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Trajectories of job resources and the timing of retirement

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Abstract

Job resources benefit and motivate workers and, therefore, facilitate longer working lives. Yet, little is known about how job resources develop over time and how, in turn, trajectories of job resources are associated with retirement timing. Accordingly, this study examines job resource trajectories of older workers and to what extent these trajectories are related to when people retire. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), growth mixture models are conducted to examine the trajectory of three job resources, namely autonomy, skill development opportunities and recognition, from age 50 until workers retired or dropped out of the survey. Four trajectories of job resources are found: stable high resources, stable low skill development opportunities, stable low recognition and stable low resources. The results of the subsequent event history analysis of retirement timing show that older workers with trajectories of job resources characterized by stable low recognition and stable low resources are at higher risk of earlier retirement compared to those with other trajectories. The findings shed light on the importance of job resource trajectories for promoting longer working lives.

Keywords: growth mixture modeling, job resources, older workers, retirement, SHARE

European countries are increasing their statutory retirement age and promoting longer working lives (OECD, 2021). This has raised scholarly concerns about the extent to which prolonged working lives are exacerbating social inequality in the transition and adjustment to retirement (van Solinge & Henkens, 2017; Visser et al., 2016; Wang et al., 2011). Previous research suggests that longer working lives are facilitated to the extent that job resources are available to support workers in older ages (Fisher et al., 2016; Pak et al., 2019; Sarandopoulos & Bordia, 2022; Virtanen et al., 2014). Resources are contextual and personal features that people can use to achieve desirable goals and outcomes (Halbesleben et al., 2014; Hobfoll, 1989). In the work context, job resources such as skill development opportunities, job autonomy, and recognition may motivate workers and, therefore, encourage them to retire later (Beehr et al., 2000; Fisher et al., 2016 for a review; Virtanen et al., 2022). However, prior studies mostly adopted cross-sectional designs (e.g., Schreurs et al., 2011) and multi-wave designs without repeated measurements of job resources, therefore precluding any conclusions about the role of changes in resources over time (e.g., Topa & Valero, 2017). We argue that studying job resources over time is of value, as changes in job attributes have been previously linked to well-being consequences above and beyond well-being consequences of job attributes at a single point in time (e.g., Fan et al., 2019; Igic et al., 2017; Mauno et al., 2016).

The goal of this research is twofold. First, using cross-national longitudinal data from the Survey of Health, Ageing and Retirement in Europe (SHARE), we examine trajectories of job resources in a sample of workers aged 50 and older as well as the heterogeneity in intra-individual change in this trajectory using growth mixture modeling (GMM). We consider two task-related resources (job autonomy and skill development opportunities) and one social resource (recognition) that are available in the SHARE data. Second, using discrete-time event history analysis, we examine how said trajectories of job resources predict the timing of retirement.

Our study offers several contributions to the literature. First, by examining differences in the way job resources develop over time for older workers, we contribute to the literature on aging at work. Examining job resource trajectories increases our understanding of how inequalities unfold over time. Indeed, from a cumulative advantage perspective (Dannefer, 2003), unequal access to job resources (i.e., some people having more job resources or more gains in job resources) may create inequalities over time in terms of the willingness and ability to retire later, with those who have more access to resources being more likely to retire later. Second, although some past research has examined how single job resources, such as work scheduling autonomy, unfold over time for older workers and predict their retirement timing, resources are often experienced in tandem with one another. As such, we contribute to Conservation of Resources theory (COR; Hobfoll, 1989, 2018) by examining the trajectory of multiple resources and examining COR theory's postulate of resources traveling together in caravans (Hobfoll et al., 2018).

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Third, we study the influence of job resource trajectories on retirement behavior, as opposed to retirement intentions (e.g., Schreurs et al., 2011; Stynen et al., 2017). This is a valuable contribution as few studies have looked at the relationship between job resources, let alone trajectories, and actual retirement behavior. Despite the overlap between these two constructs, there is oftentimes a large discrepancy between the intended and actual retirement age (Henkens & Tazelaar, 1997; Steiber & Kohli, 2017).

Theoretical background

Job resources and retirement

Ample evidence shows that job resources are vital in motivating employees, supporting their well-being, and thus in facilitating extended working lives (Pak et al., 2019). Job resources promote well-being because they are thought to fulfill workers' basic psychological needs (van den Broeck et al., 2016), enhance work meaningfulness (Humphrey et al., 2007), and enhance psychological contract fulfillment between the employer and employee (Birtch et al., 2016). According to COR theory (Hobfoll, 1989), people are motivated to protect and maintain their resources, which play an important role in their well-being, but experience stress when their resources are threatened. Research has shown that job resources are also important predictors of retirement intentions. Indeed, demanding work with low job control is associated with the intention to retire earlier (von Bonsdorff et al., 2010). Furthermore, van Solinge and Henkens (2017) showed that older workers in lower occupational classes (e.g., manual workers), who tend to have demanding jobs with fewer resources, displayed more anger towards rising retirement age policies compared to those in higher classes, who tend to have better access to resources. Taken together, these studies suggest that access to job resources is an important factor in shaping people's retirement decisions and preferences. Retirement intentions are generally good predictors of retirement behavior (Prothero & Beach, 1984). Accordingly, access to job resources should have significant implications for retirement behavior as well. To date, little research has linked resources at work and retirement behavior. Based on the above, we expect that access to high levels of or increases in these resources promote occupational well-being, which should motivate workers and help them to extend their working life. In contrast, we expect that prolonged exposure to low levels of job resources or resource losses should lead to long-term stress and poorer well-being (Hobfoll, 1989; Igic et al., 2017), discouraging people from retiring later and making it harder for them to keep working.

Prolonged working lives are facilitated by both task-related and social job characteristics, as both types of job resources are important aspects of work that promote occupational well-being and meaningful work and would therefore be conducive to longer working lives (e.g., Fisher et al., 2016; Humphrey et al., 2007; Laaser and Karlsson, 2021; for a review; Siegrist et al., 2004). Although prior work has examined the relationship between job resources and retirement, much of this research has either examined one job attribute in isolation (e.g., Virtanen et al., 2022), a multitude of job attributes at a single point in time (de Wind et al., 2014), or has modeled retirement expectations as outcome as opposed to actual retirement behavior (Beehr et al., 2000; Pak et al., 2021). In the current study, we fill these gaps by looking at the trajectory of three job resources simultaneously and their link to actual retirement behavior. This approach is important to capture a more accurate depiction of jobs, as job characteristics exist in context to one another, and to explore how resources travel together in resource caravans (e.g., Hobfoll et al., 2018).

Job autonomy, which is conceptualized here as the amount of freedom or control a worker has in making own decisions, has been shown to be positively related to occupational well-being (Humphrey et al., 2007). Job autonomy also gives workers more leeway in deciding what, how and when they carry out their tasks, which may enable them to gain additional resources that might support later retirement (e.g., von Bonsdorff et al., 2010). For example, employees with high autonomy may decide for themselves whether they want to take part in a skills training course, whereas other employees need to get approval of their supervisor for such trainings. Consequently, the autonomy the former employees enjoy may help them to acquire more resources, in this case skill development opportunities. A recent study using growth mixture modeling by Virtanen et al. (2022) has found that worktime autonomy is associated with working beyond the state pension age.

Skill development opportunities, which we conceptualize here as the opportunities that workers are provided with to develop new skills at work (e.g., through human resource management practices that involve training), have also been associated with a prolonged intention and expectation to work longer because of their potential role in helping workers gain new resources (Beehr et al., 2000; Pak et al., 2021). For instance, taking part in training might help workers acquire new skills, such as digital skills, which might make them feel more competent at work and therefore enable them to work longer. Hence, skill development opportunities should facilitate the acquisition of new work-related skills that can retain workers in the labor market.

We additionally consider the role of *recognition*, which, akin to appreciation and esteem, is operationalized as the extent to which workers experience recognition and respect from others at work (Laaser & Karlsson, 2021; Pfister et al., 2020; Siegrist et al., 2004). Previous research has found a positive relationship between experiencing appreciation at work and well-being (Pfister et al., 2020; Stocker et al., 2019). Recognition should enable people to work longer as it facilitates the accumulation of social capital, promoting access to new resources (Seibert et al., 2017). Furthermore, recognition makes people more positive about their job, which should facilitate later retirement. Prior research indeed confirmed a negative relation between recognition and early retirement (de Wind et al., 2014).

The temporal nature of job resources

Thus far, the way resources accumulate and develop over time has been underrecognized in the literature on both job resources and retirement. This is a knowledge gap in the literature for at least two reasons. First, drawing on the concept of COR (Hobfoll, 1989), having more resources protects a person from resource loss, whereas having less resources makes people more vulnerable to resource loss. This implies that resources are subject to change and fluctuations. It is thus crucial to employ a temporal approach to study how people acquire and accumulate resources over time. Such temporal patterns may significantly affect a person's ability to work longer and retire later, above and beyond understanding the relationship between access to job resources at a given point in time and the retirement transition. Second, having resources facilitates the acquisition of new resources. For example, workers who have opportunities to develop their skills at their job and use these opportunities are more likely to receive recognition among colleagues for this, which makes them more likely to also have high job autonomy since their reputation in the organization might give them more freedom and responsibilities. As a result, these workers may use this increased autonomy to take on new projects and learn new skills, which might, in turn, lead to even more recognition. Together, these resources may energize workers and keep them motivated to remain in the workforce. Additionally, the resource gains that these workers acquire may make their organization more likely to want to retain them. Indeed, resources tend to travel together through cumulative advantage mechanisms, in what is referred to as resource caravans (Dannefer, 2003; Hobfoll, 2012; Sarandopoulos & Bordia, 2022). The accumulation of job resources may support workers in prolonging their working lives by providing workers with resources that allow them and keep them motivated to work longer. All in all, resource gains may signal a transition to better work quality, which in turn is linked to favorable attitudes towards retirement, whereas resource losses may reflect a deterioration in work quality over time, making it more difficult for one to work longer and forcing early retirement.

The composition of subgroups of job resource trajectories

Examining average trajectories of job resources is useful to help us understand how job resources change in general, but this approach does not allow us to examine differences between individuals in accumulation and changes in resources over time (see Igic et al., 2017). For retirement research, studying this heterogeneity is relevant as it can help us understand how differential access to job resources over time may create inequalities in the timing of retirement. For example, Sarandopoulos and Bordia (2022) argue, in their review, that people vary in the quality and quantity of resources they have in their later working life and that this partly depends on factors, including career patterns, that accumulate and develop uniquely for different people through mechanisms of cumulative advantage and disadvantage. Certain subgroups of people may gain more job resources over time, be more likely to have more work-related resources in later working life and therefore retire later.

Given that people might start out with different initial levels of resources, we expect that there will be variation in the development of job resources over time. More specifically, some people may have trajectories characterized by change, which can be characterized by either increases (i.e., improvements) or decreases (i.e., deteriorations) in job resources over time. Consistent with the cumulative advantage mechanism and COR theory (Dannefer, 2003; Hobfoll, 1989), these changes may reflect initial levels of job resources that, when relatively high, may facilitate increases and, when relatively low, may lead to decreases. Increases in job resources may occur when people transition to positions that provide them with better resources or when they engage in job crafting (Wrzesniewski & Dutton, 2001), whereby they actively change the conditions of their jobs through, for instance, increasing their resources (Demerouti, 2014). Yet, for these processes to occur, people need to already have access to some resources. For example, changing jobs is more difficult when a person's skills are obsolete. Job crafting is more difficult when people do not have the autonomy to decide what they want to do at work and how they want to do it. Decreases in job resources could be explained by changing circumstances, particularly drastic changes such as disasters and economic shocks (e.g., wars, economic recessions, etc.) that are thought to constrain people's access to resources (see Akkermans et al., 2018; Hobfoll, 2012). Yet, decreases in job resources are probably not so common, as Igic et al. (2017) found that only 2% of their sample belonged to a profile characterized by a deterioration of job quality over time. Note that their sample was relatively young and that this pattern may differ when observing the trajectories of older workers, as they are more likely to face discrimination compared to younger workers (e.g., Marques et al., 2020), which could be associated with a decrease in job resources.

Other people may have more or less stable trajectories of job resources (Mäkikangas et al., 2010; Virtanen et al., 2022), possibly reflecting ceiling or floor effects. Accordingly, subgroups with very high or very low initial levels of a given job resource can be expected to experience more stability in the trajectory of said resource over time. From a practical sense, ceiling (floor) effects might prevent subgroups with very high (low) levels of job resources to improve (deteriorate) on these resources. According to COR theory (Hobfoll, 1989), high initial levels of resources facilitate the maintenance of these resources and prevent these subgroups from significant losses. This is because people are motivated to protect and maintain the resources they already have. They therefore invest in their current resources (when these resources are available) to preserve these resources and acquire new ones (Hobfoll, 1989). In contrast, low initial levels of resources may prevent significant gains in these resources as the level of resources in these subgroups is not sufficient to enable them to acquire higher levels. Fluctuations in resource levels (improvements or deteriorations) are therefore more likely to be observed among subgroups that have moderate initial levels of resources.

Subgroups of trajectories of job resources and the retirement transition

Due to the exploratory nature of mixture modeling techniques, developing specific hypotheses about the number and nature of subgroups is difficult. Previous studies that have employed GMM to study trajectories of work conditions (including resources) have found patterns characterized by both stability and change (Fan et al., 2019; Igic et al., 2017; Mauno et al., 2016; Virtanen et al., 2022). We expect that subgroups will vary based on their composition (i.e., which resources cluster together) and their patterns of initial levels and change. Given the role of job resources in promoting well-being and motivation, we expect that favorable trajectories, characterized by increases in or stable high levels of resources, will reflect motivating work conditions and thus aid workers in retiring later. In contrast, unfavorable trajectories, characterized by decreases in or stable low levels of job resources will reflect more stressful work conditions, and will thus be linked to earlier retirement (Hobfoll et al., 2018).

Method

Data and sample

We used longitudinal data from SHARE, the largest social sciences panel study for studying health and socio-economic conditions of older Europeans (www.share-project.org). SHARE includes both prospective and retrospective data. Prospective surveys are done bi-annually and include questions related to participants' conditions at the time the survey is administered, including job conditions. Retrospective data (Waves 3 and 7 of SHARE, called SHARELIFE) were collected in years 2008–2009 and 2017 and are based on a life history questionnaire in which participants provide information about their past life circumstances, including employment status (e.g., employed, unemployed, on sick leave, student or retired). To minimize recall bias, SHARELIFE uses a life history calendar approach to aid participants in recollecting their year-by-year employment status and is therefore less prone to such bias compared to traditional retrospective data collection methods (for more information, see Morselli & Berchtold, 2023; Schröder, 2011).

For information on job resources over time, we used the prospective SHARE data from participants from Waves 1 to 8, covering the years 2004 to pre-COVID 2020. Given that we were interested in examining how trajectories of job resources predict retirement timing, we only included participants who also participated in SHARELIFE. This is because SHARELIFE provides the exact age at which the participant retired (in the case that the participant experienced retirement). In sum, we modeled the longitudinal trajectories of job resources using the prospective SHARE data and combined this with the retrospective SHARELIFE data that contains information about participants' retirement age.

In the SHARE dataset, the target population is aged 50 and over. This means that only primary respondents aged 50 years and older (and their partner, even if the partner is younger than 50, in case the primary respondent is partnered) may participate in SHARE. As we were interested in the older working sample, we excluded observations at waves in which participants (in this case, consisting solely of partners of primary respondents) were younger than 50 years. Furthermore, as we were interested in modeling longitudinal growth, we only included participants if they provided information on their job conditions for at least two waves. All in all, participants were included (1) if they took part in SHARELIFE and (2) if they had data about their job conditions for at least two waves in which they were older than 50, which resulted in a sample size of 14,488 respondents across 21 countries. Table 1 provides descriptive information on this sample regarding demographics and key study variables.

Measures

Dependent variable: Retirement timing

Retirement timing was measured based on yearly information about participants' employment status and refers to the self-reported age of retirement. Further details on how this variable was coded can be found in the section Analytical Procedure.

Independent variables: Job resources

For each item, participants had to report the extent to which they agreed with the corresponding statement on a Likert-scale from 1 to 4. Autonomy was measured using the item "I have very little freedom to decide how I do my work." We reverse-coded this item so that higher values denote higher levels of autonomy. Skill development opportunities was measured using the item "I have an opportunity to develop new skills." Recognition at work was measured using the item "I receive the recognition I deserve for my work," which was taken from the effort-reward imbalance questionnaire (Siegrist et al., 2014).

Analytical procedure

All analyses were conducted using Mplus version 8.6. Mplus deals with missing data using Full Information Maximum Likelihood (FIML). Given that many participants participated in a few waves only, we lowered the minimal covariance coverage (i.e., proportion of data available for each variable and pairwise combinations of variables) to allow Mplus' expectation-maximization (EM) algorithm to be initiated.

Latent growth curve modeling

As a first step, we estimated a trivariate (because three job resources) latent growth curve model to ensure that the variables were not multicollinear and to test whether linear trajectories were a good fit to the data.[1] Based on fit criteria, we expected to have good fit when the CFI and TLI are around .95 and when the RMSEA and SRMR are smaller than or equal to .05 (Hu & Bentler, 1999). The loadings for each measurement point were fixed based on the number of years between waves in which most of the data collection occurred. We fixed the first time point to 0 and the second time point to 1. Given that the interval between the first two timepoints (Wave 1 and Wave 2) was 3 years, we fixed the loadings for items from subsequent waves to reflect this scaling. In other words, one unit of time was scaled to correspond to three years. Each wave between Wave 3 to Wave 7 was two years apart from the previous wave, and there was a three-year interval between Wave 7 and Wave 8. Accordingly, item loadings for Waves 3 to 8 were fixed at 1.67, 2.33, 3, 3.67, 4.33, and 5.33, respectively. Slopes and intercepts of all three resources were allowed to freely correlate (in the trivariate growth model as well as the growth mixture model).

Growth mixture modeling

To model the heterogeneity in the trajectory of job resources over time, we ran a growth mixture model. This method consists of a combination of latent growth curve modeling and mixture modeling, in that it allows us to model individual heterogeneity in longitudinal growth by grouping participants in subgroups based on their patterns of growth on our three indicators of interest: autonomy, recognition, and skills development opportunities. We used the same loadings for the items that we used in the trivariate growth

[1]We also considered modeling a quadratic trajectory for recognition. Both quadratic and linear models showed good fit. We decided to retain the linear trajectory for parsimony and ease of interpretation.

Table 1. Descriptive statistics.

	Minimum	Maximum	Mean/%	SD
Birth year	1918	1967	1952.6	5.79
Biological sex (female)			50.4%	
Number of waves	2	8	2.9	1.10
Education (ISCED-1997)				
ISCED 0			1.2%	
ISCED 1			8.7%	
ISCED 2			14%	
ISCED 3			35.3%	
ISCED 4			6.2%	
ISCED 5			32.4%	
ISCED 6			1.1%	
Missing			0.8%	
Other			0.3%	
Employment status at age 50				
Employed (full-time/part-time/self-employed)			93.2%	
Unemployed			1.8%	
Homemaker			2.6%	
Retired			0.3%	
Sick/disabled			0.6%	
Voluntary work			0.1%	
Missing			2.2%	
Other			1.1%	
Total years of unemployment from ages 15 to 49	0	35	0.85	3.27
Unemployed for one year or less			88.5%	
Unemployed for less than five years			5.4%	
Unemployed for less than ten years			3.2%	
Unemployed for ten years or more			2.9%	
Family status at age 50				
Single			4.7%	
Married			78.1%	
Cohabiting			5.8%	
Separated			9.9%	
Widowed			1.5%	
Missing			1.1%	
Country				
Austria			3.6%	
Germany			7.9%	
Sweden			8.2%	
Netherlands			4.8%	
Spain			4.9%	
Italy			5.6%	
France			7.6%	
Denmark			10%	
Greece			6.4%	
Switzerland			8.3%	
Belgium			8.7%	
Israel			3.7%	
Czechia			6.2%	
Poland			2.3%	
Ireland[a]			1.1%	
Luxembourg			0.3%	
Hungary			0.4%	
Portugal			0.8%	
Slovenia			1.5%	
Estonia			7.5%	
Croatia[a]			<0.1%	

[a]Data from these countries only used in trivariate growth model and GMM.

curve model. We estimated solutions for one to six subgroups and compared them based on their statistical fit indices and their theoretical meaningfulness (Diallo et al., 2016). Based on a simulation study by Diallo et al. (2016), we considered the Bayesian Information Criterion (BIC), the Sample-Size Adjusted Information Criterion (SABIC) and the Consistent Akaike Information Criterion (CAIC) to be the most important fit criteria. The CAIC is not automatically displayed in the M*plus* output and therefore needs to be manually calculated by adding the number of free parameters to the BIC (Chen et al., 2017). Lower values on each of these criteria reflect better fit. When the criteria keep decreasing, it is recommended to plot the information criteria in an elbow plot; when the plot is less steep, this can be indicative of no additional gains from the extraction of $k + 1$ classes (for a review on mixture modeling, see Hofmans et al., 2020). We also reported entropy and considered higher entropy values to be indicative of better classification accuracy, although we did not consider entropy as our main criterion given that simulation studies showed that it is not the most reliable in choosing the best solution (Diallo et al., 2016; Tein et al., 2013). We ran the latent profile analysis using 100 initial random sets of starting values, 20 initial stage iterations, and 20 final stage optimizations. To ensure that the best-fitting solution is not a local maximum, we ran the growth mixture model for the best-fitting solution using 500 initial random starts and 100 initial stage iterations and final stage optimizations, and compared the log-likelihood value obtained from the two solutions to make sure that it is replicated. After agreeing on the solution with best fit, we created dummy variables that represent the subgroups that emerged from the best-fitting solution (see Results).

Event history analysis

To code our retirement timing variable, we first created a person-period file. This means that we restructured the data from wide-format (every row representing a participant) to long-format (every row representing a year). This restructuring was necessary so that participants' employment status (employed or retired) is coded for each year from age 50 until the person reaches retirement or until the age at which the participant was last observed. Relying on yearly information about retirement status obtained from the retrospective SHARELIFE data is a more precise way of capturing participants' employment status (including whether they retired) than using their employment status from wave to wave (which would be less precise since the interval between waves was 2 to 3 years). Retirement timing was coded by creating a nominal dummy variable (EVENT) that distinguishes whether the participant was (still) employed or retired at a given age, starting from age 50. Once a person has experienced retirement, all their subsequent observations were excluded from the analysis, meaning we focused on single events instead of repeated ones. Note that out of the 14,488 participants, 56.9% never experienced retirement (i.e., right-censoring), while 14.3% were retired for one year, 9.8% for two years, 8.2% for three years, 4.7% for four years, 2.5% for five years, and the rest had experienced retirement for six years or longer.

We then proceeded with the event history analysis. We excluded some additional observations to run this type of analysis. To account for left-censored observations and for people to be part of the risk set, we excluded all participants who were not employed at the age of 50, who were retired before the age of 50, who were not employed at age 50 and been continuously ill from ages 40 to 49, or who were ill for more than five consecutive years between the ages of 50 and 70. This is because SHARE's target population is people aged 50 and over in Europe, which implies that only primary respondents who are 50 years and older may participate in SHARE. We also excluded all observations in which participants were aged above 70 years (if not retired) to avoid extreme cases of non-retirement and survivor bias. Note that we also excluded Irish and Croatian participants because Irish participants were part of Waves 2, 3 (retrospective survey), and 8 and Croatian participants responded to Waves 6, 7 (retrospective survey), and 8. Because we only included participants who provided information about their job resources for at least two waves for the GMM analysis, this automatically implied that Irish and Croatian respondents who experienced retirement in the retrospective waves were excluded from the study. We ended up with a total of 138,942 observations across 12,872 participants. Out of these observations, 4.1% were retirement events. The average retirement age was 63.3 years. To establish the baseline hazard, we accounted for time by adding age (in years) as a covariate in the analysis.[2] We regressed the EVENT variable on each of the dummy variables that represent the job resource trajectories (between-level) using a multilevel multinomial logistic regression in which yearly observations of employment states are nested within participants.

Control variables for event history analysis

At the between-person level, we controlled for biological sex, educational level and total number of years in which the participant was unemployed before reaching the age of 50 as factors that may influence retirement behavior. Given that the data were collected in several countries, we controlled for this by creating country-specific dummies and adding those as covariates. We also accounted for potential attrition effects by controlling for the number of waves in which the participant provided information on the study variables in question.

As a robustness check, we also considered the same model adding health and income as covariates that could influence retirement behavior. We considered the U.S. version of the self-perceived health questionnaire, which is a single-item measure of current general health based on the SF-36 questionnaire (Ware & Gandek, 1998). We operationalized financial status as total income received by all household members in an average month in the past year. Note that the health variable was measured in Waves 1 to 8, except for Wave 3, and the income variable was measured in Waves 2 to 8, except for Wave 3. For both variables, we computed the mean across waves to measure participants' overall health and financial status, both of which are important factors for retirement timing. To avoid the influence of outlier income values, especially given that some participants had way too high or way too low average incomes (e.g., 14-figure values), we excluded observations from 194 cases whose income was in the 99th or 1st percentile. Furthermore, because M*plus* cannot process variances that are greater than 1 million, we log-transformed the income variable before we included it in the event history analysis to reduce its variance.

Results

Descriptive statistics for the original sample ($N = 14{,}488$) are shown in Table 1. The trivariate linear latent growth curve model suggested good fit ($\chi^2 = 1{,}380.84$, $df = 273$, $p < .001$; RMSEA = 0.017, 90% CI = 0.016 to 0.018; CFI = 0.93; TLI = 0.93; SRMR = 0.05). We therefore proceeded with the GMM.

Growth mixture model

Table 2 displays the fit indices for the GMM. As the information criteria were continuously increasing, we plotted them in an elbow plot (see Figure 1). Based on this figure, we concluded that much of the statistical deviance was reduced at the four-class solution, which, upon examination, was also theoretically meaningful. The entropy of the four-class solution was also high, which suggests that the subgroups in this solution are sufficiently separated from one another. The log-likelihood solution of the four-class solution was replicated at 100 and 500 random starts, which suggests that this solution is not a local maximum. We therefore adopted the four-class solution, which we plotted in Figure 2. Means of intercepts and slopes for each class are displayed in Table 3. It is noteworthy to mention that all subgroups in the four-class solution were characterized by stable resources over time. This is further addressed in the Discussion section.

The first subgroup, which constituted most participants (73.9%), was characterized by relatively high levels of all three resources that remained high over time. We labeled this subgroup *stable high resources*. Given the high levels of resources experienced by this subgroup, we expected it to be favorable in promoting a longer working life. The second subgroup (11.4%) was characterized by a stable trajectory over time, with skill development opportunities being lower than the

[2]Note that we also considered modeling age quadratically, but our data suggested a linear pattern for the baseline hazard.

Table 2. Fit indices for the linear growth mixture models of autonomy, skill development opportunities, and recognition.

Solution	AIC	BIC	SABIC	CAIC	Entropy	Smallest class size
1-class	292,496.70	292,883.33	292,721.26	292,934.33	--	--
2-class	291,568.78	292,008.48	291,824.16	292,066.48	.66	3,046
3-class	291,148.69	291,641.46	291,434.90	291,706.46	.71	1,140
4-class	**290,524.13**	**291,069.96**	**290,841.15**	**291,141.96**	**.72**	**949**
5-class	290,310.97	290,909.87	290,658.82	290,988.87	.70	618
6-class	290,118.30	290,770.27	290,496.97	290,856.27	.68	291

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-size adjusted Bayesian information criterion; CAIC = consistent Akaike information criterion. The 4-class solution, which we highlighted in bold, is the best fitting solution.

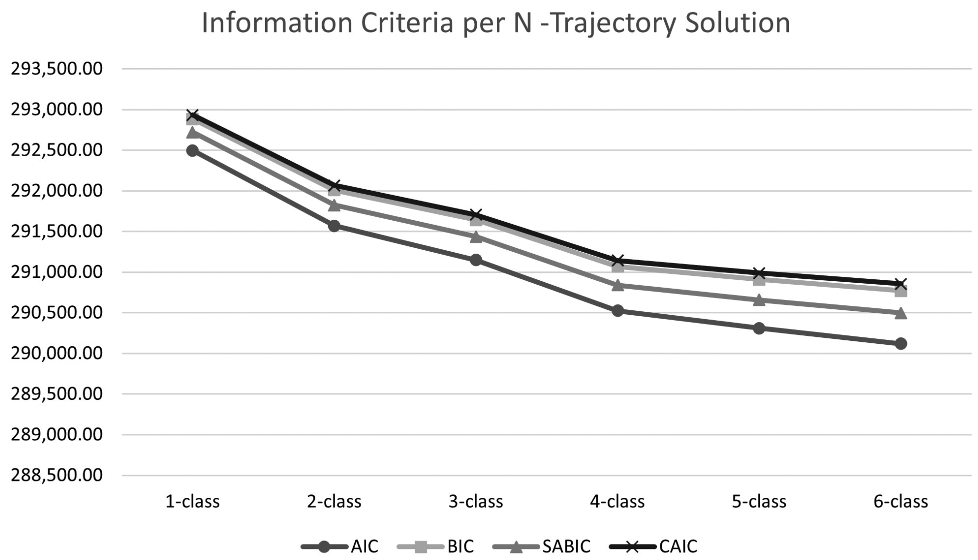

Figure 1. Elbow plot for information criteria. *Note.* AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-size adjusted Bayesian information criterion; CAIC = consistent Akaike information criterion.

other two resources. We therefore labeled this subgroup *stable resources with low skill development opportunities*. Given that this subgroup experiences low levels of skill development opportunities, we expected it to be comparatively unfavorable in terms of promoting a longer working life. The third subgroup (8.2%) was characterized by low and stable levels of all three resources. We labeled this subgroup *stable low resources*, again expecting it to be relatively unfavorable in terms of stimulating a longer working life. Although autonomy was slightly higher in this group compared to the other two resources, autonomy in this subgroup was lower than in all three other subgroups. We therefore refrained from giving this subgroup a label that refers to its relatively higher level of autonomy. The fourth subgroup (6.6%) had a similar pattern to the first subgroup, but with the difference that recognition was at a lower level than the other two resources. We labeled this subgroup *stable resources with low recognition*. Like the subgroup with low levels of skill development opportunities, we expected it to be unfavorably linked to working longer.

Table 4 shows the demographic composition of these four subgroups. In all four groups, the majority of people were born between 1951 and 1960, although there were slightly more people born between 1941 and 1950 in the low opportunities for skill development trajectory. Furthermore, women were slightly overrepresented in the low opportunities for skill development trajectory. In terms of education, both stable low trajectories and trajectories with low opportunities for skill development were underrepresented by higher educated people while stable high trajectories and trajectories with low recognition were overrepresented by higher educated people.

Event history analysis

Results of the event history analysis are displayed in Table 5. Given that the stable high resources trajectory was by far the most common and because this trajectory has a straightforward theoretical interpretability, we reported the results using this trajectory as the reference category. Note that we also conducted the analysis with the other groups as reference categories (see online supplementary material). The results show that people with stable high trajectories and with low skill development opportunities were more likely to retire later compared to other subgroups. Furthermore, we observed that people with stable low trajectories, followed by people in the low recognition subgroup, were at higher risk of retiring earlier compared to people with stable high trajectories. We did not expect that the subgroup with low skill development opportunities would not be linked to

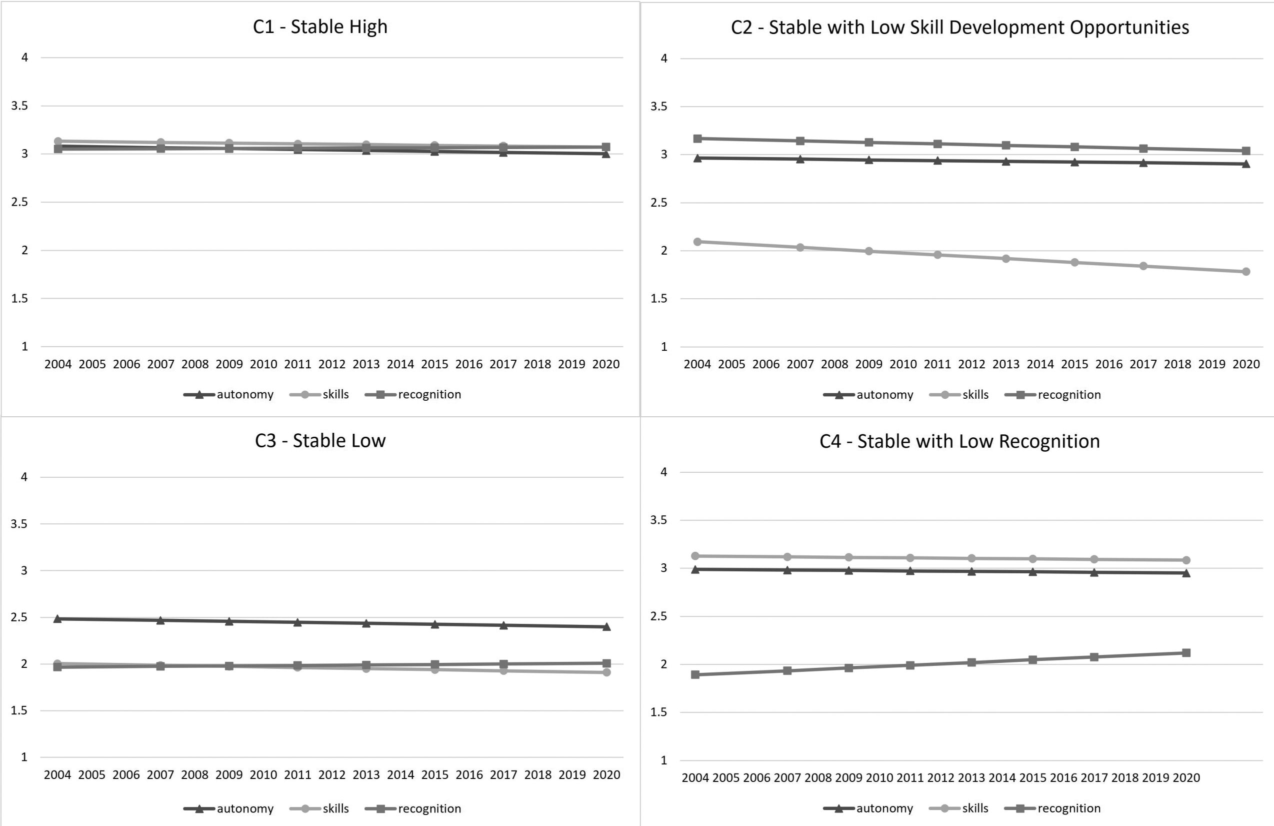

Figure 2. GMM four-class solution.

retirement timing given the importance of skill development opportunities as a resource to support workers in general (see Discussion for an elaboration on this). The observed effects are controlled for biological sex, education, total years of unemployment before the observation period, number of waves in which a person reported information on their job resources and country. Regarding these controls, we found that higher education decreases the risk of early retirement, while being female and having a longer unemployment history increases the risk of early retirement. As a robustness check, we also added average health status and average income as covariates. Results remained robust after controlling for these variables (see online supplementary material) and suggested that higher average income and higher health were both related to lower risk of retirement.

Discussion

In this study, we sought to understand how job resources unfold over time for older workers and how these trajectories of job resources predict retirement timing. Using growth mixture modeling, we identified four subgroups with distinct trajectories of job resources. All subgroups were characterized by stable trajectories with little to no change in job resources over time. One subgroup, constituting most of the sample, was characterized by stable high levels of all three resources. A second subgroup was characterized by lower levels of recognition compared to job autonomy and skill development opportunities, whereas a third subgroup was characterized by lower levels of skill development opportunities compared to autonomy and recognition. A fourth subgroup was characterized by stable low levels of all three resources. Our results suggested that those in subgroups characterized by lower recognition and those in subgroups characterized by low levels of all resources were at higher risk of early retirement. Those in subgroups characterized by stable high trajectories on all resources were least likely to retire early. The general pattern of results could therefore signify that when it comes to retirement timing, autonomy and recognition are more decisive than skill development opportunities.

Theoretical implications

The findings of this study contribute to the aging at work and occupational health literatures. First, although we expected to identify subgroups characterized by both stability and change in their levels of job resources, as previous research (e.g., Igic et al., 2017) did, the trajectories we identified were all characterized by stability, with the main differences being in level or with some subgroups consistently experiencing lower levels of one particular resource over time. Job resources tend to remain relatively stable over time for older workers, which is consistent with lifespan theories that postulate that older adults are more likely to prefer to maintain their resources and to protect them from losses over gaining new resources and increasing their current levels of resources (Baltes et al., 2006). This could also be because job resources are likely to fluctuate when people occupy new roles or positions, for example, through a promotion or job change. Older workers, who are near the end of their career, are less likely to be promoted or to change jobs, which is why their trajectories

Table 3. Unstandardized means and variances of intercepts and slopes for each class in the four-class solution of the trajectories of job resources.

	Stable high (n = 10,704)		Stable with low skill development opportunities (n = 1,650)		Stable low (n = 1,185)		Stable with low recognition (n = 949)		Variance		Correlations*					
	Estimate (SE)	p-value	Estimate (SE)	p-value	Estimate (SE)	p-value	Estimate (SE)	p-value	Estimate (SE)	p-value	1	2	3	4	5	6
1. Intercept autonomy	3.08 (.01)	<.001	2.96 (.04)	<.001	2.48 (.07)	<.001	2.99 (.06)	<.001	.29 (.02)	<.001	1					
2. Slope autonomy	−.02 (<.01)	<.001	−.01 (.01)	.39	−.02 (.02)	.44	−.01 (.02)	.72	.02 (<.01)	<.001	−.04	1				
3. Intercept skill development opportunities	3.13 (.02)	<.001	2.09 (.04)	<.001	2.00 (.06)	<.001	3.13 (.05)	<.001	.16 (.02)	<.001	.16	−.02	1			
4. Slope skill development opportunities	−.01 (.01)	<.05	−.06 (.02)	<.001	−.02 (.03)	.47	−.01 (.02)	.65	.01 (<.01)	<.001	−.03	.01	−.03	1		
5. Intercept recognition	3.05 (.02)	<.001	3.17 (.03)	<.001	1.97 (.08)	<.001	1.89 (.07)	<.001	.13 (.02)	<.001	.10	−.02	.13	−.03	1	
6. Slope recognition	<.01 (.01)	.45	−.02 (.01)	<.05	.01 (.03)	.81	.04 (.03)	.19	.01 (<.01)	<.001	−.02	.01	−.03	.01	−.03	1

Note. SE = standard error.
*All correlations are significant at $p < .001$.

of job resources could show more stable patterns. We therefore draw attention to the possibility that older workers may experience more stable working conditions than younger workers, which could be related to both their preferences as well as their career stage.

Second, our findings contribute to the literature on resource caravans, as postulated in COR theory (Hobfoll, 1989). The two subgroups that we identified with high or low of all three resources reflect this notion of resource caravans, while the other two subgroups, with one resource in each of these subgroups being underrepresented compared to the other two resources, contradict this notion. This suggests that resource caravans may not be universally applicable to everyone and that not all resources may travel together. It is important for theory building to test how and for whom resource caravans accumulate. Future studies could expand on our findings and on COR theory's core idea that resources tend to travel together (in caravans; Hobfoll et al., 2018). Specifically, future research could examine how combinations of different experiences and opportunities lead to the accumulation of different resources, and whether certain types of resources (e.g., social, task-related, knowledge-related) are more likely to travel together than other resources (see Sarandopoulos & Bordia, 2022, for a discussion). We invite future research to examine how job resources develop from the start to end of one's career and how that predicts retirement timing. We do acknowledge that such data are difficult to come by.

Third, our findings suggest that trajectories of job resources matter in predicting retirement timing, with some resources mattering more than others. A particularly interesting finding was that the subgroup characterized by relatively lower skill development opportunities did not retire earlier. This is not in line with previous research that showed that training is effective to boost older workers' motivation and job satisfaction (Visser et al., 2021) but is in line with meta-analytic evidence that older workers tend to be less inclined to participate in training and development activities at work (Ng & Feldman, 2012). Relatedly, Garcia et al. (2021) found that older workers were more aversive towards role and responsibilities expansion when they had a transactional psychological contract. Future studies could qualify our findings by examining when and how learning and training at work are beneficial and motivating for older workers and when they are not. For example, Laaser and Karlsson (2021) emphasize the importance of distinguishing between objective and subjective dimensions of job characteristics (including training opportunities). Whereas the objective dimension consists of structures that the formal organization offers (e.g., compulsory participation in training workshops), the subjective dimension is characterized by the agentic processes by which workers experience and shape their job through, for example, job crafting (e.g., learning something interesting during a discussion with a colleague). Future research could examine whether and when older workers are more motivated by objective and subjective dimensions of job characteristics and how that is linked to their retirement timing.

Fourth, the subgroup with lower recognition was more likely to retire early. This implies that receiving recognition from others at work helps people in prolonging their working life. Indeed, aging theories suggest that older adults are more likely to be motivated by social as opposed to knowledge-related goals (Carstensen et al., 1999). Furthermore, receiving recognition and appreciation from others satisfies workers' need to belong, boosts their self-esteem, and makes them feel respected,

Table 4. Demographic composition of the four classes.

	Stable high (*n* = 10,704)	Stable with low skill development opportunities (*n* = 1,650)	Stable low (*n* = 1,185)	Stable with low recognition (*n* = 949)
Birth cohort				
≤ 1930	0.2%	0.5%	0%	0%
1931–1940	2.9%	6%	1.4%	1.1%
1941–1950	28.7%	35.9%	23.6%	27.2%
1951–1960	61.9%	53.9%	69.8%	68.1%
1961+	6.3%	3.7%	5.3%	3.7%
Biological sex				
Male	50.4%	43.9%	48.4%	51.5%
Female	49.6%	56.1%	51.6%	48.5%
Education (ISCED-1997)				
ISCED 0	0.8%	2.5%	2.3%	0.9%
ISCED 1	6.7%	18.4%	15.9%	4.8%
ISCED 2	12.5%	19.3%	21.6%	12.3%
ISCED 3	34.6%	36.7%	39.6%	36.4%
ISCED 4	6.6%	4.7%	5.7%	5%
ISCED 5	36.5%	17.0%	13.7%	36.5%
ISCED 6	1.2%	0.3%	0.7%	2.7%
Missing	0.9%	0.4%	0.5%	0.7%

aspects which are related to more work engagement and meaningful work (for reviews, see Laaser & Karlsson, 2021; Semmer et al., 2019). This finding is also in line with a systematic review in which social support, another social resource, was suggested to be positively related to work ability (Pak et al., 2019). We therefore recommend management and human resources practitioners to ensure that older workers feel appreciated and recognized in their organization by implementing policies that make them feel valued, as recognition may be an important factor for extended working lives.

Practical implications

Our findings clearly have implications for practice. Our results suggest that resources are important for retirement timing. It is thus important to make sure that (older) workers have access to work resources throughout their career to help them work until the (increasing) retirement age. Practitioners who are interested in sustainable aging are encouraged to think about human resource and work design policies that are resource-oriented (e.g., increased scheduling autonomy, idiosyncratic deals, etc.) to help older workers stay in the workforce until they reach the state pension age (Jonsson et al., 2021; Virtanen et al., 2022). Our findings also suggest that recognition seems to be a particularly important factor in determining whether workers retire early or not. We recommend workplaces and organizations to ensure that older workers feel recognized and appreciated at work, by implementing interventions that target positive social relations in the organization (interventions to improve age diversity climate, reduction of negative age-related stereotypes; see Truxillo et al., 2015, for a review). Finally, our findings suggest that skills development opportunities did not matter as much as other

Table 5. Unstandardized estimates of multilevel multinomial logistic regression of retirement timing.

	Odds ratio (*SE*)	95% C.I.
Within level		
Age (in years)	1.53** (0.01)	[1.51, 1.55]
Between level		
Trajectories of job resources		
Stable high	Ref.	Ref.
Stable with low skill development opportunities	0.97 (0.07)	[0.84, 1.12]
Stable low	**1.73** (0.07)**	**[1.52, 1.97]**
Stable with low recognition	**1.38** (0.07)**	**[1.19, 1.59]**
Controls		
Education	0.94** (0.02)	[0.91,0.97]
Female	1.40** (0.04)	[1.29, 1.52]
Total number of unemployment years	0.99 (0.01)	[0.97, 1.00]
Number of valid waves	0.89** (0.02)	[0.87,0.93]
Countries		
Denmark	Ref.	Ref.
Austria	3.16** (0.14)	[2.42, 4.10]
Germany	1.37** (0.11)	[1.10, 1.71]
Sweden	0.86 (0.10)	[0.71, 1.03]
Netherlands	2.37** (0.10)	[1.93, 2.90]
Spain	1.41** (0.11)	[1.13, 1.76]
Italy	1.30* (0.13)	[1.01, 1.68]
France	3.58** (0.11)	[2.89, 4.43]
Greece	1.10 (0.11)	[0.89, 1.37]
Switzerland	0.91 (0.11)	[0.74, 1.12]
Belgium	2.88** (0.10)	[2.35, 3.54]
Israel	0.18** (0.14)	[0.14, 0.24]
Czechia	3.25** (0.11)	[2.62, 4.02]
Poland	3.71** (0.17)	[2.69, 5.12]
Luxembourg	0.16* (0.88)	[0.03, 0.87]
Hungary	0.49 (0.53)	[0.17, 1.39]
Portugal	0.24** (0.39)	[0.11, 0.53]
Slovenia	2.58** (0.18)	[1.83, 3.65]
Estonia	0.16** (0.13)	[0.12, 0.20]

Note. SE = standard error. 95% C.I. = 95% confidence interval. Significant results pertaining to relationships between subgroups of resource trajectories and retirement timing are highlighted in bold.
$^*p < .05$. $^{**}p < .01$.

resources for retirement timing. Even though opportunities for skills development may be important for the organization, practitioners should ensure that this resource is combined with other types of job resources (e.g., social resources such as recognition) to support older workers.

Limitations and future directions

This study is not without its limitations. First, we only considered the trajectory of three job resources. Even though these three resources were carefully selected due to their expected relevance for older workers, future research should test our assumptions using a wider range of job resources, for example, skill variety and task significance (e.g., Fried et al., 2007; Zaniboni et al., 2013), and should also consider the role of job stressors in predicting retirement timing. In fact, work stress theories suggest that resources at work may buffer against the negative effects of job demands, including job stressors (Bakker et al., 2005; Karasek, 1979). Relatedly, future research should investigate how these resources (and changes related to these resources) are related to organizational hierarchy, occupational sector, and type of psychological contract.

Second, we did not distinguish between voluntary and involuntary retirement, nor did we consider motives for retirement. However, previous research demonstrated that retirement intentions often differ from retirement behavior and is predicted by different factors (Damman et al., 2011; Stiemke & Hess, 2022). For example, people could be forced to retire earlier than they want if, for example, they are rendered redundant by their organization. Future research should investigate how different job attributes trajectories lead to voluntary and involuntary retirement outcomes.

Third, we acknowledge that there was panel attrition, which is almost always the case in longitudinal data collections. Although SHARE compensates for attrition by recruiting refreshment samples at every wave, the average number of valid waves in which participants provided information on job resources was 2.86, which means that, on average, participants provided data on three out of the eight waves that we considered.[3]

Fourth, although we included country as a control, we did not examine national retirement policies as a moderator of the relationship between job resource trajectories and retirement timing. This is because we did not have sufficient information about job resources to make rigorous cross-national comparisons. Future research could study whether the relationship between job resource trajectories and retirement timing differs across countries with different retirement policies, for example, by comparing data from different national panels. Indeed, in countries that offer flexible retirement age policies, job resources may play a more important role in determining when a person retires or not (Henkens, 2022). Despite this shortcoming, the use of multinational data is a unique strength, in the sense that it increases the generalizability of our findings to multiple countries and shows that our results are robust and do not merely represent country effects.

Conclusion

Using growth mixture modeling and event history analysis, we examined to what extent job autonomy, skill development opportunities and recognition develop over time for older workers and how this relates to their retirement timing. We found that workers were at a greater risk of earlier retirement if they experience all three resources at lower levels or if they experience low levels of recognition relative to the other two resources. Our study therefore suggests that recognition may be equally, if not more important than task characteristics to motivate older workers to work longer. Future research and practitioners should devote attention to older workers' social experiences at work as this seems important to promote longer working lives.

[3]Note that we conducted a dropout analysis by checking mean differences between stayers (those who remained in the study until Wave 8) and leavers (those who dropped out of the study before Wave 8) on the three job resources. Results revealed that leavers tended to report higher autonomy ($t(4847) = -0.306$, $p < .01$, Cohen's $d = -0.104$) and lower skill development ($t(4839) = -0.305$, $p < .01$, Cohen's $d = -0.111$). However, Cohen's d estimates suggested that these effects were small in size. There were no differences between leavers and stayers on recognition ($t(4816) = -1.195$, $p = .232$, Cohen's $d = -0.038$).

Supplementary material

Supplementary material is available online at *Work, Aging and Retirement* (http://www.oxfordjournals.org/our_journals/workar/)

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This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, and 8 (DOIs: 10.6103/SHARE.w1.710, 10.6103/SHARE.w2.710, 10.6103/SHARE.w3.710, 10.6103/SHARE.w4.710, 10.6103/SHARE.w5.710, 10.6103/SHARE.w6.710, 10.6103/SHARE.w7.711, 10.6103/SHARE.w8.100). See Börsch-Supan and Jürges (2005), Börsch-Supan et al. (2008), Schröder (2011), Malter and Börsch-Supan (2013), Börsch-Supan et al. (2013), Malter and Börsch-Supan (2015), Malter and Börsch-Supan (2017), Bergmann et al. (2019), Bergmann and Scherpenzeel (2019), and Bergmann and Börsch-Supan (2021), for methodological details.

Data availability

In accordance with the SHARE conditions of use, we are not allowed to share the data. SHARE data are available on the SHARE website upon request.

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