the LCGA model.

(Nonemployment and Late Employment). The three exit transitions should not be interpreted in terms of retirement arrangements (e.g., early retirement), for which we have no information. Instead, the LCGA classes indicate the approximate transition age in the observation window of 60–69. For the Standard Exit, employment probability is close to 1 between 60 and 63, then it drops sharply between 64 and 65 and remains close to zero after that. Thus, this class refers to a trajectory where an exit from employment occurs around the most common retirement age of 65 (yet it does not imply standard retirement procedure). Members of Early Exit class experience exit between 61 and 63 (yet it does not indicate early retirement). In the Late Exit class, the sharpest drop happens between 65 and 67, which is relatively late compared to the average exit ages.

The two classes with stable employment include people who have not changed their employment statuses during observation. Non-Employment includes individuals who do not work during their sixties (as the probability of employment remains close to zero at all ages). These people have left work already at an earlier point in life, most probably due to occupational early retirement arrangements (e.g., miners), after family formation (mainly women), and due to health issues or disability (mainly men). Late Employment includes those who continuously work during their 60s and most likely retire in their 70s.

Finally, the Residual Class includes all other patterns that do not fit the main five classes. We should note that using the LCGA, we found no clear classes of re-entry (e.g., re-employment after a job loss or after retirement). Such trajectories were probably too uncommon and diverse to be identified as clear patterns, and consequently, they were included in the Residual Class.

Class distribution (averaged over the period from 1990 to 2019) highly varies across countries and by gender (Table 3). Among women, the dominant trajectory in all countries is Non-Employment. It is prevalent in Russia and Germany (around 70%), and in the United Kingdom (62.1%). Combined with the Early Exit class, these three countries have the highest share of women who exit the labor force early. In the United States and Switzerland, Nonemployment applies to only about 40% of women. Late Employment stands out as a large class for women in Australia, Korea, and the United States (16–23%). Late Exit accounts for only 6.2% on average, and only in the United States, it reaches 10%. Korea has a relatively sizeable residual group of 12% unusual trajectories.

The situation looks different among men. Nonemployment is a large group, but it is dominant only in Russia (59.3%), Germany (48.5%), and the United Kingdom (43.3%). Similarly to women, these countries also appear as those with the relatively highest share of men who exit the labor force early, although standard and late exit are slightly more popular than for women. Late Employment is one of the major trajectories in Korea (43.7%), Australia, the United States, and Switzerland (between 34 and 31%). Late Exit shows high shares in Switzerland (18.4%) and Australia (14.7%). Concluding, Russia and Germany have the highest share of women and men remaining out of the labor market through their sixties. In contrast, Australia, Korea, and the United States report a much stronger tendency toward working until the late 60s.

Predictors of employment trajectories

In the next step, we include predictors of the trajectories by applying a latent class regression. Tables 4–7 presents logistic regression models for the probability of each class separately contrasted with all other classes. Model M1 includes gender, education, and time trend, model M2 adds an interaction between females and time, model M3 adds an interaction between education and time, and M4 adds two control variables (i.e., health and income). To better understand predictors' effects and interactions, we present the results in a more accessible visual form based on predicted probabilities for gender (Figure 2) and educational (Figure 3) time trends.

Model M1 in Tables 4–7 confirms that women have a significantly stronger tendency to follow the Nonemployment pattern in almost all countries and a lower to follow Late Employment, Late Exit, or Standard Exit than men. Educational differences are similar across countries for the two largest trajectories. Except in Korea, lower educated have

Table 3. Distribution of employment trajectories by country and gender (in %)

	Employment trajectory	[1] Australia	[2] Korea	[3] United States	[4] Russia	[5] Switzerland	[6] Germany	[7] United Kingdom	Total
Women									
1	Nonemployment	53.1	51.6	42.0	70.6	41.0	68.3	62.1	58.8
2	Late employment	16.3	22.5	21.4	8.9	13.2	4.7	9.8	12.2
3	Early exit	7.4	4.3	10.6	5.2	12.1	8.7	8.6	8.0
4	Standard exit	9.1	4.9	9.1	7.5	19.1	8.1	9.5	9.0
5	Late exit	9.4	4.7	8.2	3.3	6.5	5.5	6.6	6.2
6	Residual class	4.8	12.0	8.8	4.5	8.2	4.7	3.5	5.9
	Total	100	100	100	100	100	100	100	100
	n	1,273	1,438	1,325	1,559	852	2,755	3,038	12,240
Men									
1	Nonemployment	35.3	22.6	26.9	59.3	20.1	48.5	43.3	39.2
2	Late employment	23.8	43.7	31.0	9.8	23.1	8.3	16.2	19.9
3	Early exit	6.6	5.9	11.8	9.1	11.7	10.9	7.7	9.0
4	Standard exit	13.3	6.9	11.4	7.3	20.1	14.2	17.5	13.6
5	Late exit	14.7	8.3	10.9	8.2	18.4	12.6	12.7	12.2
6	Residual class	6.3	12.7	8.0	6.3	6.5	5.5	2.6	6.1
	Total	100	100	100	100	100	100	100	100
	n	1,118	1,186	1,151	793	657	2,580	2,589	10,074

Notes. Values are based on the most likely class membership, where the class with the highest value is recoded into 1, the other into 0. An alternative reporting of the results is based on estimated posterior probabilities of class membership from the LCGA model. Due to the high entropy, the results are almost identical and differences are irrelevant for interpretation.

a significantly higher probability of Nonemployment and a lower probability of Late Employment than higher educated. Additionally, the tendency for Late Exit is stronger among higher educated in Australia, the United States, Switzerland, and Germany.

Time trend in the prevalence of trajectories refers to the year when individuals reached 60 and entered observation. The linear trend from model M1 shows a significant decline in Nonemployment (except in the United States and Russia), an increase in Late Employment and Late Exit (in Australia, Korea, Germany, and the United Kingdom), and Standard Exit (in Australia, Switzerland, Germany, and the United Kingdom). However, models M2 and M3 suggest some significant gender- and education-specific time trends, which are better interpreted visually (see next section).

Model M4 ensures the stability of the results for gender and education and provides insights into the potential explanatory mechanisms, that is, variables that can mediate the effect of education and gender throughout the life course. Because the coefficients for gender and education no longer present the *total effect* (which is now partially mediated), they change. As we see, Late-Employment is positively associated with household income and negatively with self-rated health. For Nonemployment, the relationships are reversed. After controlling for these additional factors, the effects of education and gender remain mostly similar, suggesting that the new information does not explain them away.

Time trends and gender differences in the prevalence of employment trajectories

Figure 2 presents time trends based on probabilities of classes predicted from a multinomial regression model with an additional quadratic time term and interaction of time (linear and quadratic) and gender, controlled for education (an equivalent of model M2 in Tables 4–7).

The most profound result is the drop in the average probability of the Nonemployment trajectory between the 1990s and 2012 for men and women in Australia, Korea, Switzerland, Germany, the United Kingdom, and Russian women (Figure 2a). For example, in Germany, the probability dropped by half, from 88% in 1990 to 41% in 2012 for women and from 70% to 29% for men. Switzerland, after an initial drop, reports a slight increase since the late 2000s; however, the general indicators are still much lower than in the mid-1990s. Changes over time are mostly similar for men and women, although some interactions in models M2 are significant. For example, the decrease is slightly stronger for women in Australia, Germany, Russia, and the United Kingdom but slower in Korea. In the United States, we observe no significant changes over time.

The probability of Late Employment increased in most countries (Figure 2b). In Australia and Korea, the indicator almost doubled. United States and Switzerland reported an initial increase and slight drops in the last years. This trajectory was almost nonexistent in Germany and the United Kingdom in the early 1990s but reached between 10% and 20% in 2012. Only in Russia, Late Employment remains at a very low level, yet females report a significant increase over time.

Time trends for the prevalence of other trajectories are less distinct and universal, and gender differences are mostly minor. Early Exit (Figure 2c) remains mainly at a similarly low level; however, some significant gender-specific time trends are reported, including an increase for females in Australia, Russia, and Germany, and a decrease for Russian men. Standard Exit

Table 4. Predictors of class membership based on LCGA series of logit regression (R3STEP approach) by country (Australia and Korea)

	AUS				KOR			
	M1	M2	M3	M4	M1	M2	M3	M4[a]
Nonemployed								
Female	0.87***	1.03***	0.82***	0.38***	0.56***	0.31***	0.59***	0.84***
Ed. medium	−0.29**	−0.34**	−0.04	−0.70**	−0.32**	−0.21*	−0.46***	−0.25*
Ed. high	−0.80***	−0.85***	−0.70***	−0.92***	−0.06	−0.09	−0.54**	−0.12
Time trend	−0.08***	−0.06***	−0.06***	−0.10***	−0.10***	−0.16***	−0.11***	−0.12***
Self-rated health				0.19***				—
Household income				−0.53***				0.34***
Time × Female		−0.04*				0.11***		
Time × Ed. med			−0.05*				−0.04*	
Time × Ed. high			−0.03				0.10**	
Late employment								
Female	−0.55***	−0.80***	−0.53***	−0.25*	−0.41***	0.20	−0.55***	−0.67**
Ed. medium	0.22	0.28*	0.14	0.48**	0.40***	0.20	0.87***	0.31**
Ed. high	0.76***	0.81***	0.73***	0.76***	−0.09	−0.40***	0.81***	−0.05
Time trend	0.05***	0.04**	0.05**	0.07***	0.15***	0.21***	0.18***	0.17***
Self-rated health				−0.15**				—
Household income				0.37***				−0.30***
Time × Female		0.04				−0.15***	—	
Time × Ed. med			0.02				−0.09***	
Time × Ed. high			0.01				−0.16***	
Early exit								
Female	−0.22	−0.85**	−0.13	0.19	−0.79***	−0.86***	−0.79***	−0.46*
Ed. medium	−0.57*	−0.46	−1.22*	−0.18	−0.65	−0.65	−0.57	−0.45
Ed. high	−0.17	0.05	−0.53	0.08	0.30	0.32	0.35	0.41
Time trend	0.03	−0.01	0.00	0.06*	−0.07***	−0.08***	−0.06**	−0.10***
Self-rated health				−0.24***				—
Household income				0.08				0.22
Time × Female		0.11**				0.04		
Time × Ed. med			0.11				−0.03	
Time × Ed. high			0.07				−0.02	
Late exit								
Female	−0.57***	−0.43	−0.60***	−0.48**	−1.27***	−1.34***	−1.17***	−1.13***
Ed. medium	0.39*	0.36*	0.39	0.50*	−0.11	−0.07	0.13	−0.12
Ed. high	0.46**	0.43*	0.62**	0.48*	−0.30	−0.26	−0.50	−0.24
Time trend	0.06***	0.07***	0.07***	0.08***	0.04*	0.03	0.05*	0.04*
Self-rated health				−0.09				—
Household income				0.23**				−0.06
Time × Female		−0.03				0.04		
Time × Ed. med			0.00				−0.05	
Time × Ed. high			0.03				0.02	
Standard exit								
Female	−0.62***	−0.86***	−0.60***	−0.41*	−1.03***	−1.03***	−1.05***	−0.75***
Ed. medium	0.35*	0.39*	0.23	0.66***	−0.45	−0.45	−0.72	−0.42
Ed. high	0.00	0.05	−0.05	0.17	0.06	0.02	−0.33	0.12
Time trend	0.04**	0.03	0.03**	0.06**	−0.11***	−0.09***	−0.15***	−0.13***
Self-rated health				−0.14*				—
Household income				0.09				0.40***
Time × Female		0.04				−0.06		
Time × Ed. med			0.02				0.13*	
Time × Ed. high			0.02				0.15	
N	2,387	2,387	2,387	2,109	2,624	2,624	2,624	2,456

Notes: M = model. Ed. = education. Coefficients for each class are obtained from a separate logit model and refer to the probability of class membership contrasted with all other classes combined. Time trend–year effect defined as the year when respondent reached 60 (centered at 2000). Household income z-centered by country.
[a]Model M4 for Korea does not include self-rated health due to many missing values (31% of the sample of models M1–3).
*$p < .05$;
**$p < .01$;
***$p < .001$.

Table 5. Predictors of class membership based on LCGA series of logit regression (R3STEP approach) by country (United Sates and Russia)

	United States				RUS			
	M1	M2	M3	M4	M1	M2	M3	M4
Nonemployed								
Female	0.57***	0.60***	0.57***	0.35***	1.17***	1.34***	1.16***	0.54***
Ed. medium	−1.00***	−1.02***	−0.99***	−0.89***	0.00	−0.09	0.03	−0.74***
Ed. high	−1.40***	−1.42***	−1.44***	−0.96***	−0.80***	−0.90***	−0.90***	−1.52***
Time trend	−0.01	0.00	−0.01	0.01	−0.01	0.03**	−0.02	−0.02*
Self-rated health				0.07*				0.39***
Household income				−0.43***				−0.13**
Time × Female		−0.01				−0.07***		
Time × Ed. med			−0.01				0.00	
Time × Ed. high			0.00				0.03	
Late employment								
Female	−0.48***	−0.42***	−0.48***	−0.31**	−0.87***	−1.05***	−0.87***	−0.14
Ed. medium	0.88***	0.85***	0.86***	1.09***	−0.25	−0.19	−0.27	1.12***
Ed. high	1.44***	1.42***	1.47***	1.42***	0.80***	0.86***	0.91***	2.07***
Time trend	0.01	0.02	0.01	0.00	0.01	−0.03	0.03	0.01
Self-rated health				−0.16***				−0.60***
Household income				0.22***				0.11
Time × Female		−0.02				0.07***		
Time × Ed. med			0.01				−0.02	
Time × Ed. high			0.00				−0.05**	
Early exit								
Female	−0.20	0.16	−0.20	0.01	−0.86***	−1.26***	−.89***	−0.71***
Ed. medium	0.10	0.12	0.09	0.26	0.33	0.39	0.24	0.65**
Ed. high	−0.09	−0.06	−0.08	−0.49*	0.49*	0.61**	0.48	0.82**
Time trend	0.00	−0.01	−0.01	−0.01	−0.01	−0.06**	−0.04	−0.01
Self-rated health				0.17***				−0.09
Household income				0.10				0.13
Time × Female		0.02				0.12**		
Time × Ed. med			0.02				0.06	
Time × Ed. high			0.01				0.04	
Late exit								
Female	−0.55***	−0.64***	−0.55***	−1.43**	−1.81***	−2.13***	−1.80***	−1.47***
Ed. medium	0.52***	0.56***	0.51***	0.82***	−0.09	−0.04	−0.33	0.64
Ed. high	0.67***	0.71***	0.66***	0.80***	0.42	0.44	0.59*	1.64**
Time trend	0.00	−0.01	−0.02	0.00	0.03	0.02	0.02	0.07*
Self-rated health				−0.15*				−0.41***
Household income				0.08				0.33**
Time × Female		0.03				0.06		
Time × Ed. med			0.02				0.05	
Time × Ed. high			0.02				−0.03	
Standard exit								
Female	−0.43**	−0.62***	−0.45**	−0.36*	−0.65***	−0.94***	−0.65***	−0.06
Ed. medium	0.28	0.34*	0.34*	0.36	−0.31	−0.27	−0.35	0.38
Ed. high	−0.07	0.02	−0.16	−0.13	−0.02	0.07	−0.22	0.75*
Time trend	0.00	−0.02	0.05	−0.00	0.03	−0.01	0.01	0.05
Self–rated health				−0.07				−0.40***
Household income				0.13				0.09
Time × Female		0.06*				0.09**		
Time × Ed. med			−0.06				0.03	
Time × Ed. high			−0.02				0.05	
N	2,466	2,466	2,466	2,410	2,352	2,352	2,352	2,094

Notes: M = model. Ed. = education. Coefficients for each class are obtained from a separate logit model and refer to the probability of class membership contrasted with all other classes combined. Time trend–year effect defined as the year when respondent reached 60 (centered at 2000). Household income z-centered by country.

*p < .05;

**p < .01;

***p < .001.

Table 6. Predictors of class membership based on LCGA series of logit regression (R3STEP approach) by country (Switzerland and Germany)

	Switzerland				Germany			
	M1	M2	M3	M4	M1	M2	M3	M4
Nonemployed								
Female	0.80***	0.73***	0.89***	0.56***	0.77***	0.51***	0.82***	0.71***
Ed. medium	−0.72***	−0.68***	−0.83***	−0.94***	−0.42***	−0.31***	−0.51***	−0.40***
Ed. high	−1.52***	−1.48***	−1.68***	−1.68***	−1.33***	−1.22***	−1.42***	−1.00***
Time trend	−0.08***	−0.10***	−0.14***	−0.10***	−0.09***	−0.07***	−0.07***	−0.10***
Self-rated health				0.17*				0.31***
Household income				−0.20*				−0.47***
Time × Female		0.02				−0.04***		
Time × Ed. med			0.07				−0.03*	
Time × Ed. high			0.08				−0.03*	
Late employment								
Female	−0.59***	−0.81***	−0.56***	−0.42*	−0.82***	−0.82***	−0.78***	−0.72***
Ed. medium	0.03	0.12	−0.09	0.35	−0.31*	−0.31*	−0.37**	−0.21
Ed. high	0.98***	1.06***	1.05***	1.20***	0.48***	0.48***	0.47***	0.09
Time trend	0.02	0.01	0.00	0.03	0.13***	0.13***	0.19**	0.12***
Self–rated health				−0.20				−0.50***
Household income				0.21**				0.32***
Time × Female		0.04				0.00		
Time × Ed. med			0.04				−0.07	
Time × Ed. high			0.01				−0.06	
Early exit								
Female	0.02	0.37	−0.01	0.09	−0.14	−0.34**	−0.14	−0.04
Ed. medium	0.56**	0.36	0.64***	0.58*	0.16	0.18	0.10	0.31
Ed. high	−0.26	−0.47	−0.43	−0.20	0.69***	0.77***	0.70***	0.77***
Time trend	0.03	0.07**	0.05	−0.00	0.18*	0.01	0.00	0.02
Self–rated health				0.15				−0.06
Household income				0.08				0.15**
Time × Female		−0.07*				0.07***		
Time × Ed. med			−0.03				0.02	
Time × Ed. high			0.01				0.01	
Late exit								
Female	−1.22***	−1.17**	−1.29***	−1.27***	−1.20***	−2.04***	−1.18***	−1.02***
Ed. medium	0.42	0.40	0.44	0.52	−0.10	−0.02	−0.39*	0.78***
Ed. high	1.41***	1.39***	1.61***	1.52***	0.65***	0.76***	0.84***	1.20***
Time trend	0.05	0.05	0.16**	0.06	0.09***	0.07***	0.07*	0.11***
Self–rated health				−0.10				−0.37***
Household income				0.11				0.39***
Time × Female		−0.01				0.14***		
Time × Ed. med			−0.11				0.08*	
Time × Ed. high			−0.14*				−0.02	
Standard exit								
Female	−0.14	−0.20	−0.27	−0.07	−0.84***	−1.40***	−0.84***	−0.70***
Ed. medium	0.58**	0.61**	0.75***	0.44	0.08	0.18*	0.01	1.04***
Ed. high	0.30	0.33	0.65**	0.08	0.69***	0.80***	0.82***	1.43***
Time trend	0.08***	0.07***	0.18***	0.09***	0.07***	0.04**	0.07**	0.06***
Self–rated health				0.04				−0.33***
Household income				0.03				0.25***
Time × Female		0.01				0.11***		
Time × Ed. med			−0.11**				0.02	
Time × Ed. high			−0.15**				−0.03	
N	1,509	1,509	1,509	1,286	5,334	5,334	5,334	4,601

Notes: M = model. Ed. = education. Coefficients for each class are obtained from a separate logit model and refer to the probability of class membership contrasted with all other classes combined. Time trend–year effect defined as the year when respondent reached 60 (centered at 2000). Household income z-centered by country.
*$p < .05$;
**$p < .01$;
***$p < .001$.

Table 7. Predictors of class membership based on LCGA series of logit regression (R3STEP approach) by country (United Kingdom)

	United Kingdom			
	M1	M2	M3	M4
Nonemployed				
Female	0.88***	0.93***	0.85***	0.49***
Ed. medium	−0.28***	−0.29***	−0.24***	−0.56***
Ed. high	−0.40***	−0.42***	−0.31***	−0.46***
Time trend	−0.03***	−0.02***	−0.02**	−0.02***
Self-rated health				0.08***
Household income				−0.64***
Time × Female		−0.01		
Time × Ed. med			−0.02	
Time × Ed. high			−0.03*	
Late employment				
Female	−0.82***	−0.97***	−0.78***	−0.50***
Ed. medium	−0.01	0.03	−0.19	0.31**
Ed. high	0.27**	0.28***	0.19**	0.35**
Time trend	0.03***	0.02*	0.01	0.04***
Self-rated health				−0.19***
Household income				0.40***
Time × Female		0.03		
Time × Ed. med			0.05*	
Time × Ed. high			0.02	
Early exit				
Female	−0.01	−0.25	0.00	0.27*
Ed. medium	0.05	0.16	0.14	0.28
Ed. high	0.24*	0.31**	0.08	0.35*
Time trend	0.00	−0.02	0.00	0.01
Self-rated health				−0.11*
Household income				0.24***
Time × Female		0.06*		
Time × Ed. med			−0.01	
Time × Ed. high			0.03	
Late exit				
Female	−0.97***	−1.11***	−0.99***	−0.82***
Ed. medium	0.46***	0.49***	0.50***	0.63***
Ed. high	0.16	0.18	0.25	0.18
Time trend	0.05***	0.04***	0.06***	0.04**
Self-rated health				−0.01
Household income				0.36***
Time × Female		0.03		
Time × Ed. med			−0.02	
Time × Ed. high			−0.02	
Standard exit				
Female	−0.72***	−0.56***	−0.78***	−0.63***
Ed. medium	0.58***	0.54***	0.75***	0.58***
Ed. high	0.42***	0.38***	0.45***	0.30**
Time trend	0.03**	0.04**	0.05***	0.01
Self-rated health				0.05
Household income				0.32***
Time × Female		−0.03		
Time × Ed. med			−0.05*	
Time × Ed. high			−0.02	
N	5,595	5,595	5,595	4,786

Notes: M = model. Ed. = education. Coefficients for each class are obtained from a separate logit model and refer to the probability of class membership contrasted with all other classes combined. Time trend–year effect defined as the year when respondent reached 60 (centered at 2000). Household income z-centered by country.
$^{*}p < .05$;
$^{**}p < .01$;
$^{***}p < .001$.

(Figure 2d) reports a slight increase in Australia, Switzerland, and Germany (especially among women) and a decrease in Korea. Late Exit (Figure 2e) remains mainly at low levels, with slight increases in Australia, Korea, Germany, and the United Kingdom.

The results partly confirm hypothesis H1a, that Late Employment and Later Exit popularize, and Hypothesis H1b, that Nonemployment declines. These trends are recognized with different intensities in Australia, Korea, Switzerland, Germany, and the United Kingdom. However, only minor changes over time occur in the United States and Russia. We also do not see any apparent decrease in Early Exit. Women's and men's late-life employment trajectories strongly differ in prevalence. In line with hypothesis H3a, both genders experience the trend toward later exit, that is, an increase in Late Employment and a decrease in Nonemployment (only minor differences in gender-specific time trends appear for other trajectories). However, contrary to hypothesis H3b, we see no sharper trend toward the later exit for women.

Educational differences

Models M3 in Tables 4–7 include an interaction of education level with the linear time to assess how the educational differences have changed over time. Figure 3 presents time trends based on probabilities of classes predicted from a multinomial regression model with an additional quadratic time term and interaction of time (linear and quadratic) and education, controlled for gender (an equivalent of model M3 in Tables 4–7).

A general overview of Figure 3 shows that education-specific lines are mostly parallel (except in Korea), suggesting that educational differences have not changed much since 1990. Except for Korea, lower educated continue to be more likely to follow the Nonemployment trajectory and higher educated to remain in Late Employment. The educational variation in these two trajectories is particularly significant in the United States and Russia, somewhat smaller in Australia, Switzerland, and Korea, and relatively small in Germany and the United Kingdom. For other trajectories, educational differences remain much smaller.

Some significant education-specific time trends are reported in models M3 in Tables 4–7, yet they do not indicate substantial rearrangement of the trajectory probabilities. Higher educated report a stronger decline in Nonemployment in Germany and the United Kingdom. Probability of Late Employment for higher educated in the United States and Switzerland increased around 2005 and then sharply dropped. A similar yet weaker trend is observed in Russia. An exception to these trends is Korea, where lower educated show a higher likelihood of working until the late 60s. Here, Nonemployment became more popular among higher educated over time, while the probability of Late Employment sharply and continuously rose among lower and middle educated.

In line with previous literature, the results indicate educational heterogeneity in late-life employment, that is, the tendency to Late Employment rises with education. As expected (H2a), the trend toward later exit affects all educational groups. However, the results do not confirm hypothesis H2b, which expected the gap between lower and higher educated to grow over time. Time trends are relatively similar and do not re-arrange relative differences between the levels

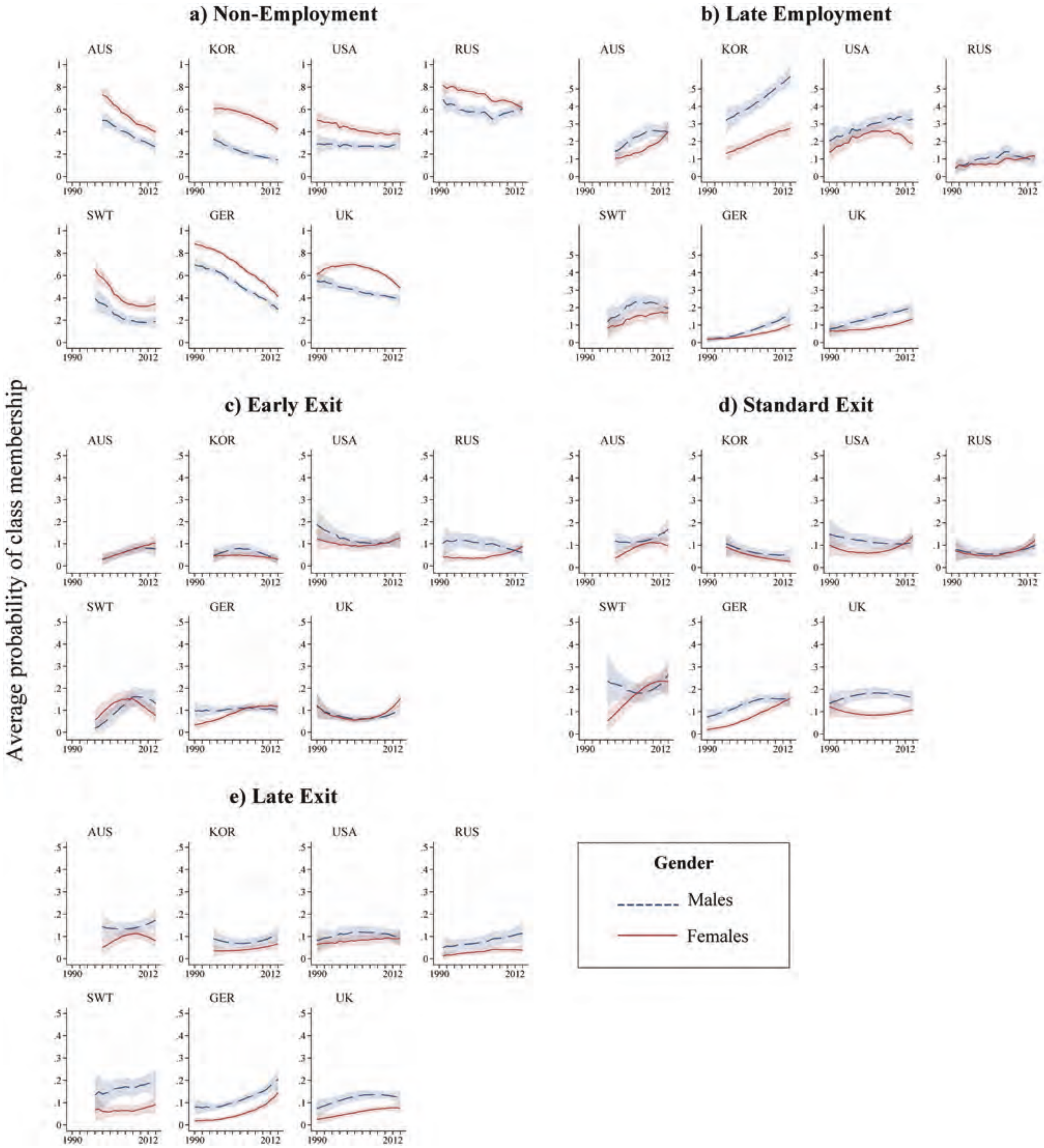

Figure 2. Time trend in the prevalence of five (a-e) major employment trajectories for age 60–69 by gender.

of education. These conclusions do not hold for Korea, which shows very different educational trends (we will come back to this issue).

DISCUSSION

This research aimed to identify the main trajectories of late-life employment, study how they have changed over time, and how they are stratified. By taking a three-decade-long, comparative, and gender-specific perspective, we gain insights into the heterogeneity of trends in extending working lives. Four main findings emerged from the analysis. First, we found five universal patterns that well represent late-life employment trajectories during the 60s, that is, Late Employment, Standard, Early and Late Exit, and Nonemployment. They were identified for men and women in all seven countries, although the prevalence differs. According to expectations, women have a much higher likelihood of being nonemployed during their 60s, whereas men more often remained employed until their late 60s.

Second, the prevalence of the most common late-life employment trajectories has significantly changed for both

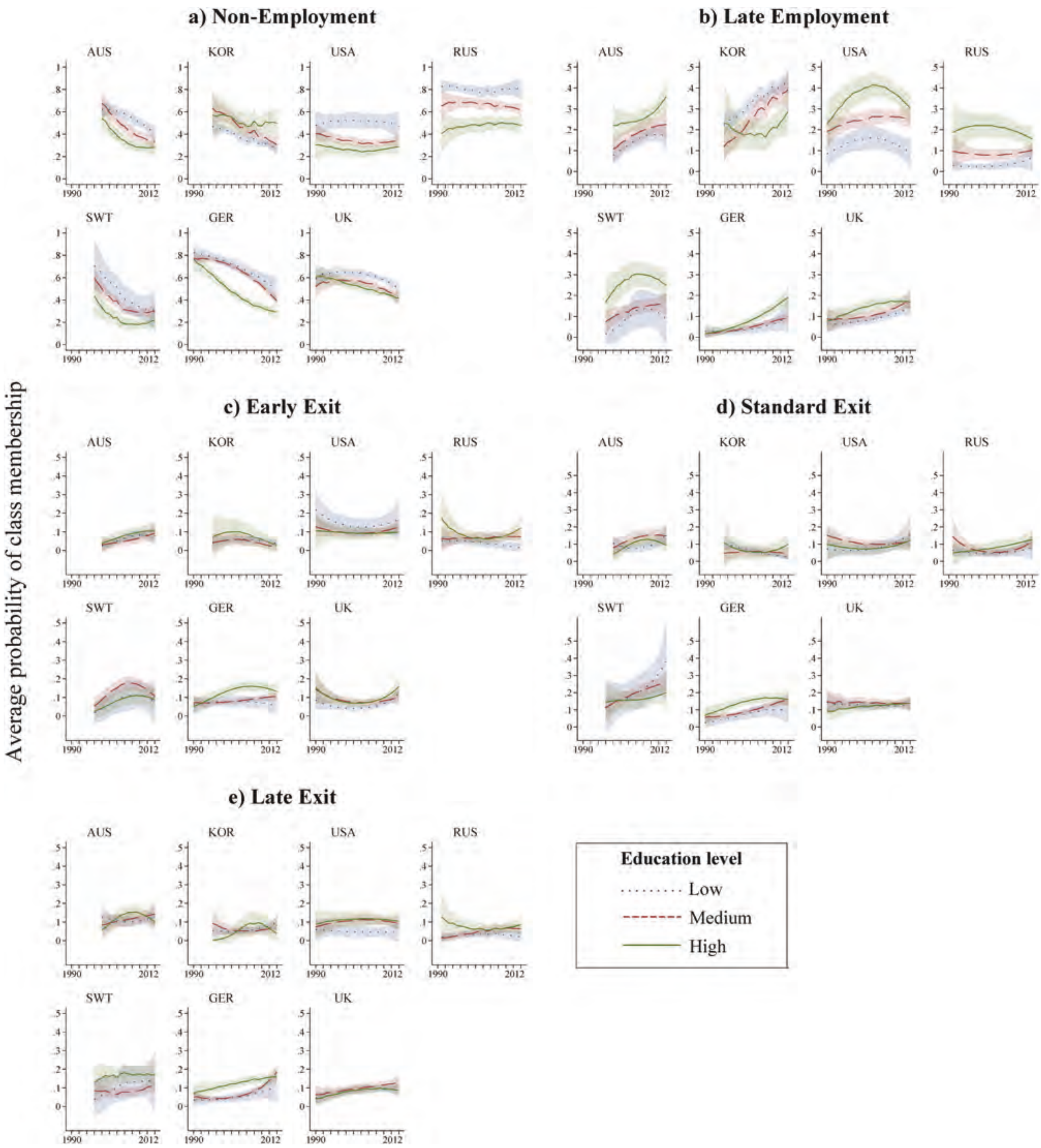

Figure 3. Time trend in the prevalence of five (a-e) major employment trajectories for age 60–69 by education level.

genders. Previous research suggests that later careers have undergone a dynamic evolution in the recent three decades, including the rising exit ages, especially for women. Our analyses indicate that these increases result from a significant drop in the Nonemployment group that dominated the age category of 60-year-old adults in the 1990s. For men, the decline was driven mainly by restrictions in access to early exit pathways, for example, due to disability (although this is also partly true for women). For women, the decline should primarily be linked to a more general increase in married women's labor force participation (Madero-Cabib & Fasang, 2016; Radl, 2013). At the same time, Late Employment—which was almost nonexisting in the 1990s—appeared on the map of older age as one of the major employment pathways. In some countries, we also observe a slight rise in the popularity of Standard and Late Exit, which additionally contributes to increases in average exit ages. The results do not show any striking gender difference in time trends in the prevalence of trajectories, suggesting that the progress toward extended employment affects men and women similarly.

Third, we find that education structures late-life employment. It is evident in the case of the two most popular trajectories, that is, Nonemployment during old age is most dominant among the lower educated, and the likelihood of Late Employment rises with education, although there are considerable country differences. Particularly important is that these educational inequalities remained mostly stable during the last three decades. It suggests that the process of extending working lives also applies to the lower educated, a group for which extended employment may be considerably more burdensome. Workers with better education, higher status, and higher-paid jobs can better plan and control their exit from employment (Hershey & Mowen, 2000). They also have higher skills and better access to opportunity structures to deal with the work-related challenges at older ages.

Fourth, our study suggests that the evolution of late careers and progress toward later employment affect all of the seven countries, yet similar to Van Winkle and Fasang (2021), we find vital country differences. The prevalence, magnitude, and speed of the evolution of late-life trajectories differ. The most significant changes occurred in Korea, Australia, and Germany, somewhat smaller in Switzerland and the United Kingdom, and fairly weak in Russia and the United States. Educational inequalities are relatively large in the United States and Russia, yet minor in Germany and the United Kingdom. Korea stands out with a different educational gradient. Lower educated Koreans are more likely to work until their late 60s, while the higher educated tend to exit the labor market earlier. These findings align with other research that suggests that the highest in OECD exit ages in Korea are driven mainly by forced and precarious prolonged employment when workers leave their career jobs during their 50s and later continue to work long in low-paid second careers as self-employed or contracted workers (Kim, 2017; OECD, 2018). This applies mainly to the lower educated in poor financial situations (the highest elderly poverty rate in the OECD) and with insufficient welfare support. Korea's situation is especially striking compared to Germany and the United Kingdom, where robust welfare systems and higher levels of social security provide stable retirement contexts, contributing to relatively small educational and gender inequalities in late careers.

This comparative aspect of our study highlights the role of the country context for retirement research. The welfare framework, including retirement procedures and benefits, social insurance, and health provision, controls older people's activity and shapes retirement patterns (Estes, 1979; Townsend, 1981). Although most OECD countries have introduced reforms to extend working lives, they still differ in retirement arrangements, normal retirement ages, or early retirement options (OECD, 2019). These contexts define baseline incentives, opportunities, and constraints for extended employment (Ferraro et al., 2009; Han & Moen, 1999; Riley, 1987). In particular, the country differences that we found show that simple generalizations of one-country findings can be risky.

This study also contributes methodologically to the research on historical trends in life course trajectories. Previously mixed findings of the progress in life-course complexity result partly from different methods, research designs, and populations of interest. We argue that the trajectory-oriented perspective has several advantages over the event-oriented studies. Following individuals over a longer time allows to distinguish specific employment patterns and eventually obtain a comprehensive map of heterogeneous life trajectories. By focusing on employment trajectories, we can also avoid problems related to various definitions and retirement arrangements, which is particularly important for multicountry studies. Instead of defining exit patterns in relation to public pension age or early exit arrangements that differ by country, we only combined employment information at specific ages. This strategy facilitates a direct descriptive comparison of the labor market patterns between countries and allows focusing on the trends to extend working lives.

Our study has several limitations, which open ways for further research. Although education and gender are the key stratification markers for life courses, they transform into differential wages, occupational levels, and job characteristics over time. These detailed variables are not included in this study. As a result, we could not establish, for example, whether differences in retirement patterns between occupational groups have increased. This study does not focus on the intervening variables and mediation mechanisms, yet they can and should be investigated. In particular, future studies should consider the role of such predictors as pension eligibility, spouse's health, occupation, industry, and homeownership. Furthermore, future studies can enrich the picture of late-life careers with more detailed aspects of employment trajectories, such as hours worked, employment type (e.g., part-time or self-employed), or other labor market statuses (e.g., disability or inactivity). Such indicators can help to distinguish various forms of gradual retirement or bridge employment. Although our study contributes with data from seven countries, we are limited in our ability to study macro-level factors as predictors of different country patterns. Additionally, our comparative approach comes at the cost of limited insights into the situation of each particular country. Finally, although LCGA allows us to compare countries and efficiently impute missing data, researchers should also consider other methods. For example, sequence analysis is suitable for a more nuanced analysis of patterns (Calvo et al., 2018; McMunn et al., 2015; Worts et al., 2016; van der Horst et al., 2017;), yet its application in multicountry research is challenging. Alternative approaches to growth mixture modeling are also worth consideration (Wang & Chan, 2011).

CONCLUSIONS

With the dawn of the 20th century, we entered a new demographic era when old rather than young groups dominate population structures. Demographers estimate that the portion of people aged 65+ will significantly rise (e.g., for Europe, from 20% in 2019 to 30% in 2050), and the old-age dependency ratio will increase (for Europe, from 31% to 52%, Eurostat projections). This enormous demographic transition poses one of the major 21st-century challenges and requires us to readjust how we work and retire. We can expect to observe further evolution of late careers toward later and more unpredictable retirement in the following decades. This study confirms that the times of easy access to an early exit and a stable and employment-free Third Age (Laslett, 1991) are gone (Han & Moen, 1999; Moen et al., 2005). The social and demographic transitions initiated a trend toward extending working lives. Globally, the increasing trend in exit ages appears to be universal and continuous. However, as we show, the progress can strongly differ between countries, stretching from rapid shifts toward trajectories of extended work (e.g., Australia, Korea, and Germany) to slower and less radical changes in employment patterns (e.g., Russia and the United States). In countries with greater change over time, the trend toward later exit ages is primarily driven by the sharp decline in the number of inactive people during their 60s. Instead, older people follow other patterns of employment. Among them, the novel and most vivid (yet not universally strong) tendency is the rising class of people who continue their employment until the late 60s or longer.

Our findings are relevant to the societal and policy processes that drive and support the transition toward actively aging societies. On the one hand, policy efforts to extend working lives in the analyzed countries appear efficient. The drop in the share of people who retire early and remain inactive during their 60s is related mainly to the reforms that have limited most early exit options since the late 90s (OECD, 2019). Similarly, the popularization of late employment was incentivized by retirement reforms and active aging policies (Boissonneault et al., 2020).

On the other hand, the efficient and universal extension of working lives can have unequal, sometimes negative, consequences for various groups. As our findings confirm, late-life employment is structured in ways that tend to reproduce life-course advantages and disadvantages (Calvo et al., 2018; Ferraro et al., 2009; O'Rand & Henretta, 1999; Riley, 1987). Longer work can have detrimental effects on the health and well-being of disadvantaged groups, for example, lower educated. As the example of Korea suggests, the general trend toward extending employment may negatively affect people in lower socioeconomic positions when the welfare system and public policies do not address their problems. An early exit is a privilege in this situation, and those who cannot afford it must continue working. In particular, prolonged employment can be forced among groups with a low income and low expected pension claims, leading to a new problem of precariatization of late-life employment and the emergence of a working-poor class (Carr, 2019; Visser et al., 2016).

The results also suggest that late-life employment remains strongly gendered, and the consequences of extending working lives can differ for men and women. Although retirement reforms aim to harmonize the gendered retirement arrangements, older women are still more vulnerable on the labor market (Madero-Cabib & Fasang, 2016; Moen et al., 2016; Noone et al., 2010; Widmer & Ritschard, 2009). Women often experience multiple and contradictory pressures during late careers. When retirement systems and low pension benefits incentivize them to work longer, family and care obligations often constrain their opportunities. As a result, women have a higher risk of experiencing extended employment as a forced and stressful trajectory.

The crucial challenge for public policies is to address the heterogeneity of life situations and biographies of older people. Unified and ungendered progress toward late employment is challenging for some groups and may deepen inequalities around retirement. Increasing longevity will only provide more time and force for the inequalities to develop. We can expect the following cohorts to continue the tendency observed in this study to extend employment until later ages, whether they want it or not.

Finally, universal progress toward increased employment of 60-year-old adults challenges companies. They must implement adequate policies and design a supportive work environment to accommodate the rising number of older employees. Employers and companies can influence workers' abilities and motivations to work and define opportunities to extend employment beyond the retirement age (Henkens, 2022). As such, they can help or hinder the chances of remaining engaged, motivated, and able to work longer. Eventually, a successful transition toward actively aging societies will require the policy reforms to be followed by the increasing willingness and ability of older people to work and an adequate work environment that allows extended employment.

Supplementary Material

Supplementary material is available online at *Work, Aging, and Retirement.*

Supplementary Figure C1. Profiles of employment trajectories estimated from separate LCGA models for males and females. *Notes*. The figure corresponds to Figure 1. Each line represent an identified employment trajectory estimated from the 6-class LCGA model. Here, we see that similar profiles are identified separately for men and women. Their interpretation corresponds to the Figure 1 with classes of exit transitions (Early, Standard and Late Exit) and stable employment patterns (Non- and Late Employment) (please refer to the text for more detailed interpretation).

Supplementary Figure C2. Profiles of employment trajectories estimated from separate LCGA models for each country. *Notes*. The figure corresponds to Figure 1. Each line represent an identified employment trajectory estimated from the 6-class LCGA model. Here, we see that similar profiles are identified separately for each country. Their interpretation corresponds to the Figure 1 with classes of exit transitions (Early, Standard and Late Exit) and stable employment patterns (Non- and Late Employment) (please refer to the text for more detailed interpretation).

Data Availability

This study uses the following data sets:

1.The British Household Panel Survey, BHPS, and Understanding Society—The UK Household Longitudinal Study, UKHLS. University of Essex, Institute for Social and Economic Research. (2021). Understanding Society: Waves 1–10, 2009–2019 and Harmonised BHPS: Waves 1–18, 1991–2009. [data collection]. 13th Edition. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-14.

2.Socio-Economic Panel (SOEP), data for years 1984–2019, version 36, SOEP, 2021, doi:10.5684/soep.core.v36eu. At https://www.diw.de/en/soep.

3.Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2021). https://psidonline.isr.umich.edu.

4.The Household, Income and Labour Dynamics in Australia (HILDA) Survey, GENERAL RELEASE 19 (Waves 1–19), Department of Social Services; Melbourne Institute of Applied Economic and Social Research, 2020, doi:10.26193/3QRFMZ, ADA Dataverse.

5.Korean Labor & Income Panel Study (KLIPS) version 22. Copyright Korea Labor Institute, 2021. www.kli.re.kr/klips_eng.

6.Russia Longitudinal Monitoring Survey, RLMS-HSE, version 2019, conducted by National Research University "Higher School of Economics" and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS (RLMS-HSE sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms).

7.Swiss Household Panel (SHP), version 21, SHP is based at the Swiss Centre of Expertise in the Social Sciences FORS. The project is supported by the Swiss National Science Foundation. https://forscenter.ch/projects/swiss-household-panel.

8.The Cross-National Equivalent File project is sponsored by the National Institute on Aging (Grant: 5-R01AG040213-10) and the Eunice Kennedy Shriver National Institute of Child Health and Human Development (Grants: 1-R03HD091871-01, 1-R03HD100924-01) and was conducted by The Ohio State University. https://www.cnefdata.org.

This article uses code from the Comparative Panel File (CPF) version 1.4 to harmonize the mentioned data sets. It is available at www.cpfdata.com. CPF was created by Konrad Turek, Matthijs Kalmijn, and Thomas Leopold. The initial version of CPF has been developed in the CRITEVENTS project (PI: Thomas Leopold) and funded by an ERA-NET Cofund grant within the NORFACE Joint Research Programme on the Dynamics of Inequality Across the Life-course (DIAL). DOI:10.17605/OSF.IO/H3YXQ. For details, see Turek, K., Kalmijn, M., and Leopold, T. (2021). The Comparative Panel File (CPF): Harmonized Household Panel Surveys from Seven Countries. *European Sociological Review.*

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We want to thank Thomas Leopold for consulting the article and the Editors and anonymous reviewers of the *Work, Aging and Retirement* for very helpful suggestions.

Appendix A. Missing Values in Employment Trajectories

Table A1. Number of missing values for employment status between ages 60–69 for the sample used for imputation

	[1] Australia	[2] Korea	[3] United States	[4] Russia	[5] Switzerland	[6] Germany	[7] United Kingdom	Total		
Missing values	%	%	%	%	%	%	%	*n*	%	Cumulative %
0	53.6	53.3	0.0	26.0	43.4	59.4	15.4	7,986	35.8	35.8
1	18.4	16.9	3.2	18.2	14.7	15.1	37.9	4,545	20.4	56.2
2	17.0	17.2	5.9	24.8	17.8	15.6	24.8	4,084	18.3	74.5
3	8.5	8.7	5.4	13.6	9.2	7.8	14.9	2,279	10.2	84.7
4	1.6	2.4	5.3	9.2	10.6	1.4	3.7	889	4.0	88.7
5	0.8	1.1	68.7	6.5	2.9	0.7	2.7	2,135	9.6	98.2
6	0.1	0.4	11.5	1.7	1.4	0.0	0.6	396	1.8	100.0
Total	100	100	100	100	100	100	100	22,314	100	—
n	2,391	2,624	2,476	2,352	1,509	5,335	5,627	—	—	—

Notes: The sample includes individuals with a minimum of four measurements between ages 60 and 69 and at least one measurement in each of the three age ranges: 60–63, 64–66, and 67–69. For example, six missing values indicate that there are four non-missing measurements.

Appendix B. Additional Details of the LCGA Analysis

Table B1. Growth parameters for the final 6-class LCGA model with linear and quadratic terms

		Mean	*SE*	*p*-value
Class 1	Intercept	12.056	2.428	.000
	Linear	−3.131	0.744	.000
	Quadratic	0.147	0.054	.006
Class 2	Intercept	−3.518	0.389	.000
	Linear	−1.341	0.052	.000
	Quadratic	0.115	0.006	.000
Class 3	Intercept	−1.746	0.395	.000
	Linear	0.103	0.045	.022
	Quadratic	−0.006	0.005	.177
Class 4	Intercept	0.713	0.443	.108
	Linear	1.083	0.091	.000
	Quadratic	−0.383	0.023	.000
Class 5	Intercept	1.644	0.424	.000
	Linear	0.485	0.063	.000
	Quadratic	−0.069	0.007	.000
Class 6	Intercept	4.112	0.068	.000
	Linear	−3.35	0.236	.000
	Quadratic	0.257	0.022	.000

Notes: Trajectory parameters are fixed equal across the countries. The LCGA model was estimated without predictors.

Table B2. Model fit evaluation information for the six-class LCGA models of employment trajectory between the age of 60 and 70: the final model and an alternative model with an additional cubic growth parameter

Number of classes	AIC	BIC	Entropy: MI data (raw data)	Classes (%)					
				Number of classes ≤ 5%	Complex classes: % (number)	Nonemployed	Late employment	Early exit	Late exit
6 (I, S, Q)	218,838	218,983	0.955 (0.859)	0	6.7 (1)	48.5	15.1	9.7	9.1
6 (I, S, Q, C)	218,276	218,573	0.959 (0.873)	2	5.3 (1)	48.0	15.8	12.7	5.3

Notes: Both models include intercept (I), linear (S), and quadratic (Q) growth terms. The second model additional has the cubic (Q) growth term. The results indicate the more complex model does not offer substantial fit improvement and is more difficult in interpretation. Both models correspond to those presented in Table 2.

Appendix C. Separate Models by Gender and Country

See Supplementary Figures C1 and C2.

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