THE LONG-TERM MENTAL HEALTH CONSEQUENCES OF EMOTIONAL AND INTERPERSONAL WORK DEMANDS

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LIDAM Discussion Paper IRES
2026 / 21



UCLouvain

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Louvain Institute of Data Analysis and Modeling in economics and statistics

The Long-Term Mental Health Consequences of Emotional and Interpersonal Work Demands

Morteza Meybodi [*] Vincent Vandenberghe [†]

Abstract

This paper examines how career-long emotional/interpersonal work demands are associated with mental health among adults aged 50 and older. Using retrospective work histories from SHARE combined with ISCO-4-level occupational characteristics from O*NET, we construct employment trajectories capturing cumulative exposure to emotionally/interpersonally demanding work and examine its association with later-life depressive symptoms, measured by the EURO-D scale. Our findings show that career-long emotional/interpersonal demands are associated with a higher risk of depression after age 50, although their relative importance is modest. Career instability, such as employment gaps, redundancies, and part-time work, emerges as a stronger predictor. Pre-labour-market factors, including childhood health and educational attainment, also play a substantial role, highlighting the lasting importance of early-life circumstances for later-life mental health.

Keywords: mental health, depressive symptoms, working conditions, emotional/interpersonal demands, career arduousness

JEL Codes: J14, I1, J26

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1 Introduction

The relationship between working conditions and health has long been a focus of the social sciences, particularly sociology, psychology, and, to a lesser extent, economics. Numerous studies have examined how the nature of one's occupation impacts various health outcomes. However, much of this literature has centred on physical health and physical demands/arduousness of jobs (see French and Jones (2017) for a review). Although there have been some notable contributions exploring the link between job demands and mental health (e.g., Llena-Nozal and Lindeboom, 2004; Cottini and Lucifora, 2013), less attention has been given, certainly in economics, as to how psychological and other aspects of work and careers (thus across the full span of working life) relate to mental health, especially over the long run.

In his review of the European economic literature, Barnay (2016) documents the growing interest in work-related health inequalities, but highlights the limitations of existing data and the reliance on cross-sectional analyses. He also notes that mental health outcomes remain under-explored in many labour-oriented health studies. This is particularly important given that mental health disorders affect a significant and rising share of the working-age population. According to Cottini and Lucifora (2013), mental health issues now affect nearly one in six Europeans, generating substantial social and economic costs. The equivalent proportion in the US is more than one in five (59.3 million in 2022; 23.1% of the U.S. adult population), according to the (US) National Institute of Mental Health (NIMH).[1]

Recent literature has begun incorporating work-related factors, such as working conditions and job strain, into analyses of mental well-being. For instance, Maclean et al. (2015) explore the association between adverse labour events—such as coworker conflict or job insecurity—and mental health, finding modest but consistent patterns. However, their study lacks detailed longitudinal data. Similarly, Llena-Nozal and Lindeboom (2004) investigate working conditions across four countries; while they find significant associations, their operationalisation of occupational exposure is coarse, relying on binary indicators or single-point satisfaction measures.

While these indicators offer a broad view of job quality, they often overlook the actual content of the, sometimes numerous, jobs that make up a career. Many studies lack a longitudinal dimension across successive jobs or fail to account for specific job content, such as the tasks workers perform and the social and physical environments in which those tasks

[1] https://www.nimh.nih.gov/health/statistics/mental-illness

are carried out.

The first limitation concerns the career dimension. Some recent studies have moved beyond single-point measures of working conditions by combining occupational information with retrospective job histories. In particular, Vandenberghe (2023) and Vandenberghe (2025) construct measures of career-long occupational exposure and relate them to late-life outcomes, particularly in the context of pension design. These studies demonstrate the usefulness of considering working conditions over the full career rather than focusing on a respondent's current or most recent job. Their analysis, however, concentrates primarily on physical arduousness, leaving the non-physical content of occupations relatively unexplored.

The second challenge concerns how job content is characterised, particularly beyond physical arduousness. A broad literature conceptualises working conditions as multidimensional, suggesting that a single dimension may inadequately capture arduousness. Belloni et al. (2022) use five job-quality indices covering the physical environment, work intensity, working-time quality, skills and discretion, and prospects. Similarly, Wang et al. (2022) consider, among other dimensions, skills and discretion, the social environment, work intensity, and the physical environment, while Brunner et al. (2019) distinguish task-related from social job stressors and resources. The multidimensional nature of work is also well established in occupational psychology. For example, Jonge and Dormann (2006) distinguish cognitive, emotional, and physical dimensions of job stressors, resources, and strains, while Morgeson and Humphrey (2006) separately identify knowledge characteristics of work – including job complexity, information processing, and problem solving – and its social/interpersonal characteristics. Taken together, this literature indicates that the non-physical content of work is heterogeneous: information processing and other knowledge requirements, interpersonal and social interactions, emotional demands, work intensity, autonomy, and related features represent distinct dimensions of working conditions.

The two strands of the literature thus address complementary aspects of the problem. Career-based studies highlight the importance of measuring occupational exposure across successive jobs, while the job-content literature shows the importance of preserving the multidimensional nature of working conditions. Much less is known about how different dimensions of detailed occupational content accumulate over an entire career and relate to mental health in later life.[2]

This paper addresses these gaps by merging detailed occupational characteristics from

[2]The Glomb et al. (2004) study, for instance, focuses on contemporary wages.

O*NET with job-history and late-life mental-health data from SHARE. We merge the datasets at the ISCO-4 level. Rather than imposing a predetermined classification of occupational demands, we apply principal component analysis to O*NET's `Work Context` and `Work Activities` modules in order to identify the main dimensions along which occupations differ. We then link the resulting occupation-level component scores to respondents' complete job histories and examine their association with depressive symptomatology beyond age 50.

In what follows, we retain three major dimensions of working conditions, based on our dimension-reduction results (discussed below) and broadly aligned with the distinctions proposed by Jonge and Dormann (2006) and Morgeson and Humphrey (2006). Our approach closely follows Glomb et al. (2004), which uses O*NET data and principal component analysis to summarise many occupational descriptors into information, managing, physical, and emotional-labour components. Our analysis distinguishes physical arduousness, emotional/interpersonal demands, and managerial/cognitive content. The emotional/interpersonal index captures demands such as assisting and caring for others, working directly with the public, and interacting with aggressive individuals (the exact items are detailed below). The managerial/cognitive-content index captures both seniority-related responsibilities, such as developing objectives and strategies, making decisions, and solving problems, and cognitively demanding tasks, such as analysing data or information.

Because our analysis relies on self-reported job histories to assign occupational characteristics and uses self-reported mental health outcomes (the EURO-D scale), we situate this work within the broader tradition of subjective health and work evaluation. Our contribution to the literature on working conditions and health is fourfold: *i)* the quantification of career working conditions using detailed occupational content rather than a small number of broad indicators; *ii)* an assessment of their association with mental health beyond age 50; *iii)* a comprehensive career perspective covering respondents' entire job histories; and *iv)* a specific focus on cumulative exposure to emotional/interpersonal job demands, alongside physical arduousness and managerial/cognitive intensity.

The empirical strategy used in this paper addresses several important sources of confounding and selection, but probably does not fully resolve endogeneity. The results should therefore be interpreted as robust associations rather than causal effects. With this caveat in mind, they point to a nuanced hierarchy of occupational risks. While prolonged exposure to emotionally/interpersonally demanding work shows a statistically significant association with late-life depression, this relationship is tentatively overshadowed by the impact of career

instability. Ceteris paribus, career fragmentation, marked by gaps between jobs, redundancy, or a dominance of part-time employment, emerges as a stronger predictor of mental health decline than the specific emotional/interpersonal demands of the job(s). Furthermore, the analysis underscores the multidimensional nature of late-life well-being, which appears to be strongly determined by pre- and non-work factors: *i)* the "long arm" of childhood adversity (both physical and mental), *ii)* institutional or cultural differences captured by the respondent's country of residence and *iii)* educational attainment.

The remainder of this text is organised as follows. Section 2 presents the empirical analysis, detailing the methods, regression models, principal component analysis (PCA) of working conditions/context data, model-explained variance decomposition (to assess the importance of (groups of) variables, and data sources. Section 3 reports and discusses the main empirical results, robustness checks and limitations. Finally, Section 4 concludes by summarising the key findings and outlining their implications.

2 Empirical Analysis

2.1 Method

2.1.1 Regression Specification

Let us define $Mhealth_{i,j}$ in eq. (1) as a measure of poor mental health/depression among older individuals, where i indexes the individual and j denotes the country of residence; more details on the precise definition of poor mental health will be provided below. We estimate, separately for each gender, the following specification for our outcome of interest:

$$Mhealth_{i,j} = \alpha + \boldsymbol{\beta}^{\top}\boldsymbol{CAR}_{i,j} + \boldsymbol{\theta}^{\top}\boldsymbol{Instab}_{i,j} + \boldsymbol{\gamma}^{\top}\boldsymbol{Hendow}_{i,j} + \boldsymbol{\eta}^{\top}\boldsymbol{X}_{i,j} + \delta_j + \lambda_t + \varepsilon_{i,j} \quad (1)$$

Here, $\boldsymbol{CAR}_{i,j}$ is the vector of career occupational-content measures, including managerial/cognitive intensity ($CAR^{manag}_{i,j}$), physical arduousness ($CAR^{phys}_{i,j}$), and emotional/interpersonal demands ($CAR^{emo}_{i,j}$). The construction of these measures, derived through principal component analysis (PCA) of O*NET's `Work Context` and `Work Activities` modules followed by oblimin rotation, is detailed in Section 2.1.4.

$\boldsymbol{Instab}_{i,j}$ captures dimensions of career instability and includes five indicators: the number of jobs held over the respondent's career, the number of 6-month-plus employment gaps throughout their working life, the number of job terminations not initiated by the respondent, the average propensity to work full-time (max=1), and the total number of years worked during the career. These variables serve to quantify the irregularity and potential precarity/instability of respondents' career trajectories. We include these instability measures as controls based on prior economic research showing that fragmented or turbulent work histories are strongly associated with poor health in general (e.g., Vandenberghe, 2023) and, in particular, poorer mental health outcomes (e.g., Adam and Flatau, 2006).

$\boldsymbol{Hendow}_{i,j}$ represents the vector of childhood health endowment measures, proxied by two principal components: the first principal component from a PCA of childhood physical health indicators and the first principal component from a separate PCA of childhood mental health indicators.

The control vector $\boldsymbol{X}_{i,j}$ includes several variables: categorical variables for education, age (50-80 unless specified otherwise), country dummies and the SHARE wave dummy.[3]

We begin by estimating eq. (1) using a binary indicator of poor mental health, defined as having a EURO-D score[4] above a threshold of 3[5], via logistic regression (regression models M1, M2 in Section 3.1). Alternatively (M3-M6), we use a continuous version of the mental health outcome (i.e., the PC summarising the EURO-D items) and use OLS.

2.1.2 Measurement and Endogeneity/Selection Concerns

Econometric results relating career occupational characteristics to later-life (mental) health are valid only if we correctly identify the relationship between the two dimensions. We see two key issues: one related to measuring occupational characteristics and one rooted in selection.

Regarding measurement, the main issue is the "time gap", i.e., the time that has elapsed between when SHARE respondents worked and when O*NET assesses occupational charac-

[3]Mental health outcomes EURO-D were not collected during wave 7, so we resorted to the closest wave where they were available.

[4]Depressive symptoms score in the SHARE dataset ranges from 0–12. It consists of the sum of the dummies corresponding to each of the items (see Table A.1)

[5]Prince et al. (1999) originally developed the EURO-D to harmonise measures of late-life depression across European population studies. Subsequent validation work by Guerra et al. (2015) found that a score of 4 or more was the optimal cut-off for identifying clinically relevant depression.

teristics. Our O*NET occupational-content indices, which describe occupations in the early 2020s, may not perfectly reflect the characteristics of the same occupations when SHARE respondents worked, particularly among older respondents with high values on the occupational indices. Assuming that the passage of time has led to the disappearance or transformation of some of the most demanding jobs, our 2021-based O*NET measures may understate some past occupational exposures. This may lead to an overestimation bias known in the literature as "expansion bias" due to censored regressors (Rigobon and Stoker, 2007). This is an X-related bias. However, it should not be confounded with the well-known attenuation bias driven by the presence of a (large) additive measurement error/random term to X. With expansion bias, X is systematically upward bounded, as high values in reality may be recorded at lower levels in the data. In such a case, the absolute value of the slope of the Y, X relationship may be exaggerated (Rigobon and Stoker, 2007). This may make the estimated associations between career occupational characteristics and later-life mental health upper bounds.

Regarding selection, we posit that non-random selection into occupations with different job characteristics may occur *i)* before labour market entry, *ii)* during individuals' time in the workforce and finally *iii)* after retirement.

Before entering the labour market, pre-existing health conditions can influence occupational choices, with healthier individuals more likely to select into more demanding jobs (the healthy worker effect), which causes upward bias, attenuating or reversing any negative effects. To account for selectivity before labour market entry, SHARE offers interesting opportunities. It provides information on educational attainment and health status up to age 15 (childhood health). These are endowment items whose levels are determined before people choose their first occupation and enter the labour market. We include these in our control set when estimating M2 to M6.

During the career, additional health-related mechanisms may bias the analysis. Suppose, for instance, that a worker experiences a health deterioration at age 45, prompting a move to a less arduous occupation or an exit from employment. Measured cumulative occupational exposure thereafter may change precisely because the worker's health has deteriorated: health thus affects subsequent exposure, rather than exposure only affecting subsequent health. This creates reverse causality and makes career-long occupational exposure partly endogenous to health. SHARE offers two ways to mitigate this concern. First, Wave 7 includes several measures of career instability, which we include as controls. These may capture some manifestations of health-induced career changes, although they cannot

fully resolve the underlying endogeneity problem. Second, SHARE lets us measure occupational characteristics at different career stages. Using the O*NET rotated component scores, we retrieve each respondent's first reported occupation and its corresponding occupational-content scores. We use these rather than career-average scores when estimating M4. Because first-occupation characteristics are measured before subsequent health shocks can reshape occupational trajectories, they should be less exposed to within-career reverse causality than career-average measures.

Finally, after retirement, a key source of selection bias arises from differential attrition rates driven by career-related factors, particularly the physical and psychological toll of demanding careers, which may contribute to higher mortality rates among certain groups. This form of bias, sometimes called career-related death attrition, can distort the generalizability of findings in studies focusing on very old retirees. In this paper, we mitigate this bias by estimating eq. 1 excluding individuals aged 70 or older (models M5 and M6), as this age group is more likely to be affected by death attrition.

2.1.3 Contribution to model-explained variance: Shapley Value Regression

To complement our regression analysis, we employ Shapley Value Regression (SVR) (Shapley, 1953; Owen, 1977; Van Kerm, 2025)[6]: a technique to quantify the relative importance of individual (or groups of) predictors/regressors in regression models (inter alia).

A common approach to measuring a predictor's importance is to examine its contribution to the model's R^2. However, this contribution is inherently order-dependent, as it depends on the sequence in which it enters the model (Gelbach, 2016). SVR addresses this problem by evaluating a regressor's contribution in terms of R^2 across all possible sub-models underpinning the full model of interest to which it can be added.[7] Specifically, for each predictor/regressor, we estimate every sub-model in which it appears, from the simplest model in which it is the sole predictor to the full model that includes all predictors. For each such model, we record the predictor's marginal contribution to R^2.

[6]Shapley Value Regression is also known as Shapley regression, Shapley Value analysis, LMG, Kruskal analysis, dominance analysis, and incremental R-squared analysis.

[7]A subset of the complete set of regressors is what defines a sub-model.

We then average these contributions using weights that reflect the number of model combinations at each model size (e.g., models where the predictor appears alone, with one additional predictor, then with two, ...). This weighting ensures a fair assessment that is not influenced by arbitrary ordering choices. The resulting Shapley value represents the predictor's average marginal improvement in model fit. Finally, these values are rescaled to sum to 100%, producing interpretable measures of each (group of) predictor(s)'s relative importance.

2.1.4 Dimensional Reduction of Occupational Measures

To reduce dimensionality, we apply principal component analysis (PCA) to the standardised occupational indicators from O*NET's `Work Context` and `Work Activities` modules. We retain L principal components and then apply an oblimin rotation to improve interpretability while allowing the rotated components to remain correlated.

Formally, let Z denote the $I \times J$ matrix of standardised occupational indicators, where I is the number of occupations and J is the number of O*NET indicators. Because the indicators are standardised, PCA is performed on their correlation matrix,

$$R = \frac{1}{I-1} Z^T Z, \tag{2}$$

where R is the $J \times J$ correlation matrix of the occupational indicators.

PCA is based on the eigendecomposition of the correlation matrix,

$$R = V D V^T, \tag{3}$$

where V is the $J \times J$ matrix whose columns are the eigenvectors of R, and D is the diagonal matrix containing the corresponding eigenvalues, ordered from largest to smallest.

Retaining the first L principal components gives the reduced representation

$$R \approx V_L D_L V_L^T, \tag{4}$$

where V_L contains the eigenvectors associated with the L largest eigenvalues and D_L is the corresponding $L \times L$ diagonal matrix of eigenvalues. The associated component-loading matrix can be written as

$$\Lambda_L = V_L D_L^{1/2}, \tag{5}$$

where Λ_L is a $J \times L$ matrix describing the relationship between the original occupational indicators and the retained principal components.

After retaining the components, we apply an oblique rotation, specifically oblimin, to enhance interpretability. Because oblimin is an oblique rotation, the resulting rotated components are allowed to correlate, facilitating the identification of distinct conceptual domains.

2.2 Data

This study combines individual-level data from the Survey of Health, Ageing and Retirement in Europe (SHARE) with occupational characteristics drawn from the U.S.-based O*NET database. The resulting dataset enables us to correlate respondents' mental health outcomes in later life with the attributes of their past careers.

2.2.1 Mental Health and Career Histories from SHARE

SHARE measures mental health after age 50 using the EURO-D scale, which comprises 12 binary items capturing depressive symptoms: depression, pessimism, suicidality, guilt, sleep disturbances, loss of interest, irritability, appetite problems, fatigue, poor concentration, lack of enjoyment, and tearfulness. These items are summed into a score ranging from 0 to 12, with higher values indicating more depressive symptoms.

The data reveal clear cross-country and gender patterns. Figure 1 shows substantial variation in average EURO-D scores across countries, with generally higher levels in Southern and Eastern Europe than in Northern Europe, albeit with some exceptions. Women also consistently report higher scores than men across all countries. Finally, Table A.1 in the Appendix shows that a sizeable share of older adults have a EURO-D score of 4 or more, corresponding to the commonly used cut-off for elevated depressive symptoms.

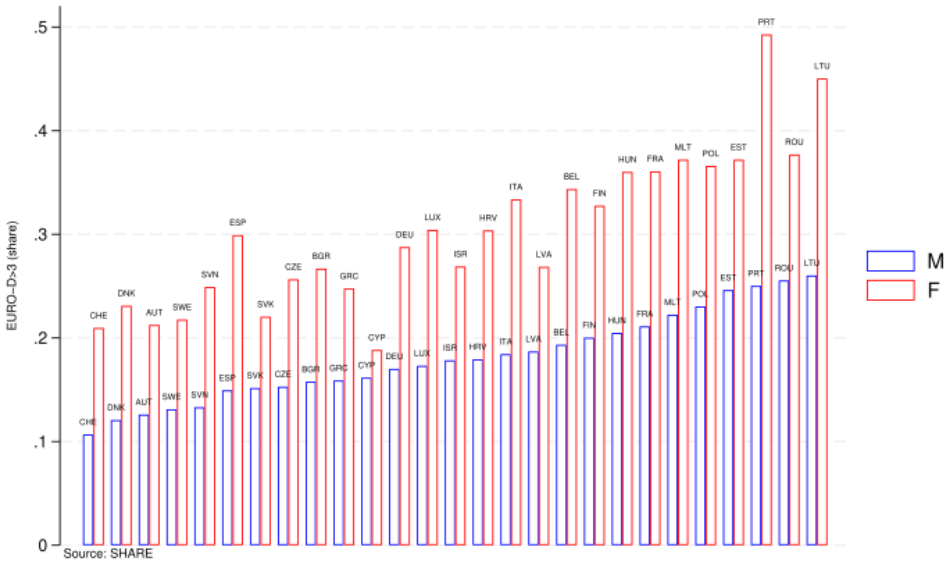


Figure 1: Proportion of individuals [50-80] with a EURO-D score greater than 3, by country and gender

Note: the EURO-D is a 12-item scale measuring depressive symptoms, with each item coded 0 (symptom absent) or 1 (symptom present), yielding a total score ranging from 0 to 12.

SHARE Wave 7 also provides retrospective job histories, recording respondents' successive jobs and associated occupational codes over their careers. Appendix A.1 illustrates how these job histories are organised as sequences of occupations.

2.2.2 Occupational Characteristics from O*NET

To characterise occupations, we rely on O*NET, a comprehensive U.S. Department of Labor database providing standardised descriptors for 879 occupations.[8] We extract data from O*NET's "Work Context" and "Work Activities" modules, which provide 98 indicators describing a broad range of occupational characteristics, including physical working conditions and exposures, interpersonal and organisational aspects of work, cognitive and information-processing activities, managerial responsibilities, work pace and time pressure, and responsibility for outcomes and other people.

We organise this comprehensive occupational dataset into a wide-format matrix comprising 879 occupations and 98 standardised variables. We then apply principal component

[8] Applying U.S.-based measures of job content to European occupations may be a limitation. We address this issue in Section 3.3.

analysis and retain three components, which together provide a parsimonious representation of the occupational indicators while preserving substantively distinct dimensions of job content. We then rotate the three components using oblimin rotation. Based on the rotated component solution, we identify three main dimensions of occupational content. The first captures managerial, cognitive, and information-processing activities; the second captures physical demands and adverse physical working conditions; and the third reflects socially and emotionally demanding work contexts. We therefore label these components *managerial/cognitive intensity*, *physical arduousness*, and *emotional/interpersonal demands*, respectively.

For each ISCO-4 occupation, we compute a score on each of the three rotated components.[9] We then assign these occupation-level scores to each job reported in the SHARE career histories, using the ISCO 2-digit level when a 4-digit occupational code is unavailable, and aggregate them across respondents' job histories. This yields individual-level career indices of managerial/cognitive intensity, physical arduousness, and emotional/interpersonal demands, which constitute the main occupational explanatory variables in equation (1).

As shown in Table A.2, the managerial/cognitive-content index captures the seniority aspects of work, such as decision-making and information processing. The physical arduousness index (Table A.3) highlights physical demands, a priori harmful environmental exposures, and bodily effort. In contrast, the third rotated component is dominated by interpersonal and emotionally demanding characteristics, including assisting and caring for others, direct work with the public, frequent contact with others and customers, interactions with aggressive or unpleasant individuals, and exposure to conflict situations (Table A.4). We therefore interpret this component as capturing *emotional/interpersonal demands*. However, the component also includes some characteristics from other domains, most notably exposure to disease or infections and frequency of decision making, and should therefore be interpreted as predominantly rather than exclusively emotional/interpersonal.

The first three unrotated principal components together explain more than 55% of the total variance in the original standardised O*NET indicators. Figure 2 presents the corresponding scree plot of eigenvalues. The eigenvalue associated with a principal component indicates the amount of variance in the original indicators explained by that component. Since the PCA is performed on the correlation matrix of 98 standardised indicators, the total variance equals 98, and the proportion explained by the first three components is given

[9] These scores locate each occupation along the dimensions defined by the retained and rotated components.

by the sum of their eigenvalues divided by 98. The figure shows a steep decline in eigenvalues over the first three components, followed by a considerably flatter pattern, suggesting diminishing gains in explained variance from retaining additional components. This pattern, together with the substantive interpretability of the rotated dimensions, supports the choice of three components. Following oblimin rotation, the resulting component scores are allowed to correlate; their estimated correlations are reported in Table 1.

For presentation purposes, Figures 3, 4, and 5 collapse ISCO 4-digit occupations into broader ISCO 2-digit occupational groups. These figures display the distribution of occupational scores along each of the three rotated dimensions.

Overall, the ordering of occupations along each dimension aligns well with common intuitions and theoretical expectations. Occupations involving managerial and cognitively intensive activities tend to score highest on the Managerial/cognitive dimension (Figure 3). Similarly, jobs involving manual labour and environmental exposure tend to rank high on the physical index (Figure 4). Occupations traditionally considered demanding in terms of emotional labour score highly on the emotional/interpersonal index (Figure 5).

While some individual rankings may appear counterintuitive, possibly reflecting within-occupation task heterogeneity or imperfect correspondence between occupational classifications and actual job content, the indices provide a meaningful, interpretable mapping of job characteristics across broad occupational categories.

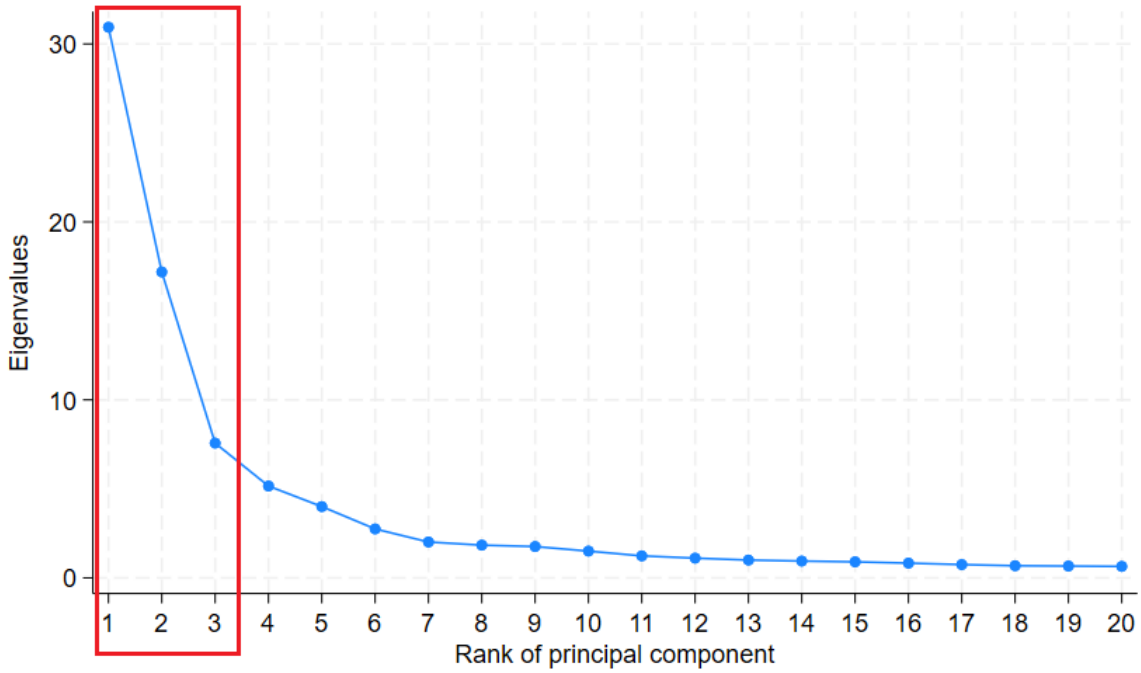


Figure 2: Scree plot of eigenvalues for the unrotated principal components
Note: Eigenvalues indicate the variance explained by each unrotated principal component of the 98 standardised O*NET indicators. The red box highlights the first three components, which together explain more than 55% of the total variance.

Table 1: Rotated component scores: correlation matrix (all ISCO-4 occupations)

	Manag./cogn. content	Phy. ardu.	Emot./interp.
Manag./cog.	1.000		
Phy. ardu.	-0.256	1.000	
Emot./interp.	0.374	-0.128	1.000

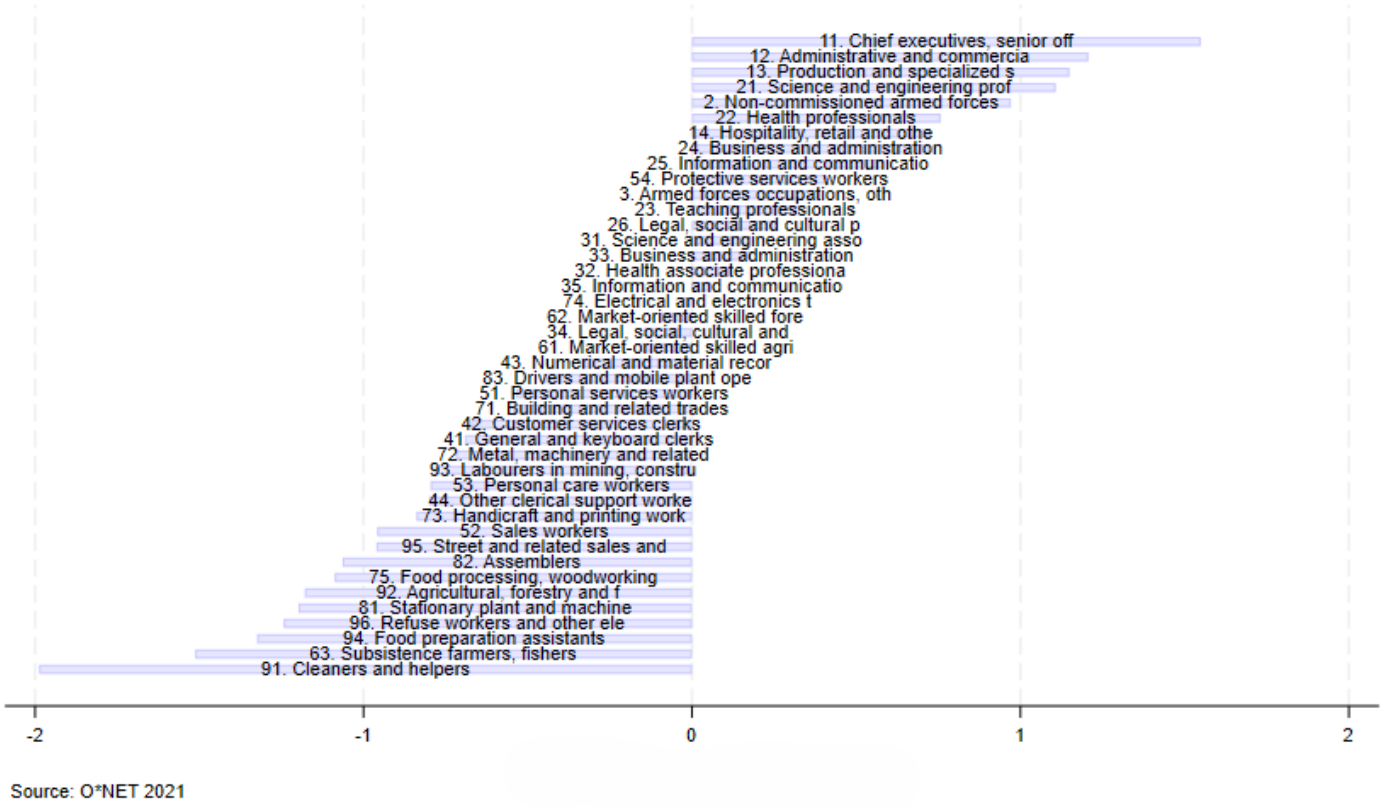


Figure 3: Manag./cogn. content [Rotated dimension 1] Score by ISCO2 occupation
Note: Scores are derived from O*NET occupational characteristics using PCA followed by oblimin rotation and are presented at the ISCO two-digit occupational-group level. Higher scores indicate greater managerial/cognitive content.

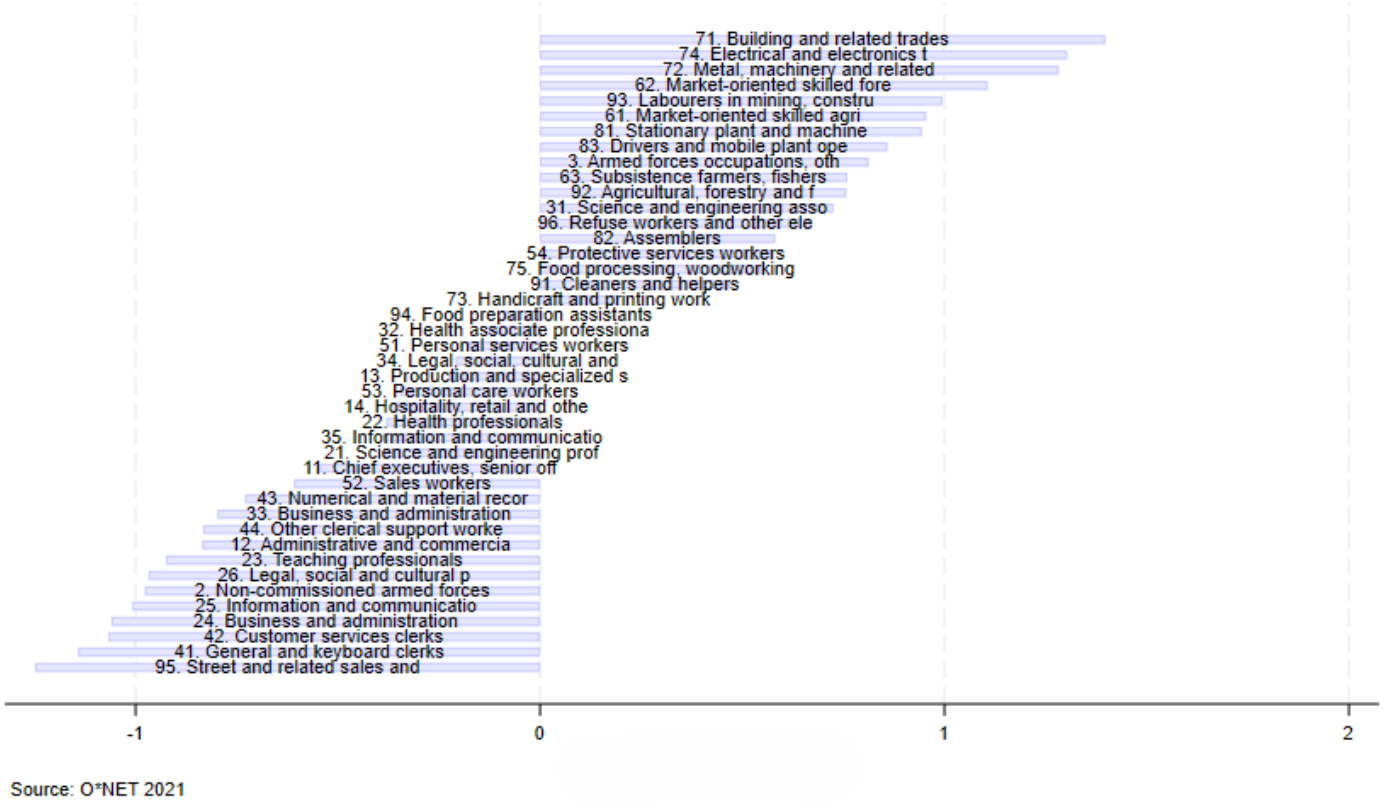


Figure 4: Physical Arduousness [Rotated dimension 2] Score by ISCO2 occupation
Note: Scores are derived from O*NET occupational characteristics using PCA followed by oblimin rotation and are presented at the ISCO two-digit occupational-group level. Higher scores indicate greater physical arduousness.

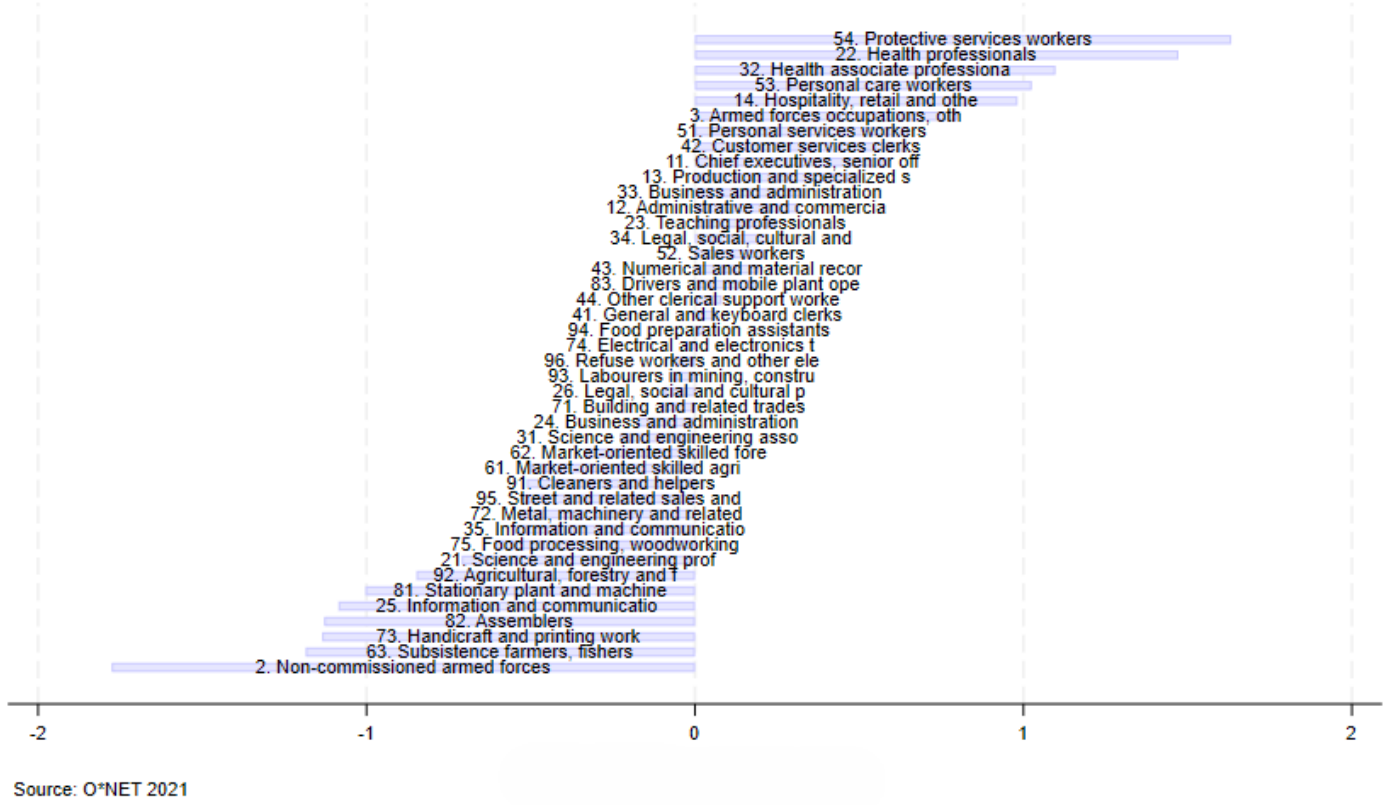


Figure 5: Emotional/Interpersonal Demands [Rotated dimension 3] Score by ISCO2 occupation

Note: Scores are derived from O*NET occupational characteristics using PCA followed by oblimin rotation and are presented at the ISCO two-digit occupational-group level. Higher scores indicate greater emotional/interpersonal demands.

3 Results and Discussion

3.1 Regression results

The key econometric results are presented in Table 2 (for female respondents) and Table 3 (for male respondents), while descriptive statistics for the main variables are reported in Appendix A.3, Table A.5. In model M1, the dependent variable is binary (Euro-D >3), and the reported (exponentiated) coefficients come from the estimation of the logistic version of eq. (1). M1 serves as a baseline. Its regressors include the three career indices, along with age, wave, and country fixed effects. Among women, the odds ratio for emotional/interpersonal demands (CAR^{emo}) is 1.048 and is statistically significantly greater than 1. The odds ratio

for physical arduousness (CAR^{phys}) is 1.213 and is statistically significant. The managerial/cognitive intensity index (CAR^{manag}) also shows a statistically significant association, with an odds ratio of 0.841, indicating a lower incidence of late-life depressive symptoms. Baseline results for men (Table 3) are qualitatively similar, with the same direction of association for all three career indices, although the emotional/interpersonal coefficient is not statistically significant for men.

With controls for career instability, education, childhood, and health endowments (M2), the signs of the three career indices remain the same as in M1. Emotional/interpersonal demands and physical arduousness are positively associated with depressive symptoms, while managerial/cognitive intensity is negatively associated with them. For women, all three coefficients are statistically significant in M2. For men, physical arduousness and managerial/cognitive intensity are statistically significant, whereas the coefficient on emotional/interpersonal demands is not.

In Model M3, and in all subsequent specifications, we replace the binary dependent variable with a continuous measure of depressive symptoms while retaining the complete set of controls. Model M4 addresses potential selection during the career by replacing the career-long occupational-content measures with those of the first job. Model M5 attempts to account for selection due to death attrition by excluding respondents aged 70 or older. The qualitative pattern remains broadly stable across these specifications.

Our preferred specification, M6, combines the first-job occupational-content measures with the restriction to respondents aged 50–69, while retaining the full set of controls. In this specification, emotional/interpersonal demands and physical arduousness are positively and statistically significantly associated with depressive symptoms for both men and women, while managerial/cognitive intensity is negatively and statistically significantly associated with depressive symptoms for both genders.

Looking across M2–M6, the signs of the three occupational-content coefficients are stable. Physical arduousness and managerial/cognitive intensity remain statistically significant for both genders throughout. The emotional/interpersonal coefficient is statistically significant for women in all specifications except M4 and for men in M3–M6 but not M2. The estimated association with physical arduousness is consistently larger in magnitude among women.

Turning to the control variables, most behave as expected. Several indicators of career instability are consistently associated with later-life depressive symptoms. A greater number of jobs, employment gaps, and redundancies are generally associated with poorer mental

health, while longer careers are associated with fewer depressive symptoms. A lower propensity to work full-time is associated with poorer mental health mainly among men. Education is negatively and statistically significantly associated with depressive symptoms, confirming its protective role across the life course.

Although the tables do not report age coefficients, the regressions reveal a statistically significant negative age gradient in depressive symptoms. This may reflect cohort effects but also genuine age-related shifts in emotional priorities and coping strategies, together with greater psychological resilience at older ages. As individuals age, they may become more selective in the situations and relationships in which they invest emotionally, place greater emphasis on emotional regulation, and draw on accumulated experience to cope with stressful circumstances. Such adaptations could reduce the psychological impact of demanding working conditions later in the career.[10] Finally, persistent, statistically significant cross-country differences, even after accounting for individual characteristics, highlight the importance of country-specific time-invariant factors, such as weather and the institutional, cultural, economic, and policy context.

In summary, our results indicate that the three dimensions of occupational content are associated with later-life mental health in different directions. Emotional/interpersonal demands and physical arduousness are generally associated with more depressive symptoms, whereas managerial/cognitive job content is associated with fewer depressive symptoms. Among career characteristics, career instability appears considerably more important than emotional/interpersonal demands in explaining variation in later-life mental health, a finding confirmed by the Shapley variance-decomposition analysis below. Finally, pre-labour-market factors, particularly early-life health adversity and educational attainment, also emerge as important predictors of depressive outcomes in later life.

[10] This interpretation is consistent with evidence from clinical psychiatry suggesting age-related differences in emotional regulation and resilience (Palmer et al., 2016).

Table 2: Determinants of (Poor) Mental Health Beyond 50. Regression results: Female

	Logit		OLS			
	M1	M2	M3	M4 (1st job)	M5 (50–69)	M6 (1st job) (50–69)
CAR^{emo}	1.048***	1.062***	0.020***	0.007	0.018**	0.012*
	(0.0137)	(0.0142)	(0.0054)	(0.0050)	(0.0065)	(0.0060)
CAR^{phys}	1.213***	1.143***	0.068***	0.048***	0.060***	0.040***
	(0.0172)	(0.0173)	(0.0062)	(0.0058)	(0.0076)	(0.0070)
CAR^{manag}	0.841***	0.913***	-0.035***	-0.029***	-0.040***	-0.038***
	(0.0107)	(0.0127)	(0.0057)	(0.0053)	(0.0069)	(0.0064)
Number of Jobs[a]		1.017*	0.009***	0.008**	0.010**	0.009**
		(0.0070)	(0.0028)	(0.0030)	(0.0033)	(0.0036)
Gaps[b]		1.075***	0.034***	0.038***	0.031***	0.034***
		(0.0142)	(0.0055)	(0.0058)	(0.0063)	(0.0067)
Redun.[c]		1.085***	0.046***	0.048***	0.049***	0.051***
		(0.0167)	(0.0065)	(0.0069)	(0.0073)	(0.0078)
Prop. ft[d]		1.059	0.014	0.019	-0.010	-0.008
		(0.0957)	(0.0368)	(0.0379)	(0.0426)	(0.0441)
Career length[e]		0.990***	-0.006***	-0.006***	-0.007***	-0.007***
		(0.0009)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Sec. educ.		0.841***	-0.099***	-0.108***	-0.107***	-0.114***
		(0.0208)	(0.0104)	(0.0106)	(0.0127)	(0.0131)
Ter. educ.		0.717***	-0.166***	-0.183***	-0.182***	-0.195***
		(0.0226)	(0.0129)	(0.0129)	(0.0157)	(0.0157)
Childh. ment. health		1.157***	0.083***	0.083***	0.079***	0.080***
		(0.0093)	(0.0035)	(0.0036)	(0.0040)	(0.0042)
Childh. phys. health		1.159***	0.081***	0.083***	0.087***	0.087***
		(0.0099)	(0.0037)	(0.0038)	(0.0044)	(0.0046)
Constant	0.140**	0.172*	-0.295	-0.281	-0.112	-0.080
	(0.0942)	(0.1178)	(0.2564)	(0.2879)	(0.2621)	(0.2932)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
N	60,705	60,705	60,705	56,617	42,059	39,015
R^2			0.078	0.078	0.080	0.080

Source: SHARE, O*NET; our calculations.
Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.
M1: Logit baseline (odds ratio); M2: Logit with full list of controls (odds ratio); M3: OLS cont. outcome; M4: OLS cont. outcome and only first job; M5 OLS. cont. outcome and restriction to respondents aged <70; M6 OLS cont. outcome, only first job & restriction to respondents aged less than 70.
(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

Table 3: Determinants of (Poor) Mental Health Beyond 50. Regression results: Male

	Logit		OLS			
	M1	M2	M3	M4 (1st job)	M5 (50–69)	M6 (1st job) (50–69)
CAR^{emo}	1.035	1.036	0.014*	0.022***	0.021**	0.025***
	(0.0200)	(0.0205)	(0.0057)	(0.0055)	(0.0068)	(0.0066)
CAR^{phys}	1.083***	1.053**	0.024***	0.018***	0.032***	0.026***
	(0.0164)	(0.0171)	(0.0047)	(0.0043)	(0.0057)	(0.0052)
CAR^{manag}	0.859***	0.907***	-0.035***	-0.024***	-0.044***	-0.026***
	(0.0158)	(0.0178)	(0.0057)	(0.0053)	(0.0069)	(0.0064)
Number of Jobs[a]		1.041***	0.015***	0.012***	0.016***	0.015***
		(0.0080)	(0.0023)	(0.0025)	(0.0028)	(0.0030)
Gaps[b]		1.047*	0.033***	0.033***	0.031***	0.035***
		(0.0202)	(0.0061)	(0.0065)	(0.0071)	(0.0075)
Redun.[c]		1.067***	0.020**	0.025***	0.020**	0.024**
		(0.0207)	(0.0062)	(0.0065)	(0.0070)	(0.0075)
Prop. ft[d]		0.638	-0.265***	-0.207**	-0.278***	-0.217*
		(0.1472)	(0.0704)	(0.0726)	(0.0815)	(0.0845)
Career length[e]		0.978***	-0.010***	-0.010***	-0.012***	-0.012***
		(0.0015)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Sec. educ.		0.785***	-0.101***	-0.105***	-0.093***	-0.093***
		(0.0249)	(0.0098)	(0.0101)	(0.0120)	(0.0124)
Ter. educ.		0.644***	-0.170***	-0.192***	-0.181***	-0.205***
		(0.0264)	(0.0121)	(0.0121)	(0.0148)	(0.0149)
Childh. ment. health		1.149***	0.065***	0.058***	0.061***	0.057***
		(0.0132)	(0.0040)	(0.0041)	(0.0046)	(0.0048)
Childh. phys. health		1.189***	0.073***	0.075***	0.077***	0.079***
		(0.0138)	(0.0038)	(0.0039)	(0.0045)	(0.0047)
Constant	0.157***	0.714	-0.326	-0.332	-0.102	-0.081
	(0.0309)	(0.2222)	(0.4688)	(0.4678)	(0.4693)	(0.4692)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
N	48,952	48,952	48,958	45,408	32,785	30,343
R^2			0.065	0.063	0.071	0.071

Source: SHARE, O*NET; our calculations.
Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.
M1: Logit baseline (odds ratio); M2: Logit with full list of controls (odds ratio); M3: OLS cont. outcome; M4: OLS cont. outcome and only first job; M5 OLS. cont. outcome and restriction to respondents aged <70; M6 OLS cont. outcome, only first job & restriction to respondents aged less than 70.
(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

3.2 Contribution to model-explained variance: Shapley Value Regression

We now assess the (relative) contributions of different groups of explanatory variables. So far, we have identified and commented on variables with statistically significant positive or negative associations with mental health. However, this does not adequately inform us about their relative importance in predicting mental health outcomes. This question becomes even more complex when our explanatory variables are organised into groups that mix continuous and categorical indicators. To address these limitations, we draw on Shapley Value Regression (SVR) as developed by Van Kerm (2025). SVR is a post-estimation technique that quantifies each regressor's contribution by computing its marginal impact on the R^2 across all sub-models nested within the full model, then averaging these contributions. We apply this method to our preferred model M6.

As reported in Table 4, our three career indices do contribute to the model-explained variance in late-life poor mental health, but their (combined) explanatory power – 5.33% for men and 7.43% for women – is modest compared with several other groups of variables. As to emotional/interpersonal demands, their share of the total model-explained variance is only .48% for men and .7% for women.

Other groups of regressors far outweigh our three career indices. Notably, the career instability measures – at 28.53% for men and 17.47% for women – are many times more predictive than emotional/interpersonal demands or even all three career-content indices combined. Additional major contributors, as shown in Table 4, include childhood health (27.22- 31.74%), country of residence (24.80-30.50%), and education (approximately 10%).

The relatively modest contribution of career arduousness indices to explained variance (as measured by Shapley values), compared with career instability, may partly reflect differences in measurement precision. First-job arduousness scores (Table 4) are constant within four-digit ISCO occupations and thus assigned identically to several respondents, whereas career instability is measured directly at the individual level. This measurement asymmetry may give career instability greater predictive power.

However, this measurement asymmetry should not be overstated. First, arduousness scores are based on relatively granular four-digit ISCO occupations, limiting aggregation. More importantly, we can re-estimate Shapley values using our `career` arduousness scores, which are `individual-specific`. These combine ISCO4-level arduousness scores with each

respondent's employment history, capturing three sources of individual variation: *i)* occupational trajectories, reflecting the sequence of occupations held; *ii)* exposure duration, measured by the years spent in each occupation; and *iii)* work intensity, accounting for full-time versus part-time employment. Thus, although the underlying job-demand scores are occupation-specific, the resulting career indices capture substantial individual heterogeneity beyond differences between ISCO4 occupations. Second, while career instability is measured directly at the individual level, many indicators are categorical or binary and therefore show limited variation. For instance, most SHARE respondents report no employment interruptions lasting six months or more. Hence, individual-level measurement does not necessarily imply greater variation or predictive power.

As announced above, to assess the empirical risk of measurement-asymmetry bias, we have re-estimated the Shapley decomposition for model M5, thus replacing first-job arduousness scores with individual-specific, career-weighted arduousness averages. The results, reported in Appendix A.5, Table A.9, closely align with our baseline estimates, supporting the robustness of our conclusions.

Nevertheless, we acknowledge the broader measurement concern: unobserved heterogeneity in actual working conditions within four-digit ISCO occupations may introduce measurement error and weaken the explanatory power of our arduousness variables. Similarly, the categorical nature of several career instability indicators may limit their ability to capture finer differences between individuals. Measurement limitations may therefore affect both sets of variables.

3.3 Assessing the role of U.S. vs. Europe occupational differences

This paper applies O*NET occupational scores derived from the U.S. labour market to a European sample spanning 27 heterogeneous countries. This may seem like a significant leap. That must be fully acknowledged. In this paper, we indeed assume that the job characteristics of a baker or a teacher in the USA are broadly comparable to those of their European counterparts, whatever dimension of arduousness/demand is considered. Ideally, we would use European occupational/job content data to quantify the arduousness of a series of occupations. Vandenberghe (2023) shows that using EWCS-based measures of career physical arduousness does not materially alter our estimates of the association between career physical arduousness and late-life health or longevity. But replicating this exercise for emotional/interpersonal demands is considerably more difficult. Identifying which O*NET

Table 4: Decomposition of (Poor) Mental Health M6-explained variance. Respondents aged 50–69.

	M	F
Total	1.000	1.000
1 Career indices (1st job)	0.0533	0.0743
Emot./interp.	0.0048	0.0070
Phys. ardu.	0.0284	0.0308
Manag./cog.	0.0201	0.0365
2 Career instab	0.2853	0.1747
Number of Jobs[a]	0.0249	0.0137
Gaps[b]	0.0504	0.0296
Redun.[c]	0.0282	0.0387
Prop. ft[d]	0.0070	0.0008
Career length[e]	0.1748	0.0919
3 Educ	0.1028	0.0958
4 Child health	0.2722	0.3174
Child h phys	0.1044	0.1546
Child h psy	0.1678	0.1628
5 Other	0.2864	0.3378
Country	0.2480	0.3050
Wave	0.0116	0.0179
Age	0.0268	0.0150

(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

items adequately capture emotional/interpersonal demands – and, in particular, distinguishing emotional-relational demands from stress, as is commonly done in the specialised literature – is far from straightforward. Establishing a sufficiently convincing correspondence between these O*NET measures and the available European Working Condition Survey (EWCS) items would therefore be problematic.

We therefore pursue an alternative robustness check[11] by re-estimating our main specifications on a restricted sample of high-income European countries whose job content is arguably most likely to resemble that of the US, namely Luxembourg, Switzerland, Sweden, Austria, Germany and Denmark. The point estimates for this restricted sample are reported in Tables A.6 and A.7 in Appendix A.4. The restricted-sample estimates generally preserve the signs and broad qualitative pattern of the full-sample results, although magnitudes and statistical significance differ in some specifications.

The results for our Variance-decomposition/Shapley analysis are reported in Appendix A.5. The main findings remain remarkably similar, particularly the relatively large contributions of career instability and pre-labour-market characteristics to predicting poor mental health in later life.

3.4 Gender differences and what they could mean

We find no clear or systematic gender difference in the associations of either career emotional/interpersonal demands or managerial/cognitive content with mental health after age 50. By contrast, the point estimates reported in Tables 2 and 3 suggest that women's mental health may be more strongly associated with the physical arduousness of work. For instance, in M2, the estimated odds ratio is 1.143 for women, compared with 1.053 for men. A similar difference in point estimates is observed across specifications M3–M6.

Another gender difference emerges from the Shapley variance-decomposition results reported in Table 4. The share of late-life mental-health variation attributable to career instability is substantially larger for men (28.53%) than for women (17.47%).

Several mechanisms could potentially account for these differences. Regarding physical arduousness, cumulative physical demands may affect late-life mental health partly through the deterioration of physical health,[12] and this pathway may be stronger for women. Using

[11] We thank an anonymous referee for this suggestion.

[12] There is strong evidence in SHARE of an association between late-life physical and mental health.

very similar SHARE/O*NET data, Vandenberghe (2025) finds that women's healthy life expectancy appears somewhat more adversely affected by the physical arduousness of work.

The larger contribution of career instability to explained mental-health variation among men may, in turn, reflect the historically greater economic and psychosocial importance of continuous employment for men in the cohorts considered, notably through the male-breadwinner role and the stronger association between employment and male social identity. Artazcoz et al. (2004), for example, find a substantially stronger association between unemployment and poor mental health among men than among women.[13] These interpretations remain tentative, however, and our data do not allow us to distinguish between these potential mechanisms.

3.5 Limitations and Future Research

While this study offers new insights into the relationship between career-long occupational characteristics and later-life mental health, several limitations warrant discussion.

First, the occupational exposure measures derived from the O*NET database are based on relatively small numbers of respondents per occupation, typically around 30. This does not mean the PCA itself is based on a small sample, as the analysis spans many more occupations. Rather, it may introduce sampling noise into the occupation-level O*NET measures used as PCA inputs. Such measurement error may attenuate correlations across job-content items and reduce the precision and stability of the resulting PCA loadings and occupational scores, particularly for occupations characterised by substantial within-occupation heterogeneity.

Second, the dimensionality-reduction technique (principal component analysis) used to summarise occupational attributes retains the first three unrotated principal components,

[13] This interpretation assumes that the larger Shapley–Owen contribution to R^2 reflects larger regression coefficients. However, it may also reflect greater variation in the predictors. To illustrate, in a simple regression $Y = \alpha + \beta X + \varepsilon$, with $\mathrm{Cov}(X, \varepsilon) = 0$, we have

$$R^2 = \frac{\beta^2 \,\mathrm{Var}(X)}{\beta^2 \,\mathrm{Var}(X) + \mathrm{Var}(\varepsilon)}.$$

Thus, holding β and the residual variance constant, greater variation in X increases its explanatory power. In our case, the question is therefore whether career instability varies more among men or women. Available European evidence suggests that women's employment histories are more heterogeneous than men's (Schmitz et al., 2023). To the extent that this translates into greater dispersion in our career instability measures, the variance-based argument would, all else equal, predict a larger contribution to R^2 among women rather than men—the opposite of what we observe.

which together explain more than 55% of the variance in the original O*NET variables. Following oblimin rotation, this solution yields interpretable dimensions of physical arduousness, managerial/cognitive content, and emotional/interpersonal demands. Nevertheless, dimensionality reduction inevitably simplifies the multifaceted nature of occupational exposures. This simplification may obscure important nuances, particularly for occupations with unique or mixed attribute profiles that do not align neatly with the dominant rotated components.

Third, as with many studies in labour economics, this research probably falls short of establishing fully causal relationships. While we control for a wide range of confounders, including early-life health conditions, attempt to limit the risk of career- and post-career selection bias, and control for country-level fixed unobservables, endogeneity concerns persist. Unaccounted health selection into occupations, unobserved heterogeneity in preferences or resilience, and unaccounted health shocks that simultaneously influence exposure to different working conditions and long-term health may bias our results; thus, they should be interpreted cautiously.

Fourth, although our study draws on large, rich datasets, it remains limited by the quality of some self-reported data. In particular, the career history information is subject to recall bias or omission, especially among the oldest respondents. While SHARE's life-history survey design mitigates this concern to some extent, measurement error may remain a limitation.

Future research could address these limitations and extend the present study in several ways. First, replicating the analysis using alternative occupational databases with larger job-level samples would help evaluate the robustness of our occupational-content indices. Second, subsequent work could apply more advanced machine-learning approaches or non-linear dimensionality-reduction techniques to derive finer-grained occupational components beyond the three extracted here.

4 Conclusion

This study examines the relationship between emotional/interpersonal demands accumulated over individuals' careers and mental health outcomes in later life. Drawing on survey data from SHARE, combined with detailed occupational information from O*NET, we analyse how long-term exposure to emotionally and interpersonally demanding work, including

frequent conflict situations, public-facing work, and interactions with difficult or aggressive individuals, is associated with depressive symptoms after age 50. Alongside this dimension, we incorporate physical arduousness and managerial/cognitive intensity to capture a broader set of occupational influences on late-life mental health.

One of our key findings is that emotional/interpersonal demands are statistically significantly associated with a higher risk of depression in later life. Physical arduousness is also positively associated with later-life depression for both women and men. In contrast, greater managerial/cognitive intensity is associated with a lower risk of depression. Taken together, these results indicate that different dimensions of occupational content are associated with later-life mental health in different directions, rather than supporting a single gradient of occupational arduousness.

Consistent with Vandenberghe (2023), we also find that indicators of career instability/fragmentation, such as job losses and employment gaps, are relatively more important predictors of late-life mental health, highlighting the potentially detrimental long-term impact of non-work job spells that, from a narrow perspective, might be considered strictly non-arduous. A still-widespread view, likely inherited from a period when most workers performed manual or physically demanding tasks, holds that work is predominantly arduous and that accumulating it is inevitably detrimental to health. However, modern labour markets probably call for a more nuanced perspective. Our results indicate that mental health may be shaped not only by exposure to work-related strain *per se* but also by the incidence of non-work episodes.

Results also show that pre-labour factors combined, like childhood health and education, account for a relatively substantial share of the observed variation in late-life mental ill-health. By comparison, career characteristics, while statistically significant, play a more modest role.

Overall, this research contributes to the growing economic literature on the long-term mental health effects of (broadly defined) working conditions. Policy implications point to a multipronged strategy: promoting healthier, more supportive workplaces while also reducing stress associated with job loss, forced mobility, and unstable career paths. Our findings underscore the need to distinguish between in-work arduousness and what we term career instability; the long-term harm may stem less from the nature of work itself than from insecure or fragmented labour-market attachment. Finally, the results indicate that some determinants of late-life mental health originate in childhood, highlighting the value

of early-life interventions alongside adult-age and labour-focused policies.

Declarations

Availability of data and material

Data will be made available on reasonable request.

Funding

None

Authors' contributions

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We confirm that we are the only authors and that no one else meets the criteria for authorship.

Acknowledgements

We thank the editor and two anonymous referees for their valuable comments and suggestions, which have substantially improved the paper.

Computational resources have been provided by the supercomputing facilities (CISM/UCLouvain) and the Consortium des Équipements de Calcul Intensif en Fédération Wallonie Bruxelles (CÉCI) funded by the Fonds de la Recherche Scientifique de Belgique (F.R.S.-FNRS) under convention 2.5020.11 and by the Walloon Region.

This paper uses data from SHARE Wave 7. See Börsch-Supan et al. (2013) for methodological details. The European Commission has funded the SHARE data collection

through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982) and Horizon 2020 (SHARE-DEV3: GA N°676536, SERISS: GA N°654221) and by DG Employment, Social Affairs & Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

During the preparation of this work, the authors used ChatGPT to improve the quality of the text in terms of grammar and language clarity. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Conflict of interest

None

References

Adam, M. and P. Flatau (2006). "Job insecurity and mental health outcomes: An analysis using waves 1 and 2 of HILDA". In: *The Economic and Labour Relations Review* 17, pp. 143–170.

Artazcoz, L., J. Benach, C. Borrell, and I. Cortès (2004). "Unemployment and mental health: understanding the interactions among gender, family roles, and social class". en. In: *American Journal of Public Health* 94.1, pp. 82–88.

Barnay, T. (2016). "Health, work and working conditions: a review of the European economic literature". In: *The European Journal of Health Economics* 17.6, pp. 693–709.

Belloni, M., L. Carrino, and E. Meschi (2022). "The impact of working conditions on mental health: Novel evidence from the UK". In: *Labour Economics* 76, pp. 1–22.

Brunner, B., I. Igic, A. C. Keller, and S. Wieser (2019). "Who gains the most from improving working conditions? Health-related absenteeism and presenteeism due to stress at work". en. In: *European Journal of Health Economics* 20.8, pp. 1165–1180.

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, and S. Zuber (2013). "Data resource profile: The survey of health, ageing and retirement in europe (SHARE)". In: *International Journal of Epidemiology* 42.

Cottini, E. and C. Lucifora (2013). "Mental health and working conditions in europe". In: *ILR Review* 66.

French, E. and J. Jones (2017). "Health, health insurance, and retirement: a survey". In: *Annual Review of Economics* 9, pp. 383–409.

Gelbach, J. B. (2016). "When Do Covariates Matter? And Which Ones, And How Much?" In: *Journal of Labor Economics* 34.2, pp. 509–543.

Glomb, T., J. Kammeyer-Mueller, and M. Rotundo (2004). "Emotional labor demands and compensating wage differentials". In: *The Journal of applied psychology* 89, pp. 700–14.

Guerra, M., C. Ferri, J. Llibre-Rodriguez, M. Prina, and M. Prince (2015). "Psychometric properties of EURO-D, a geriatric depression scale: A cross-cultural validation study". In: *BMC psychiatry* 15, p. 12.

Jonge, J. de and C. Dormann (2006). "Stressors, resources, and strain at work: a longitudinal test of the triple-match principle". en. In: *Journal of Applied Psychology* 91.6, pp. 1359–1374.

Llena-Nozal, A. and M. Lindeboom (2004). "The effect of work on mental health: Does occupation Matter?" In: *Health economics* 13, pp. 1045–62.

Maclean, J. C., D. A. Webber, M. T. French, and S. L. Ettner (2015). "The Health Consequences of Adverse Labor Market Events: Evidence from Panel Data". In: *Industrial Relations: A Journal of Economy and Society* 54.3, pp. 478–498.

Morgeson, F. P. and S. E. Humphrey (2006). "The Work Design Questionnaire (WDQ): developing and validating a comprehensive measure for assessing job design and the nature of work". en. In: *Journal of Applied Psychology* 91.6, pp. 1321–1339.

Owen, G. (1977). "Values of Games with a Priori Unions". In: *Mathematical Economics and Game Theory*. Ed. by R. Henn and O. Moeschlin. Vol. 141. Lecture Notes in Economics and Mathematical Systems. Berlin, Heidelberg: Springer, pp. 76–88.

Palmer, B. W., D. V. Jeste, A. S. Martin, D. K. Glorioso, W. K. Thompson, C. A. Depp, M. L. Thomas, and C. N. Kaufmann (2016). "Paradoxical trend for improvement in mental health with aging: a community-based study of 1,546 adults aged 21-100 years". In: *The Journal of Clinical Psychiatry* 77.8, p. 8771.

Prince, M. J. et al. (1999). "Development of the EURO-D scale–a European, Union initiative to compare symptoms of depression in 14 European centres". In: *The British journal of psychiatry : the journal of mental science* 174, pp. 330–338.

Rigobon, R. and T. M. Stoker (2007). "Estimation with censored regressors: Basic issues". In: *International Economic Review* 48.4, pp. 1441–1467.

Schmitz, W., L Naegele, F Frerichs, and L Ellwardt (2023). "Gendered late working life trajectories, family history and welfare regimes: evidence from SHARELIFE". en. In: *European Journal of Ageing* 20.1, p. 5.

Shapley, L. S. (1953). "A Value for n-Person Games". In: *Contributions to the Theory of Games II*. Ed. by H. W. Kuhn and A. W. Tucker. Vol. 28. Annals of Mathematics Studies. Princeton, NJ: Princeton University Press, pp. 307–317.

Van Kerm, P. (2025). *shapowen: A generic Shapley-Owen value calculator*. Statistical Software Components S459513. Boston College Department of Economics.

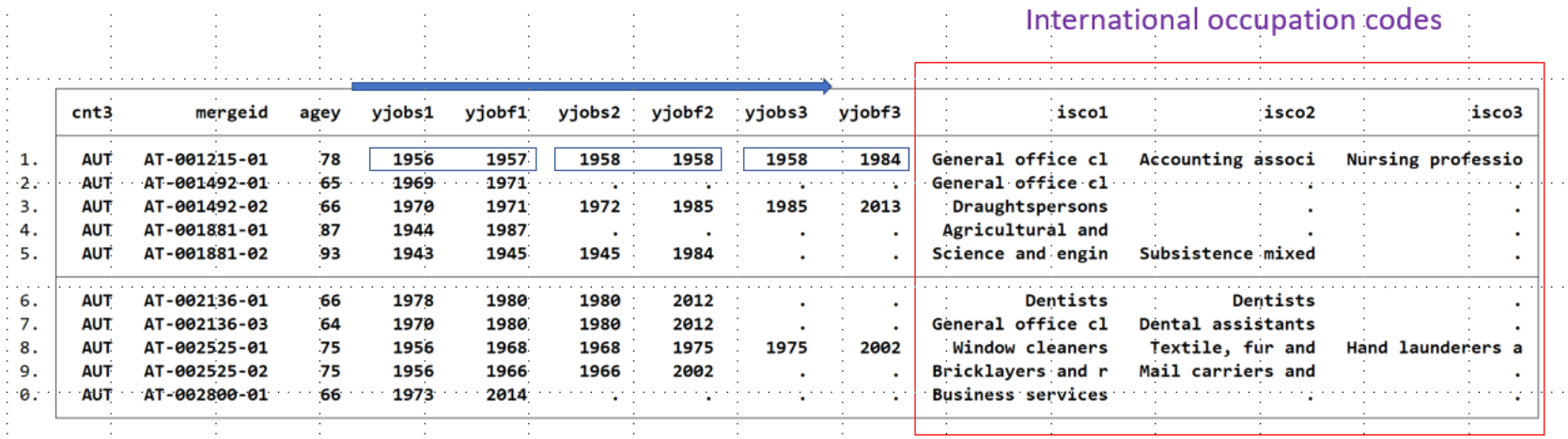
Vandenberghe, V. (2023). "Career arduousness and instability: Both matter for health beyond 50". In: *LABOUR* 37.3, pp. 343–384.

Vandenberghe, V. (2025). "Career arduousness and [healthy] life expectancy in Europe". In: *Journal of Pension Economics and Finance*, pp. 1–31.

Wang, S., D. Kamerāde, B. Burchell, A. Coutts, and S. U. Balderson (2022). "What matters more for employees' mental health: job quality or job quantity?" en. In: *Cambridge Journal of Economics* 46.2, pp. 251–274.

Appendix

A.1 SHARE Wave 7: careers/job history as succession of occupations (ISCO4)



	cnt3	mergeid	agey	yjobs1	yjobf1	yjobs2	yjobf2	yjobs3	yjobf3	isco1	isco2	isco3
1.	AUT	AT-001215-01	78	1956	1957	1958	1958	1958	1984	General office cl	Accounting associ	Nursing professio
2.	AUT	AT-001492-01	65	1969	1971	.	.	.	.	General office cl	.	.
3.	AUT	AT-001492-02	66	1970	1971	1972	1985	1985	2013	Draughtspersons	.	.
4.	AUT	AT-001881-01	87	1944	1987	.	.	.	.	Agricultural and	.	.
5.	AUT	AT-001881-02	93	1943	1945	1945	1984	.	.	Science and engin	Subsistence mixed	.
6.	AUT	AT-002136-01	66	1978	1980	1980	2012	.	.	Dentists	Dentists	.
7.	AUT	AT-002136-03	64	1970	1980	1980	2012	.	.	General office cl	Dental assistants	.
8.	AUT	AT-002525-01	75	1956	1968	1968	1975	1975	2002	Window cleaners	Textile, fur and	Hand launderers a
9.	AUT	AT-002525-02	75	1956	1966	1966	2002	.	.	Bricklayers and r	Mail carriers and	.
0.	AUT	AT-002800-01	66	1973	2014	.	.	.	.	Business services	.	.

Figure A.1: SHARE w7: job history/spells (sample)

Note: Each row represents an individual respondent. The variables `cnt3`, `mergeid`, and `agey` identify the country, respondent, and age, respectively. The variables `yjobs1`, `yjobf1`, etc. indicate the start and end years of successive jobs, while `isco1`, `isco2`, etc. identify the corresponding occupations. Dots indicate missing entries.

A.2 Descriptive and rotated components tables

Table A.1: SHARE: Averages of EURO-D[$]. Items by Country: respondents aged 50-80

Country	Depression	Pessimism	Suicidality	Guilt	Sleep (lack of)	Interest (lack of)	Irritability	Appetite (lack of)	Fatigue	Concentration (lack of)	Enjoyment (lack of)	Tearfulness	More than 3[a]	PC [b]
AUT	0.37	0.05	0.03	0.06	0.32	0.05	0.22	0.06	0.24	0.10	0.12	0.21	0.18	-0.26
BEL	0.42	0.10	0.10	0.10	0.35	0.07	0.28	0.09	0.36	0.19	0.07	0.31	0.27	0.01
BGR	0.27	0.29	0.04	0.04	0.26	0.13	0.11	0.08	0.31	0.18	0.17	0.22	0.22	-0.15
CHE	0.38	0.06	0.04	0.05	0.28	0.04	0.26	0.05	0.27	0.11	0.06	0.20	0.16	-0.28
CYP	0.25	0.18	0.05	0.02	0.22	0.11	0.18	0.07	0.20	0.13	0.09	0.21	0.18	-0.30
CZE	0.41	0.15	0.07	0.08	0.37	0.06	0.24	0.07	0.31	0.11	0.04	0.21	0.22	-0.14
DEU	0.48	0.06	0.05	0.07	0.38	0.06	0.31	0.06	0.32	0.13	0.11	0.23	0.23	-0.09
DNK	0.32	0.04	0.02	0.11	0.34	0.06	0.24	0.06	0.32	0.11	0.05	0.18	0.18	-0.26
ESP	0.32	0.19	0.06	0.06	0.28	0.12	0.22	0.07	0.33	0.16	0.09	0.23	0.22	-0.13
EST	0.48	0.21	0.05	0.14	0.48	0.08	0.34	0.07	0.49	0.11	0.10	0.21	0.33	0.12
FIN	0.40	0.10	0.03	0.08	0.38	0.09	0.32	0.06	0.44	0.14	0.09	0.28	0.27	-0.02
FRA	0.47	0.18	0.10	0.09	0.39	0.07	0.34	0.07	0.35	0.17	0.10	0.25	0.29	0.06
GRC	0.28	0.20	0.04	0.05	0.17	0.14	0.20	0.07	0.21	0.14	0.13	0.22	0.20	-0.24
HRV	0.37	0.17	0.05	0.05	0.31	0.09	0.30	0.07	0.37	0.16	0.08	0.21	0.24	-0.10
HUN	0.35	0.20	0.09	0.10	0.34	0.10	0.27	0.09	0.39	0.16	0.14	0.29	0.30	0.05
ISR	0.30	0.13	0.04	0.09	0.32	0.10	0.31	0.07	0.26	0.16	0.08	0.24	0.23	-0.14
ITA	0.33	0.13	0.04	0.08	0.26	0.11	0.43	0.08	0.29	0.18	0.17	0.21	0.25	-0.07
LTU	0.47	0.24	0.05	0.12	0.49	0.13	0.39	0.11	0.51	0.19	0.12	0.27	0.38	0.27
LUX	0.45	0.09	0.06	0.10	0.34	0.06	0.33	0.06	0.33	0.16	0.10	0.24	0.24	-0.06
LVA	0.34	0.13	0.02	0.03	0.38	0.09	0.26	0.06	0.42	0.10	0.05	0.23	0.24	-0.15
MLT	0.36	0.45	0.05	0.14	0.29	0.10	0.33	0.05	0.27	0.14	0.21	0.27	0.29	0.06
POL	0.46	0.27	0.05	0.09	0.39	0.08	0.34	0.06	0.34	0.14	0.21	0.19	0.31	0.05
PRT	0.52	0.39	0.09	0.07	0.42	0.11	0.32	0.11	0.30	0.25	0.18	0.36	0.37	0.27
ROU	0.42	0.17	0.07	0.06	0.37	0.22	0.30	0.12	0.29	0.18	0.16	0.30	0.32	0.11
SVK	0.22	0.30	0.02	0.02	0.22	0.12	0.28	0.08	0.24	0.08	0.25	0.15	0.19	-0.21
SVN	0.36	0.23	0.04	0.08	0.34	0.06	0.27	0.05	0.26	0.09	0.07	0.17	0.20	-0.20
SWE	0.34	0.05	0.03	0.08	0.31	0.06	0.20	0.06	0.34	0.11	0.11	0.23	0.18	-0.22

Source: SHARE. $:The EURO-D items are part of the SHARE survey's validated scale for assessing mental health and depressive symptoms among older adults. All EURO-D indicators are binary variables, where 1 indicates the presence of a specific symptom, and 0 indicates its absence. Since SHARE Wave 7 does not include the EURO-D items, we captured these measures for all individuals who answered the job history module in Wave 7 by using data from the closest available wave.
a: proportion of individuals with a EURO-D score greater than 3.
b: average respondents' score on the 1st principal component summarising the 12 EURO-D dimensions.

Table A.2: O*NET: Managerial/cognitive content (Rotated component 1 loadings)

3LVAnalyzing_Data_or_Information	0.176
3LVCoaching_and_Developing_Others	0.161
3LVCommunicating_with_Persons_Outside_Organization	0.141
3LVCommunicating_with_Supervisors_Peers_or_Subordinates	0.171
3LVCoordinating_the_Work_and_Activities_of_Others	0.171
3LVDeveloping_Objectives_and_Strategies	0.180
3LVDeveloping_and_Building_Teams	0.166
3LVDocumentingRecording_Information	0.151
3LVDrafting_Laying_Out_and_Specifying_Technical_Devices_Parts_and_Equipment	0.101
3LVEstablishing_and_Maintaining_Interpersonal_Relationships	0.119
3LVEstimating_the_Quantifiable_Characteristics_of_Products_Events_or_Information	0.170
3LVEvaluating_Information_to_Determine_Compliance_with_Standards	0.147
3LVGetting_Information	0.158
3LVGuiding_Directing_and_Motivating_Subordinates	0.167
3LVIdentifying_Objects_Actions_and_Events	0.150
3LVInteracting_With_Computers	0.135
3LVInterpreting_the_Meaning_of_Information_for_Others	0.168
3LVJudging_the_Qualities_of_Things_Services_or_People	0.166
3LVMaking_Decisions_and_Solving_Problems	0.184
3LVMonitor_Processes_Materials_or_Surroundings	0.134
3LVMonitoring_and_Controlling_Resources	0.152
3LVOrganizing_Planning_and_Prioritizing_Work	0.168
3LVPerforming_Administrative_Activities	0.135
3LVProcessing_Information	0.168
3LVProvide_Consultation_and_Advice_to_Others	0.181
3LVResolving_Conflicts_and_Negotiating_with_Others	0.123
3LVScheduling_Work_and_Activities	0.178
3LVSelling_or_Influencing_Others	0.103
3LVStaffing_Organizational_Units	0.151
3LVThinking_Creatively	0.164
3LVTraining_and_Teaching_Others	0.156
3LVUpdating_and_Using_Relevant_Knowledge	0.169
4Duration_of_Typical_Work_Week	0.140
4Electronic_Mail	0.125
4Letters_and_Memos	0.100
4Spend_Time_Making_Repetitive_Motions	-0.118
4Structured_versus_Unstructured_Work	0.102

Source: O*NET work activities-level [3LV] & context [4] items, our calculations.
a: displayed loadings are those $> .1$ in abs. value; highlighted ones are those $> .17$.

Table A.3: O*NET: Physical arduousness (Rotated component 2 loadings) [> .1 in abs. value]

3LVControlling_Machines_and_Processes	0.173
3LVDrafting_Laying_Out_and_Specifying_Technical_Devices_Parts_and_Equipment	0.123
3LVHandling_and_Moving_Objects	0.163
3LVInspecting_Equipment_Structures_or_Material	0.177
3LVMonitor_Processes_Materials_or_Surroundings	0.107
3LVOperating_Vehicles_Mechanized_Devices_or_Equipment	0.186
3LVPerforming_General_Physical_Activities	0.178
3LVRepairing_and_Maintaining_Electronic_Equipment	0.134
3LVRepairing_and_Maintaining_Mechanical_Equipment	0.182
4Consequence_of_Error	0.120
4Cramped_Work_Space_Awkward_Positions	0.175
4Exposed_to_Contaminants	0.172
4Exposed_to_Hazardous_Conditions	0.175
4Exposed_to_Hazardous_Equipment	0.188
4Exposed_to_High_Places	0.167
4Exposed_to_Minor_Burns_Cuts_Bites_or_Stings	0.169
4Exposed_to_Whole_Body_Vibration	0.154
4Extremely_Bright_or_Inadequate_Lighting	0.174
4In_an_Enclosed_Vehicle_or_Equipment	0.117
4In_an_Open_Vehicle_or_Equipment	0.163
4Indoors_Environmentally_Controlled	-0.125
4Indoors_Not_Environmentally_Controlled	0.169
4Outdoors_Exposed_to_Weather	0.151
4Outdoors_Under_Cover	0.143
4Pace_Determined_by_Speed_of_Equipment	0.124
4Responsibility_for_Outcomes_and_Results	0.101
4Responsible_for_Others_Health_and_Safety	0.162
4Sounds_Noise_Levels_Are_Distracting_or_Uncomfortable	0.156
4Spend_Time_Bending_or_Twisting_the_Body	0.139
4Spend_Time_Climbing_Ladders_Scaffolds_or_Poles	0.158
4Spend_Time_Keeping_or_Regaining_Balance	0.147
4Spend_Time_Kneeling_Crouching_Stooping_or_Crawling	0.142
4Spend_Time_Sitting	-0.121
4Spend_Time_Standing	0.111
4Spend_Time_Using_Your_Hands_to_Handle_Control_or_Feel_Objects_Tools_or_Controls	0.109
4Spend_Time_Walking_and_Running	0.118
4Very_Hot_or_Cold_Temperatures	0.175
4Wear_Common_Protective_or_Safety_Equipments	0.181
4Wear_Specialized_Protective_or_Safety_Equipment	0.165

Source: O*NET work activities-level [3LV] & context [4] items, our calculations.
a: displayed loadings are those > .1 in abs. value; highlighted ones are those > .17.

Table A.4: O*NET: Emotional/interpersonal demands (Rotated component 3 loadings)

3LVAssisting_and_Caring_for_Others	0.251
3LVDrafting_Laying_Out_and_Specifying_Technical_Devices_Parts_and_Equipment	-0.127
3LVEstablishing_and_Maintaining_Interpersonal_Relationships	0.100
3LVEstimating_the_Quantifiable_Characteristics_of_Products_Events_or_Information	-0.106
3LVPerforming_for_or_Working_Directly_with_the_Public	0.215
3LVResolving_Conflicts_and_Negotiating_with_Others	0.134
3LVThinking_Creatively	-0.106
4Consequence_of_Error	0.115
4Contact_With_Others	0.264
4Coordinate_or_Lead_Others	0.158
4Deal_With_External_Customers	0.245
4Deal_With_Physically_Aggressive_People	0.246
4Deal_With_Unpleasant_or_Angry_People	0.292
4Exposed_to_Disease_or_Infections	0.244
4Exposed_to_Radiation	0.108
4FacetoFace_Discussions	0.122
4Frequency_of_Conflict_Situations	0.253
4Frequency_of_Decision_Making	0.227
4Impact_of_Decisions_on_Coworkers_or_Company_Results	0.187
4Importance_of_Repeating_Same_Tasks	0.109
4Letters_and_Memos	0.106
4Physical_Proximity	0.245
4Responsible_for_Others_Health_and_Safety	0.132
4Telephone	0.122
4Work_With_Work_Group_or_Team	0.161

Source: O*NET work activities-level [3LV] & context [4] items, our calculations.
a: displayed loadings are those $> .1$ in abs. value ; highlighted ones are those $> .2$.

A.3 Descriptive statistics - regression analyisis variables

Table A.5: Descriptive statistics - regression analyisis variables

	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Mental ill health				
Ment. ill h. (cont.)[a]	-0.261	0.820	0.050	0.960
Ment. ill h. (binary)[b]	0.171	0.377	0.296	0.456
Career arduousness				
CAR^{emo}	-0.080	0.702	0.191	0.829
CAR^{phys}	0.364	0.888	-0.331	0.671
CAR^{manag}	-0.181	0.785	-0.426	0.842
CAR^{emo} 1st job	-0.199	0.756	0.132	0.933
CAR^{phys} 1st job	0.492	0.966	-0.308	0.731
CAR^{manag} 1st job	-0.322	0.835	-0.517	0.913
Career instability				
Number of Jobs[c]	2.852	1.906	2.711	1.823
Gaps[d]	0.351	0.684	0.561	0.868
Redun.[e]	0.312	0.657	0.306	0.633
Prop. ft[f]	0.987	0.052	0.942	0.113
Career length[g]	38.325	8.424	32.239	11.655
Other controls				
Educ attain.[h]	1.991	0.734	1.973	0.735
Childh. ment. health[i]	-0.039	0.931	0.055	1.105
Childh. phys. health[j]	0.011	1.006	0.097	1.077
Age	65.860	7.290	65.260	7.582

Source: SHARE, O*NET; our calculations.
(a) Mental Ill health a 1st PC summarising the EURO-D items (models M3-M6) (b) Mental ill health as 4+ depression symptoms (EURO-D) (models M1-M2) (c) number of jobs held over the respondent's career, (d) the number of 6-month-plus employment gaps throughout their working life, (e) the number of job terminations not initiated by the respondent, (f) the average propensity to work full-time (max=1), (g) the (unweighted) number of years worked during the career, (h) simplified ISCED (1 less then upper secondary, 2 upper secondary, 3 tertiary), (i) 1st principal component of childhood mental health indicators (j) 1st principal component of childhood physical health indicators.

A.4 Regression tables - robustness

Table A.6: Determinants of (Poor) Mental Health Beyond 50. Regression results: Female - **Rich European countries only**

	Logit		OLS			
	M1	M2	M3	M4 (1st job)	M5 (50–69)	M6 (1st job) (50–69)
CAR^{emo}	1.080***	1.094***	0.028***	0.020**	0.031***	0.028***
	(0.0196)	(0.0204)	(0.0071)	(0.0066)	(0.0084)	(0.0077)
CAR^{phys}	1.192***	1.125***	0.057***	0.043***	0.042***	0.028**
	(0.0237)	(0.0237)	(0.0082)	(0.0078)	(0.0098)	(0.0092)
CAR^{manag}	0.853***	0.924***	-0.029***	-0.027***	-0.034***	-0.033***
	(0.0152)	(0.0180)	(0.0075)	(0.0070)	(0.0089)	(0.0083)
Number of Jobs[a]		1.011	0.008*	0.008*	0.004	0.004
		(0.0093)	(0.0035)	(0.0038)	(0.0041)	(0.0044)
Gaps[b]		1.100***	0.038***	0.040***	0.037***	0.040***
		(0.0194)	(0.0070)	(0.0074)	(0.0079)	(0.0084)
Redun.[c]		1.095***	0.044***	0.040***	0.051***	0.049***
		(0.0232)	(0.0086)	(0.0092)	(0.0095)	(0.0101)
Prop. ft[d]		1.261	0.080	0.091	0.054	0.055
		(0.1506)	(0.0455)	(0.0468)	(0.0524)	(0.0540)
Career length[e]		0.990***	-0.006***	-0.006***	-0.006***	-0.007***
		(0.0012)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Sec. educ.		0.844***	-0.092***	-0.092***	-0.107***	-0.102***
		(0.0293)	(0.0139)	(0.0142)	(0.0170)	(0.0176)
Ter. educ.		0.734***	-0.151***	-0.157***	-0.180***	-0.181***
		(0.0320)	(0.0170)	(0.0170)	(0.0206)	(0.0208)
Childh. ment. health		1.145***	0.075***	0.079***	0.073***	0.077***
		(0.0120)	(0.0044)	(0.0046)	(0.0050)	(0.0053)
Childh. phys. health		1.161***	0.081***	0.081***	0.089***	0.089***
		(0.0139)	(0.0049)	(0.0051)	(0.0058)	(0.0060)
Constant	0.084***	0.089***	-0.610*	-0.633*	-0.425	-0.417
	(0.0583)	(0.0634)	(0.2552)	(0.2851)	(0.2702)	(0.2995)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
N	33,479	33,479	33,479	31,027	23,978	22,084
R^2			0.078	0.078	0.077	0.077

Source: SHARE, O*NET; our calculations.
Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.
M1: Logit baseline (odds ratio); M2: Logit with full list of controls (odds ratio); M3: OLS cont. outcome; M4: OLS cont. outcome and only first job; M5 OLS. cont. outcome and restriction to respondents aged <70; M6 OLS cont. outcome, only first job & restriction to respondents aged less than 70.
(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

Table A.7: Determinants of (Poor) Mental Health Beyond 50. Regression results: Male - **Rich European Countries only**

	Logit		OLS			
	M1	M2	M3	M4 (1st job)	M5 (50–69)	M6 (1st job) (50–69)
CAR^{emo}	1.043	1.036	0.017*	0.024***	0.023**	0.023**
	(0.0275)	(0.0280)	(0.0073)	(0.0070)	(0.0086)	(0.0084)
CAR^{phys}	1.067**	1.043	0.021***	0.008	0.023**	0.011
	(0.0220)	(0.0231)	(0.0061)	(0.0056)	(0.0073)	(0.0067)
CAR^{manag}	0.831***	0.876***	-0.042***	-0.027***	-0.052***	-0.033***
	(0.0206)	(0.0234)	(0.0073)	(0.0068)	(0.0087)	(0.0082)
Number of Jobs[a]		1.041***	0.013***	0.010**	0.012***	0.011**
		(0.0108)	(0.0030)	(0.0031)	(0.0035)	(0.0037)
Gaps[b]		1.057*	0.036***	0.037***	0.041***	0.047***
		(0.0278)	(0.0079)	(0.0084)	(0.0090)	(0.0096)
Redun.[c]		1.089**	0.025**	0.030***	0.021*	0.024*
		(0.0287)	(0.0079)	(0.0085)	(0.0089)	(0.0096)
Prop. ft[d]		0.490*	-0.352***	-0.260**	-0.401***	-0.305**
		(0.1530)	(0.0920)	(0.0949)	(0.1048)	(0.1088)
Career length[e]		0.978***	-0.009***	-0.009***	-0.011***	-0.012***
		(0.0021)	(0.0006)	(0.0007)	(0.0008)	(0.0008)
Sec. educ.		0.813***	-0.088***	-0.093***	-0.081***	-0.077***
		(0.0372)	(0.0137)	(0.0141)	(0.0168)	(0.0174)
Ter. educ.		0.642***	-0.158***	-0.186***	-0.177***	-0.200***
		(0.0373)	(0.0164)	(0.0165)	(0.0200)	(0.0203)
Childh. ment. health		1.164***	0.074***	0.063***	0.060***	0.056***
		(0.0178)	(0.0051)	(0.0053)	(0.0059)	(0.0061)
Childh. phys. health		1.182***	0.072***	0.072***	0.081***	0.082***
		(0.0192)	(0.0050)	(0.0051)	(0.0060)	(0.0062)
Constant	0.238***	1.439	-0.873	-0.899	-0.229	-0.300
	(0.0318)	(0.5032)	(0.9063)	(0.9015)	(0.4671)	(0.4666)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
N	27,591	27,591	27,598	25,407	18,883	17,324
R^2			0.071	0.067	0.075	0.074

Source: SHARE, O*NET; our calculations.
Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.
M1: Logit baseline (odds ratio); M2: Logit with full list of controls (odds ratio); M3: OLS cont. outcome; M4: OLS cont. outcome and only first job; M5 OLS. cont. outcome and restriction to respondents aged <70; M6 OLS cont. outcome, only first job & restriction to respondents aged less than 70.
(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

A.5 Contribution to model-explained variance: Shapley Value Regression - robustness

Table A.8: Decomposition of (Poor) Mental Health. M6-explained variance. Respondents aged 50–69 – **Rich European countries only**

	M	F
Total	1.000	1.000
1 Career indices (1st job)	0.0422	0.0510
Emot./interp.	0.0042	0.0049
Phys ardu	0.0128	0.0198
Manag./cog.	0.0253	0.0263
2 Career instab	0.2669	0.1678
Number of Jobs[a]	0.0170	0.0090
Gaps[b]	0.0607	0.0328
Redun.[c]	0.0271	0.0381
Prop. ft[d]	0.0124	0.0011
Career length[e]	0.1496	0.0867
3 Educ	0.0954	0.0791
4 Child health	0.2862	0.3409
Child h phys	0.1055	0.1585
Child h psy	0.1807	0.1824
5 Other	0.3093	0.3612
Country	0.2589	0.3173
Wave	0.0164	0.0225
Age	0.0340	0.0213

(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

Table A.9: Decomposition of (Poor) Mental Health. M5-explained variance. Respondents aged 50–69 – **Using entire career arduousness averages**

	M	F
Total	1.000	1.000
1 Career indices (whole career)	0.0696	0.0883
Emot./interp.	0.0024	0.0047
Phys ardu	0.0316	0.0447
Manag./cog.	0.0356	0.0390
2 Career instab	0.2858	0.1714
Number of Jobs[a]	0.0281	0.0156
Gaps[b]	0.0512	0.0292
Redun.[c]	0.0269	0.0377
Prop. ft[d]	0.0059	0.0007
Career length[e]	00.1737	0.0881
3 Educ	0.0919	0.0869
4 Child health	0.2675	0.3170
Child h phys	0.0988	0.1533
Child h psy	0.1687	0.1637
5 Other	0.2853	0.3363
Country	0.2458	0.3032
Wave	0.0117	0.0176
Age	0.0278	0.0155

(a) number of jobs held over the respondent's career, (b) the number of 6-month-plus employment gaps throughout their working life, (c) the number of job terminations not initiated by the respondent, (d) the average propensity to work full-time (max=1), (e) the (unweighted) number of years worked during the career.

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ISSN 1379-244X D/2026/3082/21

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