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The Long-Term Mental Health Consequences of Psychological Career Arduousness

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Abstract

Poor working conditions can adversely affect health and impose substantial costs on individuals and society. While many studies have documented the negative effects of physical job demands on health, fewer have explored the role of psychological work-related stressors. This study investigates the relationship between psychological risks accumulated over the course of a person's career and mental health outcomes after age 50. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE) and detailed occupational information from O*NET, we link individual job histories to multidimensional measures of occupational arduousness and assess their association with late-life depressive symptoms.

Our regression results show that long-term exposure to psychologically demanding work is significantly associated with a higher likelihood of depressive symptoms after age 50, while physical arduousness also raises risk, and cognitively engaging (information-management intense) careers show a protective effect. Variance decomposition analyses reveal that, although occupational characteristics are statistically significant, their relative explanatory power is modest compared to current physical health.

Keywords: mental health, psychological arduousness, depressive symptoms, arduous job, work environment, job characteristics, career arduousness

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Contents

1 Introduction

The relationship between working conditions and health has been a longstanding area of interest in the social sciences, particularly in economics, sociology, and psychology. Numerous studies have examined how the nature of one's occupation correlates with various health outcomes, though much of this literature has centered on physical health and physical demands (see French et al. (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 et al. 2013), Less attention has been given to how psychological aspects of work relate to mental health, especially over the long run and across the full span of working life.

In a broad review of the European economic literature, Barnay (2015) document the growing interest in work-related health inequalities but highlight the limitations of existing data and the reliance on cross-sectional analyses. They also note that mental health outcomes remain under-explored in many labor-oriented health studies. This is particularly important given that mental health disorders affect a significant share of the working-age population. According to *High-Level Conference on Mental Health and Work* (2024), mental health issues now affect nearly one in six Europeans, generating substantial social and economic costs.

Several recent studies have begun to incorporate indicators of working conditions and job strain into their analyses of mental well-being. For instance, Maclean et al. (2015) explore the association between adverse labor events, such as conflicts with coworkers or job insecurity, and self-reported mental health, finding modest but consistent patterns. However, the study lacks detailed career-level data. Llena-Nozal (2009) similarly investigate the link between working conditions and mental health across four countries, using measures of job strain and psychological demands. Although their findings point to significant associations, their operationalization of occupational exposures is typically coarse, often relying on binary indicators (e.g., insecure vs. secure contracts) or single-point satisfaction measures. These simplified indicators provide a broad view of job quality but may overlook important nuances in occupational experiences, such as the distinction between emotional demands versus managerial pressure. In contrast, more granular approaches, such as those based on higher dimensional survey instruments, enable a richer characterization of occupational exposures. This strategy is exemplified in Vandenberghe (2022), which uses several relatively large datasets to assess how cumulative physical job demands over a career relate to mental health later in life. Their study leverages retrospective job histories, allowing for a career-wide view of occupational exposure. However, their analysis focuses primarily on physical arduousness, leaving psychological and cognitive job features largely unaddressed.

In parallel, efforts have emerged to classify the psychological and emotional demands of occupations using occupational classification systems such as O*NET. For example, Glomb et al. (2004) use O*NET data to quantify emotional labor demands across occupations, proposing factor-analytic methods to distill complex job characteristics into interpretable dimensions. Yet these typologies are rarely linked to individual-level health data, limiting their application to population-based studies of well-being.

Taken together, the literature provides partial and often fragmented insights into how different aspects of work are related to mental health. Few studies integrate comprehensive occupational taxonomies like O*NET with population-based data such as SHARE. Fewer still examine the psychological dimension of occupational demands over the entire career trajectory and its correlation with later-life mental health.

This study addresses these gaps by merging occupational exposure measures from O*NET with detailed job history and mental health data from SHARE. By extracting latent factors from O*NET's Work Context and Work Activities modules and linking them to individual-level SHARE records, we are able to investigate how physical, psychological, and informational job demands relate to depressive symptomatology beyond age 50. Both our dependent variable (EURO-D) and our key predictors (occupational characteristics) are self-reported, capturing perceived rather than purely objective dimensions of job content and mental well-being. The analysis is therefore positioned within the broader tradition of subjective health and work evaluation, with an emphasis on documenting correlational patterns rather than causal mechanisms. Our contribution to the work arduousness/health literature will essentially be fourfold: i) provide a quantification of arduousness based on a detailed description of the content of occupations ii) a focus on the long-term (i.e. beyond 50) health consequences of arduousness, iii) a focus on career arduousness (i.e. we consider the workers' entire job history), and iv) a focus on psychological career arduousness and its impact on mental health.

Our key findings show that long-term exposure to psychological and physical job demands is significantly linked to poorer mental health outcomes, after age 50, while careers with high information-management intensity appear to have a protective effect on mental health. Additionally, indicators of career instability, such as job losses and employment gaps, emerge as strong predictors of later-life mental health outcomes. These results highlight the enduring impact of career-long occupational characteristics on well-being in older age.

The remainder of this text is organized as follows. Section 2 presents the empirical analysis, detailing the methods, regression models, dimensional reduction, variance decomposition, and data sources. Section 3 reports and discusses the main empirical results, robustness checks and limitations. Finally, Section 4 concludes by summarizing the key findings and outlining their implications.

2 Empirical Analysis

2.1 Method

2.1.1 Regression Specification

Let us define $Mhealth_{i,j}$ as a measure of poor mental health among older individuals, where i indexes the individual and j denotes the country of residence; more details on poor mental health precise definition will be provided below. We estimate the following linear specification for our primary outcome:

$$Mhealth_{i,j} = \alpha + \beta^\top CAR_{i,j} + \theta^\top Instab_{i,j} + \gamma^\top Hendow_{i,j} + \eta^\top X_{i,j} + \delta_j + \lambda_t + \varepsilon_{i,j}$$

Here, $CAR_{i,j}$ is the vector of career arduousness measures, including physical arduousness (CAR^{phys}), information-management intensity (CAR^{info}), and psychological arduousness (CAR^{psych}). The construction of these measures, including how they were derived from factor scores obtained via a factor analysis of O*NET's *Work Context* and *Work Activities* modules, is detailed in Section 2.1.3.

$Instab_{i,j}$ captures dimensions of career instability and includes two indicators: the number of times the respondent experienced a job termination not initiated by themselves, and the number of significant employment gaps throughout their working life. These variables serve to quantify the irregularity and potential precarity 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 poorer mental health outcome (e.g., Adam et al. 2006).

$Hendow_{i,j}$ represents the vector of childhood health endowment measures, proxied by the first two principal components derived separately from PCA analyses of childhood physical health indicators and childhood mental health indicators, resulting in four components in total.

The control vector $X_{i,j}$ includes poor physical health, captured via principal component analysis of 17 physical functioning indicators. Prior economic research has shown that physical health is strongly associated with mental health outcomes in older populations (e.g., Doan et al. 2022). The vector also includes gender, years in the workforce, and categorical variables for education and age.

We begin by using a binary indicator of poor mental health, defined as having a EURO-D score (depressive symptoms in the SHARE dataset; range 0–12) above a threshold of 3, and estimate a corresponding logistic regression model. This specification is estimated on the full analytic sample of respondents with complete data on all model variables (Model 1), as well as on a restricted subsample of individuals who report only one job over their life course (Model 2); this restriction addresses the possibility of reverse causality — that is, individuals changing occupations in response to poor mental health. Finally, we estimate a linear model with a continuous mental health measure — the first principal component of the twelve EURO-D items (Model 3) — which enables variance decomposition across explanatory variables.

2.1.2 Variance Decomposition

To assess the relative importance of different explanatory (blocks) in the model, we use variance decomposition. While standardized coefficients allow continuous predictors to be compared on a common scale (interpreting effects in terms of standard deviation units), they have clear limitations when comparing the importance of groups of variables, particularly when these groups combine continuous and categorical predictors. To address this, we apply a decomposition of the model-explained variance, following the approach pioneered by Shorrocks (1982) and widely used in labor and health economics (e.g., Fields 2003; Jusot et al. 2013). This method allows us to partition the total variance explained by the model across (blocks of) predictors, offering a clearer and more comprehensive assessment of how much each explanatory domain contributes to observed differences in late-life mental health.

Specifically, using the linear specification where the dependent variable is a continuous poor mental health measure, we decompose the model-predicted variance into components attributable to distinct (blocks of) variables: career arduousness, career instability, childhood health endowments, current physical health, controls (including gender, education, and age), country fixed effects, and wave fixed effects.

At stage 1, we compute the predicted outcome based on each block:

$$\widehat{Mhealth}_{i,j}^{CAR} \equiv \beta^\top CAR_{i,j}$$
$$\widehat{Mhealth}_{i,j}^{Instab} \equiv \theta^\top Instab_{i,j}$$
$$\widehat{Mhealth}_{i,j}^{Hendow} \equiv \gamma^\top Hendow_{i,j}$$

$\widehat{Mhealth}^{X}_{i,j} \equiv \eta^{\top} X_{i,j}$
$\widehat{Mhealth}^{\delta}_{i,j} \equiv \delta_j$
$\widehat{Mhealth}^{\lambda}_{i,j} \equiv \lambda_t$

At stage 2, we decompose the explained variance of the predicted outcome $\widehat{Mhealth}_{i,j}$ as:

$\mathrm{Var}(\widehat{Mhealth}_{i,j}) = \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{CAR}_{i,j})$
$+ \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{Instab}_{i,j})$
$+ \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{Hendow}_{i,j})$
$+ \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{X}_{i,j})$
$+ \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{\delta}_{i,j})$
$+ \mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{\lambda}_{i,j})$

The relative importance (or covariance share) of each variable (or group of variables) is then computed as:

$$s_v = \frac{\mathrm{Cov}(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}^{v}_{i,j})}{\mathrm{Var}(\widehat{Mhealth}_{i,j})} \times 100$$

where v refers to a specific variable or set of variables (e.g., career arduousness, instability, health endowment, controls, country fixed effects, or wave fixed effects).

This decomposition provides a clear breakdown of how much each variable (or group of variables) contributes to explaining differences in late-life mental health.

2.1.3 Dimensional Reduction of Occupational Measures

To construct summary measures of physical arduousness, psychological arduousness, and information-management intensity in respondents' careers, we apply factor analysis to occupational data from O*NET's *Work Context* and *Work Activities* modules. Specifically, we use maximum likelihood factor analysis to extract latent factors that capture shared variance across multiple occupational characteristics.

Formally, let Σ (a $J \times J$ matrix) be the observed covariance matrix of the J occupational indicators measured across I occupations. Factor analysis models this covariance as:

$$\Sigma = \Lambda\Lambda^T + \Psi$$

where:

- Λ is the $J \times L$ matrix of factor loadings, describing how each observed occupational variable relates to the L latent factors.
- Ψ is the $J \times J$ diagonal matrix of specific (unique) variances, representing the variance in each observed variable that is unexplained by the common factors.

To enhance interpretability, we apply an oblique rotation, specifically the oblimin rotation, which allows the extracted factors to correlate and better capture distinct conceptual domains. Let R denote the oblimin rotation matrix; the rotated loadings matrix Λ^* is computed as:

$$\Lambda^* = \Lambda R$$

where Λ^* provides rotated factor loadings that simplify interpretation by concentrating high loadings on a smaller subset of variables per factor, even if this permits some correlation between factors.

The resulting factors are interpreted as capturing the key latent dimensions underlying occupational characteristics, which we use to derive summary measures for each respondent's career.

From the rotated solution, we identify three key factors: (1) physical arduousness, capturing the physical demands of work; (2) psychological arduousness, reflecting the psychological and emotional demands; and (3) information-management intensity, reflecting management, cognitive and information-processing demands. For each occupation, we compute factor scores based on the rotated loadings. We then use these scores to construct individual-level career measures by aggregating the occupational characteristics across each respondent's reported job history. This process yields summary indices of career-long physical arduousness, psychological arduousness, and information-management intensity, reflecting the cumulative exposure an individual has experienced throughout their working life. These constructed indices serve as core explanatory variables in our regression models linking career characteristics to later-life mental health outcomes.

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 allows us to relate respondents' mental health outcomes in later life to the characteristics of their past careers.

2.2.1 Mental Health and Career Histories from SHARE

The individual-level data source is SHARE, a cross-national longitudinal survey covering individuals aged 50 and over across 28 European countries and Israel. We use data from Wave 7 (SHARELIFE, 2017) for detailed retrospective information on employment histories and childhood conditions, and data from other waves for contemporaneous measures of physical and mental health.

SHARE provides a measure of mental health through the EURO-D scale, based on 12 items capturing various depressive symptoms: depression, pessimism, suicidality, guilt, sleep disturbances, loss of interest, irritability, appetite problems, fatigue, poor concentration, lack of enjoyment, and tearfulness. These binary items are summed to create a continuous scale ranging from 0 to 12. Table 1 displays the item-level averages by country. Figures 1, 2, and 3 illustrate the mean EURO-D scores and the proportion of individuals with scores above a threshold of 3, overall and by gender (some studies (e.g. Brunello et al. 2016) have used this threshold). These figures reveal clear patterns across countries and between genders. Figure 1 shows notable cross-country variation in average EURO-D scores, with higher averages in Southern and Eastern European countries compared to Northern Europe, although some exceptions are present. Figure 2 highlights that a considerable share of older adults score above the threshold of 3, indicating elevated depressive symptoms. Figure 3 further breaks down these proportions by gender, showing that women consistently report higher depressive symptom scores than men across all countries.

Table 1: Averages of EURO-D Items by Country

	Country	Depression	Pessimism	Suicidality	Guilt	Sleep (lack of)	Interest (lack of)	Irritability	Appetite (lack of)	Fatigue	Concentration (lack of)	Enjoyment (lack of)	Tearfulness
1	Austria	0.38	0.06	0.03	0.05	0.34	0.05	0.2	0.09	0.3	0.12	0.13	0.22
2	Belgium	0.43	0.12	0.1	0.1	0.36	0.08	0.28	0.1	0.37	0.21	0.07	0.31
3	Bulgaria	0.33	0.32	0.06	0.05	0.33	0.16	0.15	0.11	0.34	0.21	0.21	0.27
4	Croatia	0.39	0.18	0.06	0.06	0.32	0.1	0.32	0.08	0.39	0.16	0.08	0.22
5	Cyprus	0.32	0.18	0.05	0.01	0.25	0.11	0.18	0.06	0.24	0.17	0.08	0.26
6	Denmark	0.32	0.04	0.03	0.1	0.33	0.05	0.24	0.06	0.33	0.12	0.05	0.17
7	Estonia	0.47	0.23	0.06	0.14	0.51	0.11	0.33	0.09	0.51	0.13	0.12	0.2
8	Finland	0.4	0.11	0.03	0.07	0.39	0.11	0.32	0.07	0.44	0.15	0.1	0.26
9	France	0.45	0.21	0.12	0.1	0.4	0.08	0.32	0.09	0.38	0.18	0.11	0.26
10	Germany	0.48	0.06	0.05	0.07	0.38	0.05	0.3	0.06	0.32	0.13	0.1	0.23
11	Greece	0.34	0.27	0.05	0.07	0.22	0.18	0.22	0.09	0.28	0.19	0.17	0.25
12	Hungary	0.37	0.25	0.11	0.1	0.38	0.13	0.29	0.11	0.44	0.19	0.2	0.3
13	Israel	0.34	0.18	0.06	0.08	0.35	0.12	0.36	0.1	0.31	0.19	0.1	0.22
14	Italy	0.34	0.16	0.04	0.08	0.29	0.12	0.43	0.09	0.33	0.21	0.18	0.21
15	Latvia	0.41	0.17	0.02	0.04	0.43	0.14	0.27	0.06	0.43	0.15	0.08	0.28
16	Lithuania	0.47	0.28	0.06	0.11	0.5	0.15	0.39	0.11	0.49	0.19	0.13	0.27
17	Luxembourg	0.45	0.09	0.06	0.1	0.35	0.06	0.34	0.07	0.34	0.17	0.1	0.24
18	Malta	0.3	0.54	0.04	0.11	0.29	0.09	0.29	0.07	0.26	0.16	0.23	0.28
19	Poland	0.51	0.29	0.05	0.1	0.43	0.08	0.35	0.08	0.4	0.16	0.22	0.2
20	Portugal	0.52	0.41	0.1	0.06	0.42	0.11	0.33	0.11	0.32	0.26	0.19	0.37
21	Republic	0.41	0.16	0.07	0.08	0.39	0.05	0.22	0.08	0.34	0.12	0.04	0.21
22	Romania	0.44	0.18	0.09	0.08	0.4	0.23	0.3	0.14	0.29	0.22	0.16	0.31
23	Slovakia	0.24	0.33	0.02	0.03	0.26	0.13	0.31	0.11	0.26	0.12	0.29	0.19
24	Slovenia	0.36	0.21	0.05	0.07	0.36	0.07	0.27	0.06	0.28	0.11	0.08	0.17
25	Spain	0.32	0.23	0.06	0.05	0.27	0.13	0.21	0.09	0.35	0.18	0.12	0.23
26	Sweden	0.33	0.06	0.03	0.08	0.32	0.07	0.2	0.07	0.36	0.11	0.12	0.22
27	Switzerland	0.37	0.07	0.04	0.04	0.3	0.04	0.24	0.06	0.29	0.1	0.06	0.2

Notes: The EURO-D items presented here 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.

In addition to health outcomes, SHARE collects full employment histories, including all job spells along with job duration, contract type (full-time or part-time), career interruptions, and redundancy episodes. Critically, each job is coded according to the ISCO 4-digit occupational classification, allowing us to map respondents' career trajectories in terms of occupational titles. We use this information to construct detailed indicators of total career duration and average career arduousness.

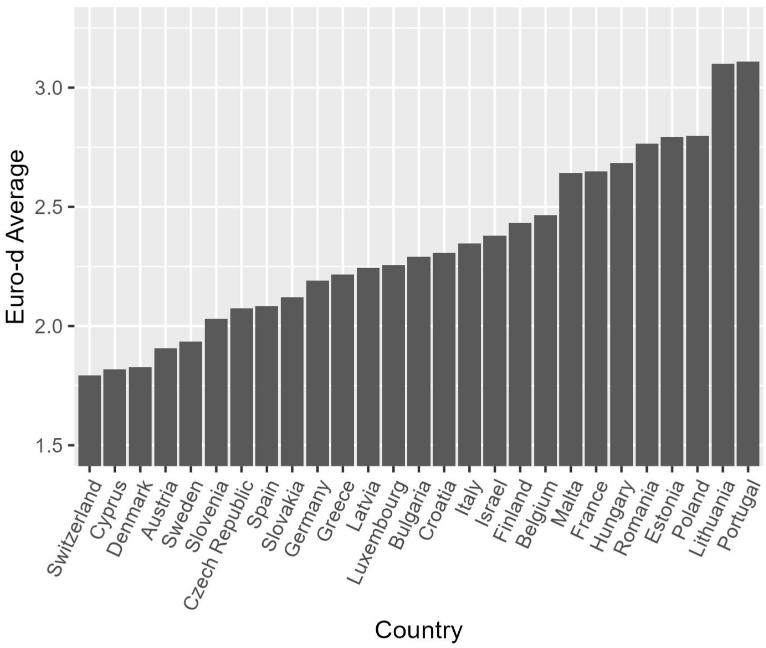

Figure 1: Average EURO-D score by country (The EURO-D is a 12-item scale measuring depressive symptoms, with each item coded 0 (symptom absent) or 1 (symptom present), yielding a total score ranging from 0 to 12).

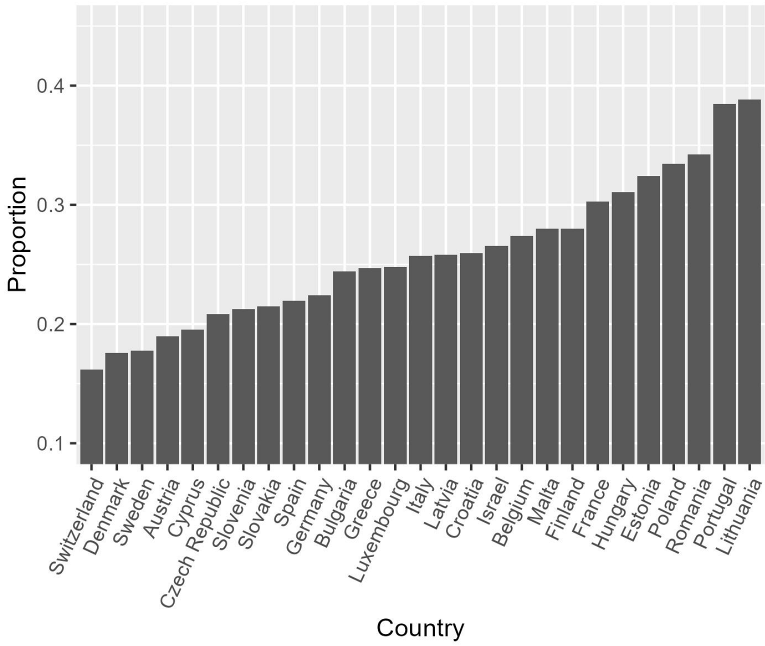

Figure 2: Proportion of individuals with a EURO-D score greater than 3 in different countries (The EURO-D is a 12-item scale measuring depressive symptoms, with each item coded 0 (symptom absent) or 1 (symptom present), yielding a total score ranging from 0 to 12).

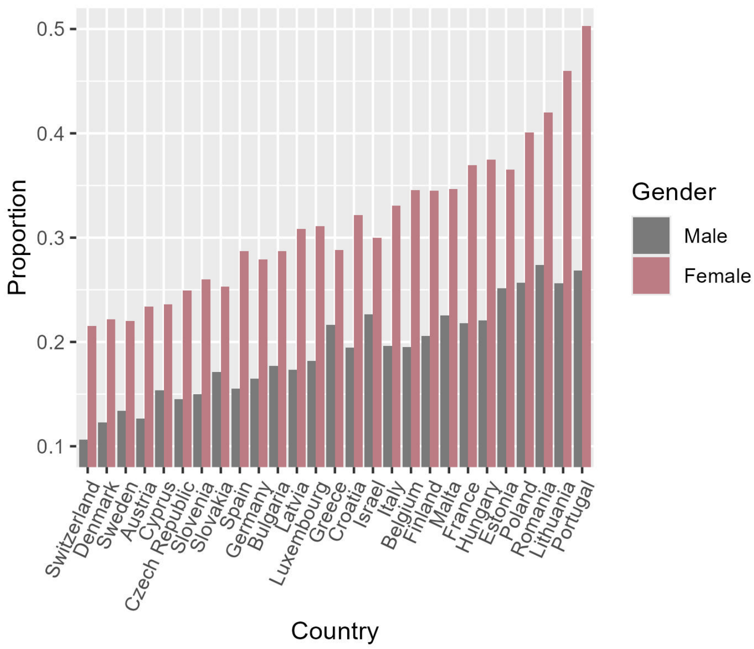

Figure 3: Proportion of individuals with a EURO-D score greater than 3, by country and gender (The EURO-D is a 12-item scale measuring depressive symptoms, with each item coded 0 (symptom absent) or 1 (symptom present), yielding a total score ranging from 0 to 12).

2.2.2 Occupational Characteristics from O*NET

To quantify occupational arduousness, we rely on O*NET — a comprehensive database maintained by the U.S. Department of Labor that provides standardized descriptors for over 800 occupations. We specifically extract data from the "Work Context" and "Work Activities" modules, which offer 98 indicators covering physical demands (e.g., exposure to contaminants, bending/twisting, extreme temperatures), psychological demands (e.g., responsibility for others' safety, emotional conflict, time pressure), and cognitive complexity (e.g., information processing, decision-making, teamwork).

We structure this rich occupational dataset into a wide-format matrix of 879 occupations by 98 variables, preparing it for dimensional reduction. To distill the key latent dimensions underlying these multidimensional features, we apply a factor analysis to the standardized variables. Using a three-factor maximum likelihood extraction with oblimin rotation, the resulting factors are interpreted as capturing (1) physical arduousness, (2) information-management intensity, and (3) psychological arduousness. This interpretation is based on dominant loadings above 0.4, as detailed in Table 2. This labeling of the three factors, draws directly on the framework established by Glomb et al. (2004) in their study on emotional labor demands and compensating wage differentials. Their factor analysis of occupational data, based on a smaller dataset, revealed similar underlying dimensions, and our results closely replicate their structure, reinforcing the robustness of these latent constructs across different datasets.

Table 2 shows that the psychological arduousness index mostly captures elements such as exposure to conflict situations, dealing with aggressive individuals, or working under high emotional strain. The physical arduousness index emphasizes physical demands, environmental exposures, and bodily effort, while the information-management intensity highlights cognitive and communicative aspects of work, such as decision-making, information processing, and frequent interpersonal interactions.

Together, the three factors explain approximately 50% of the variance in the original items (Factor 1 (physical arduousness): 23.5%, Factor 2 (information-management intensity): 19.2%, Factor 3 (psychological arduousness): 7.5%), providing a parsimonious yet meaningful summary of occupational characteristics. Importantly, the factors are not orthogonal. The estimated factor correlation matrix reveals moderate negative correlation between physical and information-management demands ($r = -0.223$), a mild positive correlation between physical and psychological demands ($r = 0.097$), and a weaker positive correlation between information-management and psychological demands ($r = 0.062$). These interrelations underscore the complex, intertwined nature of occupational environments.

Table 2: Rotated Factor Loadings (Oblimin) for Occupational Characteristics from O*NET; Facrors: Physical Arduousness, Information-Management Intensity, and Psychological Arduousness

	Phys. Ard.	Info-Manage. Int.	Psych. Ard.
Public_Speaking		0.407	
Telephone_Conversations		0.561	
EMail	-0.436	0.621	
Written_Letters_and_Memos		0.577	
FacetoFace_Discussions_with_Individuals_and_Within		0.443	
Contact_With_Others			0.626
Work_With_or_Contribute_to_a_Work_Group_or_Team		0.438	
Deal_With_External_Customers_or_the_Public_in_Gene			0.546
Coordinate_or_Lead_Others_in_Accomplishing_Work_Ac		0.553	

Continued on next page

Table 2 – continued from previous page

	Phys. Ard.	Info-Manage. Int.	Psych. Ard.
Health_and_Safety_of_Other_Workers	0.722		
Work_Outcomes_and_Results_of_Other_Workers	0.442	0.468	
Conflict_Situations			0.531
Dealing_With_Unpleasant_Angry_or_Discourteous_Peop			0.690
Dealing_with_Violent_or_Physically_Aggressive_Peop			0.615
Indoors_Environmentally_Controlled	-0.583		
Indoors_Not_Environmentally_Controlled	0.803		
Outdoors_Exposed_to_All_Weather_Conditions	0.685		
Outdoors_Under_Cover	0.645		
In_an_Open_Vehicle_or_Operating_Equipment	0.786		
In_an_Enclosed_Vehicle_or_Operate_Enclosed_Equipme	0.530		
Physical_Proximity			0.714
Exposed_to_Sounds_Noise_Levels_that_are_Distractin	0.771		
Exposed_to_Very_Hot_or_Cold_Temperatures	0.841		
Exposed_to_Extremely_Bright_or_Inadequate_Lighting	0.810		
Exposed_to_Contaminants	0.846		
Exposed_to_Cramped_Work_Space_Awkward_Positions	0.839		
Exposed_to_Whole_Body_Vibration	0.708		
Exposed_to_Radiation			
Exposed_to_Disease_or_Infections			0.635
Exposed_to_High_Places	0.785		
Exposed_to_Hazardous_Conditions	0.850		
Exposed_to_Hazardous_Equipment	0.921		
Exposed_to_Minor_Burns_Cuts_Bites_or_Stings	0.825		
Spend_Time_Sitting	-0.572		
Spend_Time_Standing	0.541		
Spend_Time_Climbing_Ladders_Scaffolds_or_Poles	0.733		
Spend_Time_Walking_or_Running	0.585		0.420
Spend_Time_Kneeling_Crouching_Stooping_or_Crawling	0.677		
Spend_Time_Keeping_or_Regaining_Balance	0.660		
Spend_Time_Using_Your_Hands_to_Handle_Control_or_F	0.576		
Spend_Time_Bending_or_Twisting_Your_Body	0.668		
Spend_Time_Making_Repetitive_Motions		-0.500	
Wear_Common_Protective_or_Safety_Equipment_such_as	0.868		
Wear_Specialized_Protective_or_Safety_Equipment_su	0.752		
Consequence_of_Error	0.595		
Impact_of_Decisions_on_Coworkers_or_Company_Result		0.447	
Frequency_of_Decision_Making			
Freedom_to_Make_Decisions		0.452	
Degree_of_Automation			
Importance_of_Being_Exact_or_Accurate			
Importance_of_Repeating_Same_Tasks			
Determine_Tasks_Priorities_and_Goals		0.489	
Level_of_Competition			
Time_Pressure			
Pace_Determined_by_Speed_of_Equipment	0.654		
Work_Schedules			
Duration_of_Typical_Work_Week		0.551	
Getting_Information		0.695	
Monitoring_Processes_Materials_or_Surroundings	0.607	0.496	
Identifying_Objects_Actions_and_Events		0.654	
Inspecting_Equipment_Structures_or_Materials	0.865		
Estimating_the_Quantifiable_Characteristics_of_Pro	0.472	0.562	
Judging_the_Qualities_of_Objects_Services_or_Peopl		0.591	
Processing_Information		0.726	
Evaluating_Information_to_Determine_Compliance_wit		0.659	
Analyzing_Data_or_Information		0.772	
Making_Decisions_and_Solving_Problems		0.864	
Thinking_Creatively		0.519	
Updating_and_Using_Relevant_Knowledge		0.772	
Developing_Objectives_and_Strategies		0.759	
Scheduling_Work_and_Activities		0.705	
Organizing_Planning_and_Prioritizing_Work		0.748	
Performing_General_Physical_Activities	0.716		
Handling_and_Moving_Objects	0.735		
Controlling_Machines_and_Processes	0.812		
Operating_Vehicles_Mechanized_Devices_or_Equipment	0.852		
Working_with_Computers	-0.412	0.616	

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Table 2 – continued from previous page

	Phys. Ard.	Info-Manage. Int.	Psych. Ard.
Drafting_Laying_Out_and_Specifying_Technical_Devic	0.603		
Repairing_and_Maintaining_Mechanical_Equipment	0.868		
Repairing_and_Maintaining_Electronic_Equipment	0.667		
DocumentingRecording_Information		0.693	
Interpreting_the_Meaning_of_Information_for_Others		0.745	
Communicating_with_Supervisors_Peers_or_Subordinat		0.714	
Communicating_with_People_Outside_the_Organization		0.618	
Establishing_and_Maintaining_Interpersonal_Relatio	-0.403	0.525	
Assisting_and_Caring_for_Others			0.755
Selling_or_Influencing_Others			
Resolving_Conflicts_and_Negotiating_with_Others		0.507	0.508
Performing_for_or_Working_Directly_with_the_Public			0.689
Coordinating_the_Work_and_Activities_of_Others		0.679	
Developing_and_Building_Teams		0.701	
Training_and_Teaching_Others		0.577	
Guiding_Directing_and_Motivating_Subordinates		0.712	
Coaching_and_Developing_Others		0.633	
Providing_Consultation_and_Advice_to_Others		0.772	
Performing_Administrative_Activities		0.570	
Staffing_Organizational_Units		0.624	
Monitoring_and_Controlling_Resources		0.570	

Note: Data source: O*NET, specifically the "Work Context" and "Work Activities" modules, covering 879 occupations and 98 indicators. The factors presented are the outcome of factor analysis with oblimin rotation. Only loadings with absolute values greater than or equal to 0.4 are shown.

For reasons of feasibility, we aggregate the detailed ISCO 4-digit occupations into broader ISCO 2-digit occupational groups, for the visualization stage. Figure 4, 5, and 6 visualize the distribution of occupational scores across ISCO 2-digit occupational groups for the three factors identified through factor analysis of O*NET's "Work Context" and "Work Activities" modules.

Overall, the ordering of occupational groups along each dimension aligns well with common intuitions and theoretical expectations. Occupations traditionally considered demanding in terms of emotional labor score highly on the psychological index. Similarly, jobs involving manual labor and environmental exposure tend to rank high on the physical index, while managerial and analytical roles tend to score highest on the information-management intensity dimension.

While some individual rankings may deviate from expectations, likely due to limitations in how occupational codes aggregate heterogeneous tasks or how external coding systems map to specific job realities, these indices provide a meaningful and interpretable mapping of occupational characteristics across major job categories.

Figure 4: Psychological Arduousness Index by ISCO 2-digit

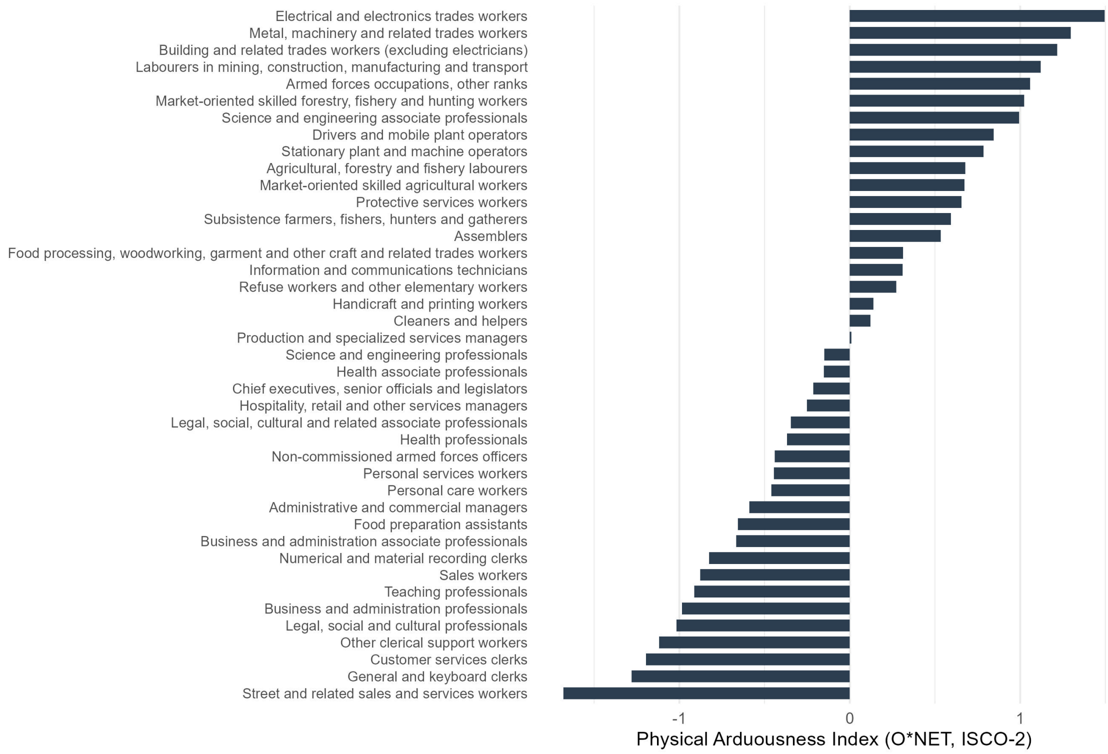

Figure 5: Physical Arduousness Index by ISCO 2-digit

Figure 6: Information-Management Intensity Index by ISCO 2-digit

Finally, we merge the resulting occupation-level factor scores with individual-level SHARE data on career history using ISCO 4-digit codes. This integration allows us to compute average career exposure across all jobs held by each respondent, enabling an evaluation of how accumulated occupational exposures relate to mental health outcomes after age 50.

3 Results and Discussion

3.1 Regression results

We investigate the relationship between the psychological characteristics of career experience and the likelihood of elevated depressive symptoms (Eurod-d higher than 3) beyond the age of 50.

The results, presented in Table 3, indicate that occupational characteristics are significantly associated with the likelihood of elevated depressive symptoms. A one-unit increase in average psychological arduousness is associated with a significantly higher probability of reporting depressive symptoms (log-odds coefficient $\beta = 0.044$, $p < 0.001$), as is physical arduousness ($\beta = 0.034$, $p < 0.01$). In contrast, a higher level of information-management intensity is associated with reduced odds of poor mental health ($\beta = -0.053$, $p < 0.001$). These findings suggest that careers marked by psychological and physical strain may carry long-term mental health costs, while cognitively engaging work environments may have protective effects.

Career instability is proxied by the total number of job losses (`nfire`) and the number of non-employment gaps between jobs (`ngaps`). Both indicators are strong and significant predictors of depressive symptoms later in life (`nfire`: $\beta = 0.097$, $p < 0.001$; `ngaps`:

$\beta = 0.065$, $p < 0.001$), suggesting that fragmented or turbulent work trajectories leave a lasting mental health toll. These findings align with existing evidence linking job insecurity and unemployment spells to psychological distress.

Control variables behave as expected. The poor physical health index (`xphi_`), constructed from a principal component analysis of 17 indicators of physical functioning (e.g., mobility limitations, recent hospitalization history), is strongly associated with depressive symptoms ($\beta = 0.896$, $p < 0.001$), highlighting the close link between current physical and mental health in older age. We also control for childhood health conditions by including four principal component variables: summarizing physical and mental health issues experienced during childhood. These components capture early-life health adversity, and some are significantly associated with the probability of reporting depressive symptoms in later life.

Female respondents are significantly more likely to report depressive symptoms ($\beta = 0.517$, $p < 0.001$), and there is a clear negative age gradient, either because older individuals experience a shift in emotional priorities or exhibit greater psychological resilience with age, or possibly reflecting survivor bias among the oldest respondents. Education is negatively associated with poor mental health risk, reaffirming the role of socio-economic status in long-term mental health. Substantial differences are observed across countries, even after controlling for individual characteristics, underscoring the role of institutional, cultural, or policy differences.

Taken together, the findings suggest that the psychological and physical characteristics of work play a meaningful role in shaping mental health at older ages. However, current physical condition and early-life health adversity remain strong and persistent determinants of depressive outcomes later in life.

Table 3: Regression Results for the Analysis of the Link Between Career Arduousness and Late-Life Mental Health

	M0 Euro-D High (binary)	M1 Euro-D High (binary)	M2 Euro-D High (binary, one job only)	M3 First PC of Euro-D items (continuous)
Career Arduousness / Intensity				
CAR^{phys}	0.035***	0.034**	0.058**	0.011**
	(0.013)	(0.016)	(0.026)	(0.005)
CAR^{info}	−0.238***	−0.053***	−0.099***	−0.014***
	(0.013)	(0.015)	(0.024)	(0.005)
CAR^{psych}	0.107***	0.044***	0.069***	0.011**
	(0.014)	(0.016)	(0.023)	(0.005)
Career Instability				
Number of Job Losses (nfire)	No	0.097***	0.093**	0.037***
		(0.019)	(0.043)	(0.007)
Number of Employment Gaps (ngaps)	No	0.065***	0.044	0.032***
		(0.016)	(0.038)	(0.005)
Health Endowment				
Childhood Physical Health (PC1)	No	0.041***	0.061***	0.021***
		(0.009)	(0.015)	(0.003)
Childhood Physical Health (PC2)	No	0.005	0.025	0.001
		(0.011)	(0.017)	(0.004)
Childhood Mental Health (PC1)	No	0.107***	0.103***	0.051***
		(0.010)	(0.017)	(0.004)
Childhood Mental Health (PC2)	No	−0.001	0.006	0.003
		(0.011)	(0.018)	(0.004)
Controls				
Years in Workforce (dur_w)	No	−0.006***	−0.006***	−0.003***
		(0.001)	(0.002)	(0.0004)
Poor Physical Health (xphi_)	No	0.896***	0.909***	0.413***
		(0.015)	(0.023)	(0.005)
Female	No	0.517***	0.474***	0.189***

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Table 3 – continued from previous page

	M0 Euro-D High (binary)	M1 Euro-D High (binary)	M2 Euro-D High (binary, one job only)	M3 First PC of Euro-D items (continuous)
		(0.030)	(0.049)	(0.009)
Education	No	Yes	Yes	Yes
Age Group	No	Yes	Yes	Yes
Country	No	Yes	Yes	Yes
Wave	No	Yes	Yes	Yes
Constant	-1.221^{***}	-1.235	0.123	-0.287
	(0.012)	(1.090)	(1.205)	(0.296)
Observations	53,693	53,693	21,741	53,693
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.			

Notes: Model M0 is a logistic regression estimating the binary outcome `eurod_high`, which equals 1 when the EURO-D score exceeds 3 and 0 otherwise, without including any control variables. Model M1 extends this by adding the full set of control variables. Model M2 repeats the M1 specification but restricts the sample to individuals who reported only one job over their life course. Model M3 is a linear regression estimating the first principal component summarizing the twelve EURO-D items, as a continuous measure of depressive symptoms.

3.2 Endogeneity Concerns

Estimating the causal effect of occupational arduousness on mental health in later life is subject to several endogeneity concerns. First, individuals' health at the time of labor market entry, may influence their initial occupational choice. Second, adverse health events experienced during the career could lead individuals to transition away from more physically or psychologically demanding jobs, introducing simultaneity or reverse causality bias. Third, unobserved characteristics, such as personality traits, cognitive skills, or risk tolerance, could jointly influence both career trajectories and mental health, leading to omitted variable bias.

As is common in this literature, we are not able to fully resolve the issue of unobserved heterogeneity. However, we take several steps to address the first two sources of endogeneity. To mitigate concerns about health-based selection into occupations, we control for a rich set of early-life health indicators. Specifically, we include principal components summarizing retrospective reports of childhood physical and mental health problems. These measures capture individuals' baseline health endowment prior to occupational entry.

To address the risk of reverse causality, our analysis focuses on health outcomes observed after age 50, while occupational exposure is measured across the full career. This lag structure helps limit the risk that contemporaneous health shocks drive both job changes and mental health deterioration. Moreover, we include a model (M2) restricted to individuals with only one reported job across their career. Belloni et al. (2022) suggested that such restrictions reduce the bias from endogenous job mobility in response to health events. If health shocks lead individuals to leave demanding occupations, focusing on the longest or sole job helps isolate exposure that is less likely to be influenced by such shocks.

While we cannot fully rule out the influence of unobserved traits, our robustness checks show consistent results across specifications. This increases confidence that the documented associations reflect genuine long-term effects of occupational arduousness.

3.3 Robustness Checks

To validate the consistency of our findings, we estimate multiple alternative model specifications. In Model 1, we use a binary outcome indicating elevated depressive symptoms, defined as a EURO-D score greater than three. In Model 3, we instead use a continuous measure of mental health: the first principal component of the twelve EURO-D items. This approach captures more detailed differences in mental health and serves as a robustness check for our main results.

In light of potential biases from job trajectories influenced by mental health, we estimate the model on a subsample restricted to individuals reporting a single lifetime occupation (Model 2).

The consistency in the direction and significance of key coefficients across models provides reassurance about the robustness of our findings. Notably, the physical arduousness component remains positively associated with worse mental health in both binary and continuous outcomes, while the information-management aspect shows a protective or beneficial association. Psychological arduousness is consistently and strongly linked to higher depression scores.

Model M2, which restricts the sample to individuals who report having held only one job over their entire career, yields career arduousness/intensity coefficients with larger absolute values compared to the full-sample model (M1). This pattern suggests that the estimated associations between career arduousness and late-life mental health may be attenuated in the broader sample by reverse causality — that is, by individuals with declining health actively selecting out of more arduous jobs over time.

Lastly, the inclusion of a comprehensive set of controls — including early-life health indicators, education, country fixed effects, and survey wave dummies — further attenuates concerns about omitted variable bias. Together, these checks suggest our main results are not driven by model specification or sample selection.

3.4 Variance Decomposition

As reported in Table 4, the majority of the variance in predicted mental health outcomes is accounted for by current physical health, followed by gender and country fixed effects. Notably, the contribution of psychological arduousness (CAR^{psych}) is small. The physical and informational dimensions also make minor contributions. These findings underscore that, although career characteristics are statistically significant, their explanatory power is limited when compared to present physical health status and demographic factors.

Table 4: Variance Decomposition: Contributions of Predictors to Poor Mental Health

Variable	Contribution
xphi_	0.7789
Gender	0.0692
Country	0.0498
Health Endowment	0.0473
Employ. Duration	0.0208
Career Instability	0.0139
Education	0.0134
CAR^{info}	0.0054
Wave	0.0016
CAR^{psych}	0.0016
CAR^{phys}	−0.0009
Age	−0.0011

Notes: `xphi_` is a measure of current physical health

3.5 Limitations and Future Research

While the findings of this study offer 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 a relatively small number of respondents per occupation, typically around 30 individuals. This limited sample size may introduce measurement error in the occupational-level indices and potentially bias the estimation of psychological, physical arduousness and information-management intensity at the occupation level.

Second, the dimensionality reduction technique used to summarize occupational attributes resulted in three factors that explain approximately 50% of the variance in the original O*NET variables. While this approach provides interpretable constructs of physical arduousness, information-management intensity, and psychological demands, it inevitably simplifies the multi-faceted nature of occupational exposures. Important nuances may be lost in this abstraction. This dimensionality reduction may overlook meaningful nuances, particularly for occupations with unique or mixed attribute profiles that do not align neatly with the dominant factor structure

Third, as with many observational studies in labor economics, this research does not establish causal relationships. While we control for a wide range of confounders, including early-life health conditions and country-level fixed effects, endogeneity concerns remain. Health selection into occupations, unobserved heterogeneity in preferences or resilience, and health shocks that influence career trajectories may bias the estimated associations. Our estimates should thus be interpreted as descriptive associations rather than causal effects.

Fourth, although our study includes a rich set of control variables and draws on a large dataset spanning multiple countries, it remains limited by the quality and granularity of self-reported data. In particular, the career history information is subject to recall bias, especially among older respondents. While SHARE's life-history design mitigates this concern to some extent, measurement error remains a possible limitation.

Future research could address these limitations and build upon the current study in several ways. First, replication using alternative occupational databases with larger sample sizes for each job, would help validate the robustness of our occupational arduousness indices. Second, future studies may explore more sophisticated machine learning or non-linear dimensionality reduction techniques to extract finer-grained occupational factors beyond the three we retained. Finaly, While the current study controls for gender, socioeconomic status, and country-level differences, future work could explore whether the magnitude of associations between occupational characteristics and mental health varies across these groups, shedding light on potential effect heterogeneity.

4 Conclusion

This study investigates the relationship between the psychological demands of individuals' careers and their mental health outcomes in later life. Using survey data from SHARE combined with detailed occupational measures from O*NET, we focus on how long-term exposure to psychological arduousness, such as frequent conflict situations or emotionally demanding work, relates to depressive symptoms after age 50. While the main focus is on psychological demands, we also included physical and informational job characteristics in the analysis to account for their known relevance in shaping mental health risks. Our findings show that psychological and physical job demands are significantly associated with higher risks of depression in later life, whereas cognitively engaging work appears to have a protective effect. Additionally, indicators of career instability, such as job losses and employment gaps, emerge as important predictors of later-life mental health.

Importantly, our findings reinforce the notion that the conditions and characteristics of work are not merely short-term concerns but carry potential lifelong implications for well-being. The inclusion of comprehensive control variables, including early-life health endowments, gender, education, and country-specific factors, strengthens the robustness of our results, though causal inferences remain beyond the scope of this study. Variance decomposition further suggests that current physical health accounts for the largest share of explained variance in mental health outcomes, while career characteristics, though statistically significant, play a more modest explanatory role.

Overall, this research contributes to a growing body of economic evidence highlighting the enduring impact of working conditions on health across the life course, underscoring the need for policy efforts that promote healthier work environments to support well-being into old age.

Note: ChatGPT was used in the preparation of this document solely for the purpose of improving language and expression.

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