Anita Abramowska-Kmon[1], Milena Chełchowska[1], Martin Piotrowski[2], Paweł Strzelecki[1]

[1]Institute of Statistics and Demography, SGH Warsaw School of Economics, Poland

[2]Department of Sociology, University of Oklahoma, USA

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Life course employment patterns and resilient adult-stage life courses in selected European countries

Background and the aim of the analysis

Resilience is a multifaceted construct that has gained significant attention across various disciplines. In the scientific literature, resilience has been defined, conceptualized, and measured in numerous ways, often with field-specific characteristics (Olsson, Jerneck, Thoren, Persson, & O'Byrne, 2015). Resilience, defined as well-being despite adversity (Masten, 2001) is a useful—though narrow—starting point, as it connects risks and adversity to inequalities in socio-economic outcomes, emphasizing that resilience cannot be understood by analyzing outcomes or risks in isolation.

Research on resilience in older adults has highlighted the importance of integrating emotional, personal, and social factors (Ong, Bergeman, & Boker, 2009). Building on this integrative approach, research by Ong et al. (2009) examined the complex nature of resilience through the lens of daily processes in late adulthood. The findings suggest that resilience to daily stress is influenced by multiple protective pathways. Positive emotions emerge as a critical factor, potentially mitigating the impact of stressors and facilitating more rapid adaptation to subsequent challenges.

The life course perspective posits that experiences and events throughout an individual's life significantly shape outcomes in later years. Within this framework, remembering the fact that economic employment is linked to positive later life outcomes, employment history emerges as a crucial factor in understanding resilience among older adults. Because it is known that employment brings a sense of belonging to a social network (Wahrendorf, 2015), a sense of control and autonomy (Haidt & Rodin, 1999) and a sense of reward (Siegrist & Marmot, 2004). In the subject of this study, a crucial question is then to understand how individuals' work-life trajectories could influence their capacity for resilience in older age.

While the importance of employment history in shaping later-life outcomes is evident, research has shown that this relationship is far from simple. This complexity was highlighted in the work of (Zacher & Rudolph, 2017) who reviewed various theories of successful aging at work. They noted significant differences in how success is defined in the context of aging, ranging from subjective well-being to more objective outcomes such as health status or job performance.

To better understand the long-term effects of employment history on resilience, researchers have turned to broader theoretical frameworks. Life course theory and cumulative (dis)advantage theory provide valuable context through which to examine the long-term effects of employment history. These theories suggest that advantages or disadvantages accumulated over time can significantly impact an individual's resources and ability to cope with challenges in later life (Ferraro & Shippee, 2009). Likewise, the same applies to the more specific topic of socioeconomic status. Socioeconomic position (SEP) advantages and disadvantages act and accumulate across the life-course, resulting in widening socioeconomic inequalities in successful aging (SA) in later life (Whitley, Benzeval, & Popham, 2018). The authors found that all SEP indicators were positively associated with an overall SA score and that the relationships between SEP and SA were generally consistent across genders and age groups.

Life course employment history plays a significant role in shaping resilience in older age, and while employment generally promotes resilience, the relationship is complex and influenced by various individual and societal factors. Different types of work may influence resilience in distinct ways, depending on the nature of stressors and challenges faced within each profession.

In general, the different employment trajectories experienced by people aged 50+ in Europe are the result of both individual choices made throughout adult life and external circumstances. As a result, they can have an impact on an individual's situation in later life in terms of health status, subjective well-being and mental health, as well as financial situation, which can be a marker of resilience.

The main aim of the paper is therefore to present the results of the analysis of the determinants of belonging to different groups describing resilience, taking into account both individual characteristics and employment history.

Data and analytical strategy

Data. We used the 9th wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) conducted in 2021/2022 and the SHARELife module which includes employment histories. We limited the sample to individuals aged 50+ with no missing values and the final analytical sample included 39,982 respondents in 28 European countries: Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, Czech Republic, Poland, Luxembourg, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania, Slovakia.

Variables in Latent Class Model. To group individuals into homogeneous classes describing resilience, we used the following variables describing psychological well-being (CASP-12 measure, short version of the UCLA loneliness scale, and depression level based on the EURO-D scale), health status (1+ ADL limitations, having at least two chronic diseases, having limitations in activities (GALI)), and subjective financial situation based on the household's ability to make ends meet.

Variables in Regression Modelling. We controlled for basic socio-demographic characteristics of the respondents (such as gender, age, presence of a cohabiting partner, level of education, presence of children in the social network, household size), variables describing social connectedness and satisfaction with the social network and European region. The key explanatory variable describing life course employment history was based on the results of the sequence analysis technique, which allowed us to assess the extent to which people's life courses are similar in terms of changes in respondents' work status. The most typical sequences of events in people's life courses were selected and then the differences in these sequences compared to the chosen employment path were assessed. The next step was to group individuals into clusters (based on quintiles) on the basis of the calculated differences between individuals. In this way, five clusters of employment histories were identified (from stable full-time employment to high non-employment over the life course).

Methodology. We applied Latent Class Modelling (Collins & Lanza, 2010; Lanza et al., 2010) to group observations into homogenous sub-groups, or latent classes, based on observed measures of physical health, subjective well-being, and financial situation (i.e., the observed endogenous variables).

The Latent Class Model can be specified as follows:

$$P(Y = y|x_i) = \sum_{c=1}^{C} \gamma_c(x_i) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \rho_{mk|c}^{I(y_{im}=k)} \quad (1)$$

In this equation, C represents the number of estimated classes based on *m* categorical items. Y_i is a vector of individual *i's* responses to *M* items, where Y_{iM} = 1, 2, ..., r_m, and c_i = 1, 2, ..., C denotes individual *i*'s latent class membership. The indicator function $I(y = k)$ equals 1 if response *y* is *k*, and 0 otherwise. The covariate *x* for individual *i* is related to the probability of class membership (γ), and the ρ's represent item-response probabilities (or means for continuous items) conditioned on latent class membership, reflecting the relationship between observed items and latent classes. A multinomial logit model is estimated simultaneously, where latent class membership is predicted by observed exogenous variables. Logistic regression parameters (β) estimate class membership, with γ parameters expressed for a single covariate *x* as:

$$\gamma_c(x_i) = P(C_i = c|x_i) = \frac{\exp(\beta_{0c} + x_i\beta_{1c})}{1 + \sum_{j=1}^{C-1}(\beta_{0j} + x_i\beta_{1j})} \quad (2)$$

for *c = 1*, ..., *C*-1 where class *C* is the reference class in the multinomial logistic regression.

Results

Model Fit Statistics. Table 1 presents fit statistics for models with varying numbers of latent classes, used to identify the optimal number of classes. The five-class model provided the best fit, with the lowest values for log likelihood, Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC).

[Table 1 about here]

Table 2 shows that the classes differ notably in demographics, household size, social networks, and regional residence across Europe. While all classes had an average age of 70 or older, Classes 4 and 5 are slightly older, with an average of 75 years. Classes 1 and 2 are the most educated, with 36% and 29% having tertiary education, and the lowest rates of non-employment histories (11% and 15%, respectively). Class 3 tends to live in larger households, with over 20% having three or more people. Social connection is weakest in Classes 3 and 5, with respective scores of 1.84 and 1.83, and they report the lowest social network satisfaction. Classes 1 and 3 have the highest percentages of children absent from their social networks, likely reflecting their younger ages. In terms of regional distribution, Classes 1 and 2 are most common in Western

Europe (38% and 46%), while Classes 3 and 5 are evenly split between Central/Eastern Europe (48% and 35%) and Southern Europe (42% and 32%). Class 4 is primarily found in Central/Eastern Europe (42%) and Northern Europe (23%).

[Table 2 about here]

Item Response Statistics. Table 3 presents descriptive statistics for the full sample and by latent class, showing distinct characteristics across the five classes. These classes represent, respectively: Class 1: Best overall health, well-being, and financial situation; Class 2: Second best overall, but worse physical health; Class 3: Good physical and mental health but worse financial situation; Class 4: Second worst, especially in physical health; Class 5: Worst overall profile. Class 1 reports the greatest financial ease, with 52% "easily making ends meet," compared to just 3%, 11%, and 14% in the most financially challenged classes. Only 14% of Class 1 reports activity limitations, compared to 79%, 34%, 93%, and 79% in the others. Additionally, 29% of Class 1 has two or more chronic diseases, versus 78%, 48%, 87%, and 75% in the other groups. Virtually no one in Class 1 reports ADL limitations, compared to 15%, 1%, 33%, and 28% in other classes. Class 1 also scores highest on the CASP quality of life scale (42.31), while the other classes report 38.91, 35.03, 31.28, and 28.80. On the EURO depression scale, Class 1 reports the lowest score (1.25), compared to 2.43, 1.63, 4.80, and 5.45 in other classes. Similarly, Class 1's UCLA loneliness score (3.36) is noticeably lower than the others (3.72, 3.89, 4.12, and 7.09).

[Table 3 about here]

Determinants of Class Membership. Table 4 presents results from a multinomial logistic regression analysis, showing that demographic, economic, and sociological factors differentiate class membership. Compared to Class 1 (best overall profile), Classes 2, 4, and 5 are significantly older and more likely to be female. Having a co-resident partner reduces the likelihood of being in Classes 3, 4, and 5 relative to Class 1. Higher education levels generally make it less likely to belong to a worse class. Employment histories marked by part-time work or high non-employment rates increase the likelihood of being in a class with a worse profile compared to Class 1. Except for Class 2, this also applies to full-time work histories with many gaps. Two-person households are less likely to belong to Classes 3 or 5, but more likely to be in Class 4. Larger households (3+ people) are more likely to be in Class 4, but less likely to be in Class 5 (relative to Class 1). Social network connectedness is associated with a lower likelihood of being in Classes 3, 4, and 5, but a higher likelihood for Class 2 (compared to Class 1). Social network satisfaction is negatively associated with membership in all classes relative to Class 1. Having children in one's social network increases the likelihood of being in Classes 2 and 3, while their absence is associated with a lower likelihood of being in Class 4 (compared to Class 1). Regionally, compared to Central and Eastern Europe, Classes 3–5 are less likely to be in Northern or Western Europe. For Southern Europe, Classes 2 and 4 have a negative association, while Classes 3 and 5 are more likely to be found there.

[Table 4 about here]

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TABLES

Table 1: Fit Statistics for Model Selection

	ll	df	AIC	BIC
1 Class	-406688.8	12	813401.7	813504.7
2 Classes	-386591.6	22	773227.3	773416.2
3 Classes	-380518.6	32	761101.2	761375.9
4 Classes	-374899.1	42	749882.2	750242.8
5 Classes	-373441.7	52	746987.4	747433.9

Source: Authors' calculations based on SHARE data.

Table 2: Decriptive Statistics

	Class 1		Class 2		Class 3		Class 4		Class 5		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age (in Yrs)	69.03	7.39	74.91	8.19	69.34	7.70	75.06	8.97	75.28	9.31	71.78	8.57
Sex (male)	0.47		0.41		0.45		0.30		0.29		0.41	
Has Coresident Partner	0.74		0.65		0.70		0.56		0.42		0.66	
Highest Degree Earned												
Primary or Less	0.07		0.12		0.21		0.25		0.31		0.16	
Lower Secondary	0.11		0.15		0.23		0.24		0.21		0.17	
Upper-Post Secondary	0.45		0.45		0.45		0.38		0.34		0.43	
Tertiary	0.36		0.29		0.11		0.12		0.15		0.24	
Employment History Clusters												
Stable Full-Time	0.36		0.35		0.35		0.34		0.29		0.35	
Mostly Full-Time	0.08		0.08		0.08		0.07		0.06		0.08	
Full-Time with Gaps	0.23		0.20		0.18		0.18		0.17		0.20	
Part-Time Prevalence	0.21		0.21		0.18		0.21		0.19		0.20	
High Non-Employment	0.11		0.15		0.21		0.21		0.29		0.17	
Household Size												
1 Person	0.20		0.31		0.23		0.32		0.50		0.28	
2 People	0.65		0.61		0.55		0.52		0.39		0.58	
3+ People	0.14		0.09		0.22		0.16		0.11		0.15	
Scale of Social Connectedness	2.27	0.86	2.37	0.83	1.84	0.78	2.04	0.82	1.83	0.78	2.12	0.85
Social Network Satisfaction	9.32	0.92	9.13	1.08	8.89	1.33	8.94	1.29	8.42	1.68	9.04	1.23
Children in Social Network												
No Children	0.08		0.09		0.09		0.07		0.13		0.09	
Has Children in Social Network	0.61		0.69		0.61		0.68		0.64		0.64	
Has Children, not in Social Network	0.30		0.23		0.30		0.25		0.23		0.27	
Region												
Central and Eastern	0.25		0.22		0.48		0.42		0.35		0.33	
Northern	0.25		0.27		0.08		0.23		0.14		0.20	
Southern	0.12		0.05		0.42		0.19		0.32		0.20	
Western Europe	0.38		0.46		0.02		0.16		0.19		0.28	
N	13249		9165		8901		4390		4277		39982	

Source: Authors' calculations based on SHARE data.

Table 3: Item Responses

	Latent Classes				
	1	2	3	4	5
Household Ability to Make Ends Meet					
Great Difficulty	0.01	0.01	0.17	0.17	0.26
Some Difficulty	0.11	0.13	0.51	0.41	0.36
Fairly Easily	0.36	0.39	0.30	0.31	0.25
Easily	0.52	0.46	0.03	0.11	0.14
Limitation with activities	0.14	0.79	0.34	0.93	0.79
2+ Chronic Diseases	0.29	0.78	0.48	0.87	0.75
1+ Activity of Daily Living Limitation	0.00	0.15	0.01	0.33	0.28
CASP index: Quality of Life and Well-Being	42.31	38.91	35.03	31.28	28.80
EURO Depression Scale	1.25	2.43	1.63	4.80	5.45
UCLA Loneliness Scale (Short Version)	3.36	3.72	3.89	4.12	7.09

Source: Authors' calculations based on SHARE data.

Table 4: Multinomial Logit of Latent Class Membership

	Latent Class[a]			
	Class2 β/SE	*Class3* β/SE	*Class4* β/SE	*Class5* β/SE
Age (in Yrs)	0.08***	−0.00	0.08***	0.07***
	0.00	0.00	0.00	0.00
Sex (male)	−0.18***	−0.02	−0.59***	−0.51***
	0.05	0.05	0.05	0.05
Has Coresident Partner	−0.10	−0.29***	−0.62***	−0.71***
	0.07	0.07	0.07	0.07
Highest Degree Earned				
Primary or Less				
	.ref	*.ref*	*.ref*	*.ref*
Lower Secondary	−0.25**	−0.01	−0.36***	−0.38***
	0.09	0.08	0.08	0.08
Upper-Post Secondary	−0.40***	−0.50***	−0.99***	−0.95***
	0.08	0.07	0.07	0.07
Tertiary	−0.68***	−1.46***	−1.86***	−1.60***
	0.08	0.09	0.09	0.09
Employment History Clusters				
Stable Full-Time				
	.ref	*.ref*	*.ref*	*.ref*
Mostly Full-Time	0.13	0.11	0.16	0.15
	0.08	0.08	0.09	0.10
Full-Time with Gaps	0.06	0.30***	0.28***	0.35***
	0.06	0.06	0.07	0.07
Part-Time Prevalence	0.21***	0.42***	0.50***	0.58***
	0.06	0.06	0.07	0.07
High Non-Employment	0.24***	0.57***	0.55***	0.89***
	0.07	0.07	0.07	0.07
Household Size				
1 Person				
	.ref	*.ref*	*.ref*	*.ref*
2 People	−0.02	−0.24**	0.20*	−0.54***
	0.07	0.08	0.08	0.08
3+ People	−0.01	−0.05	0.46***	−0.43***
	0.09	0.09	0.09	0.09
Scale of Social Connectedness	0.12***	−0.55***	−0.27***	−0.55***
	0.03	0.03	0.03	0.03
Social Network Satisfaction	−0.23***	−0.51***	−0.50***	−0.71***
	0.02	0.02	0.02	0.02

Children in Social Network				
No Children				
	.ref	*.ref*	*.ref*	*.ref*
Has Children in Social Network	−0.00	0.37***	0.25**	0.15
	0.07	0.09	0.09	0.08
Has Children, not in Social Network	−0.10	−0.05	0.02	−0.21*
	0.08	0.09	0.10	0.09
Region				
Central and Eastern				
	.ref	*.ref*	*.ref*	*.ref*
Northern	0.04	−1.44***	−0.58***	−1.03***
	0.06	0.07	0.06	0.07
Southern	−1.05***	0.44***	−0.58***	0.14*
	0.10	0.06	0.07	0.07
Western Europe	−0.01	−3.14***	−1.53***	−1.48***
	0.06	0.12	0.08	0.07
Intercept	−3.87***	6.70***	−0.01	3.57***
	0.32	0.33	0.36	0.32
N	39982			

Note: [a]Reference Category is Class 1

Source: Authors' calculations based on SHARE data.