The Long-Term Mental Health Consequences of Career Arduousness and Instability

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Abstract

This paper explores the long-term consequences of career arduousness and instability for mental health. It finds a positive link between career arduousness (i.e. the sum of job demands individuals have been exposed to during their entire career) and late-life mental ill-health, but also evidence that career instability (i.e. career gaps, job insecurity, displacements, unemployment spells) could matter more than arduousness as such.

Keywords: Mental Health, Career, Job Demands, Occupation Arduousness & Instability, Variance Decomposition

JEL Codes: I10, J26, J28

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1 Introduction

This paper aims at contributing to the economic literature on long-term consequences of career arduousness and career instability on mental health; and by long-term we mean after the age of 50. In that sense, this paper relates the literature on demanding occupations and (early)retirement provision or retirement differentiation (Pestieau and Racionero, 2016; Vermeer et al., 2016) and that on work capacity at an older age (Wise, 2017), although the focus hereafter is more on mental health and its work-related determinants, than on the implications for retirement policy.

The impact of work/occupation on health has long been investigated in epidemiology, psychology, sociology and also in economics. Most research and policy debates underline various negative consequences of adverse working conditions such as stress, physical exhaustion in terms of work-induced disabilities, overall poor physical health as well as premature death. There are many works of the relationship between work or retirement and physical health (see French and Jones, 2017 for a recent review), physical health and work capacity (Jousten et al., 2010; Coile et al., 2016; Banks et al., 2016 or Wise, 2017). But the focus here is more on mental health, which has so far received a bit less attention, at least by economists. Notable exception comprise the work of Catalano et al. (1999); Lu et al. (2009); Clarfield (2009); OECD (2012); Frijters et al. (2010); Frijters et al. (2014). In particular Maclean et al. (2015) find a negative relationship between self-assessed adverse labor market events (problems with coworkers, employment changes, financial strain) and mental health. Still, this paper is a response to invitations to pay more attention to mental health in economics (Layard, 2013). Beyond improving our understanding of the link between work/occupations and mental health, this paper essentially aims at three things.

The first is to better account for the role of *career arduousness*. Conceptually, hereafter, *arduousness* relates to the way that concept is defined in the job demands and job quality literature (Bakker and Demerouti, 2007: Chen et al., 2017). A more arduous/demanding occupation or job requires more physical and/or psychological effort or skills and consumes more physiological and/or psychological resources. We will explain later how this is quantified in our data. For the moment, the key point is that the job demands literature has abundantly shown that occupations are not equally stressful or physically demanding and that they may impact individuals' job performance and health. What differentiate our approach from most of the job demands literature is we are not just interested in analysing the consequences of the current or most recent job, but the succession of jobs forming a complete *career*. That objective directly derives from the recent availability of data that can be used to quantify the arduousness throughout someone's career. With these data, we can account for the duration of these occupations and, as people change occupation, of how these changes contribute to the cumulative degree of arduousness people have been exposed to as they age. As far as we know, quantifying the arduousness over the entire career and analysing its (long-term) impact on mental health is something new in the economic literature.

Second, a career is not just a succession of more or less arduous (full-time) jobs. People may work part time, alternate part-time and full-time jobs, experience spells of non- or unemployment, have been made redundant more or less frequently. All these features contribute to career heterogeneity, not so much in terms of career arduousness, but in what we call people's "career profile". And some career profiles can be synonymous with stability/security while others hint at poor labour-market attachment, job insecurity, displacements risk of loss of income, unemployment or low employability. And there is evidence that these elements can also contribute to mental ill-health (Vodopivec et al., 2021, Bassanini and Caroli, 2015). This paper intends to disentangle the contribution of career arduousness *per se* from that of the career profile/instability. There are works on the relationship between job arduousness/demands and mental health (Barnay, 2016). Many papers focus on unemployment or job insecurity and subjective well-being (see Chadi and Hetschko, 2021 for a recent review); some on these dimensions and mental health. Riumallo-Herl et al. (2014) find that with job loss, the symptoms of depression in older people who are approaching retirement age increase by 4.8% in the U.S. and 3.4% in European countries. Based on a panel analysis for individual workers in five countries (Australia, Canada, Korea, Switzerland and the United Kingdom), OECD (2008) also confirms that mental health suffers when individuals move from employment to unemployment or inactivity. There are few papers, at least by economists, that look simultaneously at arduousness *and* career profile/instability and their impact on mental health. Logically, both can undermine mental health and professional pathways cumulatively over the life course (Lindeboom, 2012). We aim at examining the role of both, and also, to quantify their respective contribution to the risk of late-life mental ill-health.

Third, we try to account for what epidemiologists call people's health endowment and other *pre-labour-market* entry determinants of late-life mental health. There is a literature that stresses the long-lasting effects of family and social background (including educational attainment) on general health status in adulthood. Three concurrent channels of transmission from one generation to another have been identified (Trannoy et al., 2010): a direct channel where social background influences adult health following a latency period; an indirect channel where social background influences health through its influence on employment and life trajectories; and the third channel is an inter-generational transmission of health a common genetic capital within families. More generally, a large body of literature equally acknowledges the role played by the social determinants of health (Marmot and Wilkinson, 2005). Current evidence and research of the life course approach on the association between early life and mental health in old age are fragmentary.[1] This paper aims at filling that relative void by examining the "long-arm" effect of the health endowment on mental health in a European context. The data we use comprise the health status during childhood[2] and also information about the death status of parents (more on this below in 3). These variables allow us to account for the respondent's health endowment, control for the latter's direct impact on late-life mental health but also its potential role on entry-level occupational choice. From an econometric point of view, these represent a source of selection bias. They must be taken into account to properly measure the net effect of professional occupation (be it its arduousness or instability) on mental health. The point here is that we now have access to data to control for the role of these early-stage factors. That puts us in a position to account for selectivity issues and deliver a more accurate estimation of the causal impact of people's career on their long-term mental health.

In terms of data sources, two things demarcate this paper. First, its use of 7$^{\text{th}}$ wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) (Börsch-Supan et al., 2013). The 7$^{\text{th}}$ wave contains several "retrospective" modules, that provide detailed data about the respondent's history, including their childhood health and parental longevity. What is more, extensive information is provided about job history. We can identify each respondent's last and the first occupation, and all those occupied in between. SHARE informs on the number of jobs spells, the number of gaps between these, whether people worked part-time or full-time or the number of times they were made redundant. That information can be used to build the career profile of the respondent i.e. things like the overall duration of the career, but also several proxies of its (in)stability. Second, although SHARE provides a lot of information about people's career, it falls short of informing about the arduousness of successive jobs. But other data sources can be mobilised for that. One is O*NET from the US. Another one is the European Working Conditions Survey (EWCS). More will be said about these in data Section 3, but, in short, both O*NET and EWCS collect information about the work content and the working conditions for a wide range of occupations (referenced using international classifications like ISCO). And that information can be used to compute arduousness indices.

[1] One exception is the recent paper by Zhu and Liao (2021), using data from the Chinese equivalent of SHARE, the China Health and Retirement Longitudinal Study(CHARLS).

[2] Before the respondent turn 15.

Then, as we do in this paper, these indices can be imported in SHARE and applied to each job spell forming SHARE respondents' career, using the ISCO code as a merge variable.

Another specificity of the paper is that it uses a variance decomposition method to quantify (and compare) the contribution of career arduousness vs. instability to mental health past the age of 50; or that of professional career vs. early-life determinants. Traditionally, economists rely on the direct comparison of regression coefficients. But this approach has limitations. One of them is that the underlying metrics differ greatly and compromise interpretation. For instance, how to compare the coefficient capturing the contribution of average career arduousness and those delivered by a categorical variable reflecting people's number of career breaks or redundancies? To overcome this non-comparability/non-commensurability problem we propose using the method pioneered by Fields (2003) in labour economics and used more recently by Jusot et al. (2013) in health economics. It consists of combining regression analysis and variance decomposition. Fields (2003) shows how regression models can be supplemented by variance decomposition analyses to learn the relative importance of different explanatory factors.[3] In regression analyses, the emphasis is on coefficients and statistical significance; in decomposition, it is on the information content of the variables in question. In short, the idea is to consider the variance of mental health explained by the different groups of variables of the model, singularly those quantifying respondents' career arduouness and instability, and compute the respective shares that can be attributed to each group. The ratio of these shares provides an estimate of the relative importance in determining mental health beyond 50.

Finally, it is worth stressing that we quantify the impact of career arduousness or instability on mental health simultaneously for 19 European countries (Austria- AUT, Belgium-BEL, Switzerland- CHE, Czech Rep.- CZE, Germany - DEU, Denmark- DNK, Spain- ESP, Estonia -EST, France- FRA, Greece- GRC, Croatia-HRV, Hungary-HUN, Israel-ISR, Italy-ITA, Luxembourg-LUX, Poland- POL, Portugal-PRT, Slovenia-SVN, Sweden-SWE). And compared to existing works on mental health in an international context, this one has the advantage that it uses only a fully harmonised data set.

The rest of this paper is organised as follows. In Section 2, we present our method of analysis. The data on mental health, career history and arduousness by ISCO occupation used in this empirical paper are presented in Section 3. Section 4 presents the main results of the paper as well as our discussion of endogeneity issues. Section 5 concludes.

[3] The term "decomposition" has been used in this sense in many early studies in the literature on inequality decomposition by factor components (e.g. Shorrocks, 1982).

2 Method

The aim of this paper is to analyse the link between career arduousness or career profile/instability and mental health at older age. Let us consider $Mhealth_{i,j}$, a measure of poor mental ill-health of elderly individual i in country j. We consider that $Mhealth_{i,j}$ is a function that can be written as follows:

$$Mhealth_{i,j} = \alpha + \beta_1\, CAR^{ard}_{i,j} + \beta_2\, CAR^{prof}_{i,j} + \gamma\, Hendow_{i,j} + \eta\, X_{i,j} + \delta_j + \epsilon_{i,j} \qquad (1)$$

where CAR^{ard} is the respondent's career arduousness. The career profile (duration, breaks, redundancies...) is CAR^{prof}, while $Hendow$ is the respondents health endowment (childhood health, parental death status...). The model comprises a vector of controls X which systematically include gender and age that we interact systematically. The model also systematically comprises a country fixed effect δ.

The first part of the analysis consists of estimating these above model using different definitions of career arduousness (i.e. mean value over an entire career, arduousness of first job or last job, of the job held before the age of 30 vs. the one(s) done past the age à 50...). The second part is the one where we decompose the variance to analyse the relative importance of career arduousness versus others variables, starting with the career profile/instability. We draw from the method pioneered by Shorrocks (1982) and used by Fields (2003) in labour economics and Jusot et al. (2013) in health economics. It consists of combining regression analysis with variance decomposition. The procedure has two stages. At stage 1, using equation (1), we predict the respondent's mental ill-health based on the (block of) regressors and the corresponding estimated coefficients:

$$\begin{aligned}
\widehat{Mhealth}^{CAR^{ard}_{i,j}} &= \widehat{\beta}_1 \times CAR^{ard}_{i,j} \\
\widehat{Mhealth}^{CAR^{prof}_{i,j}} &= \widehat{\beta}_2 \times CAR^{prof}_{i,j} \\
\widehat{Mhealth}^{X^k_{i,j}} &= \widehat{\gamma}^k \times X^k_{i,j} \\
\widehat{Mhealth}^{\delta_{i,j}} &= \widehat{\delta}_j
\end{aligned} \qquad (2)$$

At stage 2, we use the variance of health as a reference to quantify the contribution of each (block of) variables. The decomposition is given by the covariance between each (block of) regressor(s) and the predicted mental ill-health.

$$\begin{aligned}\sigma^2\left(\widehat{Mhealth}_{i,j}\right) = \sigma\left(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}_{i,j}^{CAR^{ard}}\right) + \sigma\left(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}_{i,j}^{CAR^{prof}}\right) \\ + \sigma\left(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}_{i,j}^{X^k}\right) + \sigma\left(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}_{i,j}^{\delta}\right)\end{aligned} \quad (3)$$

Therefore, the relative importance of a particular variable (or block of variables) is the ratio of its covariance divided by the total model-explained ill-health variance. For instance, for career arduousness

$$ratio^{CAR^{ard}} = \frac{\sigma\left(\widehat{Mhealth}_{i,j}, \widehat{Mhealth}_{i,j}^{CAR^{ard}}\right)}{\sigma^2\left(\widehat{Mhealth}_{i,j}\right)} \quad (4)$$

3 Data

3.1 SHARE wave 7

As stated above, this paper makes an extensive use of the 7$^{\text{th}}$ wave of the Survey on Health, Ageing and Retirement in Europe (SHARE). This wave was conducted across 28 European countries and Israel in 2017. The 7$^{\text{th}}$ wave contains several "retrospective" modules that provide detailed data about the respondent's history. Extensive information is provided about, among others, childhood health and job history. Data limitations of different sorts (missing values for one of the key dimensions of our analysis...) explain that we retain only 19 out of the 29 participating countries: Austria- AUT, Belgium- BEL, Switzerland-CHE, Czech Rep.- CZE, Denmark- DNK, Spain- ESP, Estonia -EST, France- FRA, Greece-GRC, Croatia-HRV Hungary-HUN, Ireland-IRL, Israel-ISR, Italy-ITA, Luxembourg-LUX, the Netherlands-NLD, Poland- POL, Portugal-PRT, Slovenia-SVN, Spain, Sweden-SWE. The number of observations by country and wave is reported in the Appendix (Table A1).

Our first variable of interest is mental health. In SHARE, mental ill-health essentially means depression/suicidality: melancholy, diminished interest, sleep disorders or suicidal thoughts... The detailed list of items used to assess mental health is reported in Table 1. It logically covers the above-listed dimensions of respondents' mood or feelings. They represent depressive symptoms that, once taken together, fairly show people's mental health. The 12 items are those used to build the EURO-D scale, which has been validated in earlier cross-European studies of depression prevalence (Prince et al., 1999; Guerra et al., 2015).

Another crucial variable is the respondent's job history. In the 7$^{\text{th}}$ wave of SHARE, respondents are asked to retrace their complete job history by providing the starting/ending year of each of their successive jobs, and whether these were done on a full- or part-time basis.[4] This permits calculating the duration of their entire career, both in absolute years and in equivalent-full-time years. Also, the occupation title is reported for each of the successive jobs at ISCO-4 digits. We merge that information with arduousness indices that have been estimated separately for each ISCO-4 occupation (more on this below in Section 3.2). The combination of SHARE job history data and arduousness data puts us in a position to compute, *inter alia*, an average career arduousness index and examine how it correlates with late life mental health.

One strength of this paper is that SHARE enables us to control for the initial health endowment. We can control for the (self-reported) health status of the individual up to the age of 15. SHARE respondents also say if their parents are currently alive and inform about the age at which they died. These items can be used to proxy the "genetic" background of the respondent under the assumption of intergenerational transmission of health Trannoy et al. (2010).

3.2 O*Net & EWCS

SHARE provides a lot of information about people's careers and represents significant progress. But, as mentioned above, it falls short of providing information about the arduousness of successive jobs. To overcome that limitation, we turn to O*NET, but also to the European Working Condition Survey (EWCS).

O*Net is a US survey about working conditions by occupation that contains over 180 variables. Those variables are included in different modules. Here, we concentrate on the

[4] The participant's history is reported retrospectively and thus a long time after it happened (i.e. a retiree in 2017 must recall her work history since 1970 if she started working at 20). This can lead to memory biases. To reduce this problem, the SHARE surveyors used a "Life History Calendar" approach to help the respondent report accurately.

Work context module. Items composing this module are related to physical working conditions (e.g. exposition to contaminants, spending time bending or twisting the body, working in very hot or cold temperatures), structural job characteristics (e.g. consequence of error, time pressure, freedom to decide), and interpersonal relationship at work (e.g. contact with others, responsibility for other's health and safety, face-to-face discussions). We use a principal component analysis to get a summary indicator of occupation arduousness (the first component). Figure 1 presents the 1st principal component (PC) at ISCO 2 level. Logically, we see that typical manual/outdoor occupations (e.g. building and related trades works) translate into high arduousness PC values, while more intellectual/indoors occupations (e.g. Business and Administration) display much lower values.

What is important is to stress what we have done with these arduousness data. Once injected into SHARE, we use these to compute a series of career arduousness indices. For instance, we compute for each SHARE respondent the weighted average of all O*NET-estimated PC for his consecutive ISCO 4-digit occupations in reports in SHARE wave 7. The weights reflect the duration (in years) of the consecutive occupation spells. Note that the years have been multiplied by .5 and if the occupation was declared to be always part-time, 1 if always full-time and .75 when variable. We will mostly use the entire (average) career arduousness index. And often we will resort to the *percentile* of that index. Occasionally, we will also use the arduousness index corresponding to the first job vs. the last job, or for the jobs hold before the age of 30 vs. those occupied beyond 50.

The principal objection to the use of O*NET is that the resulting career arduousness indices rest on data assembled in the US, reflecting working conditions in jobs as they exist in the US; whereas SHARE is about health and career history in Europe. Working conditions by occupation are likely to be similar, but they may also diverge to an extent. As a robustness check, we will compare the results we get when using the US O*Net-based measure of career arduousness to the ones delivered by a European measure, namely the one we find in EWCS. Since 1991, Europe has been monitoring working conditions across Europe through its European Working Conditions Survey (EWCS). The survey's primary aim is like the one pursued by O*Net, namely to measure working conditions across European countries on a harmonised basis. We use the 1991-2015 combined version of the survey. More precisely, we exploit six of the indices that have been developed by the authors of the survey and added to the raw data. The six job quality indices we use are: Physical environment, Work intensity, working time quality, social environment, skills and discretion, and job prospect.[5] We inverse the sign of each of these indices (as we are interested in arduousness, while

[5] Note the similarity with the dimensions forming the O*Net "Work Context module".

these indices quantify the "quality" of jobs) and compute their average. A limitation with EWCS is that respondents' occupation is only available at ISCO 2-digit level, while O*NET information exists at ISCO 4-digit. But again, the major advantage of EWCS in this paper is that the underlying observations of occupations come from Europe and might thus be more in line with what SHARE respondents have experienced throughout their professional life. Our regression analysis will use measures of career arduousness based on EWCS to assess whether these deliver results that deviate from O*NET-based ones. A first, purely descriptive, comparison of O*NET and EWCS is reported on Figure 2. We simply plot the arduousness values delivered by EWCS against those stemming from O*NET. As stated above, the comparison can only be done for ISCO 2-digit. It hints at a strong correlation, but also at differences for some ISCO2 occupations.

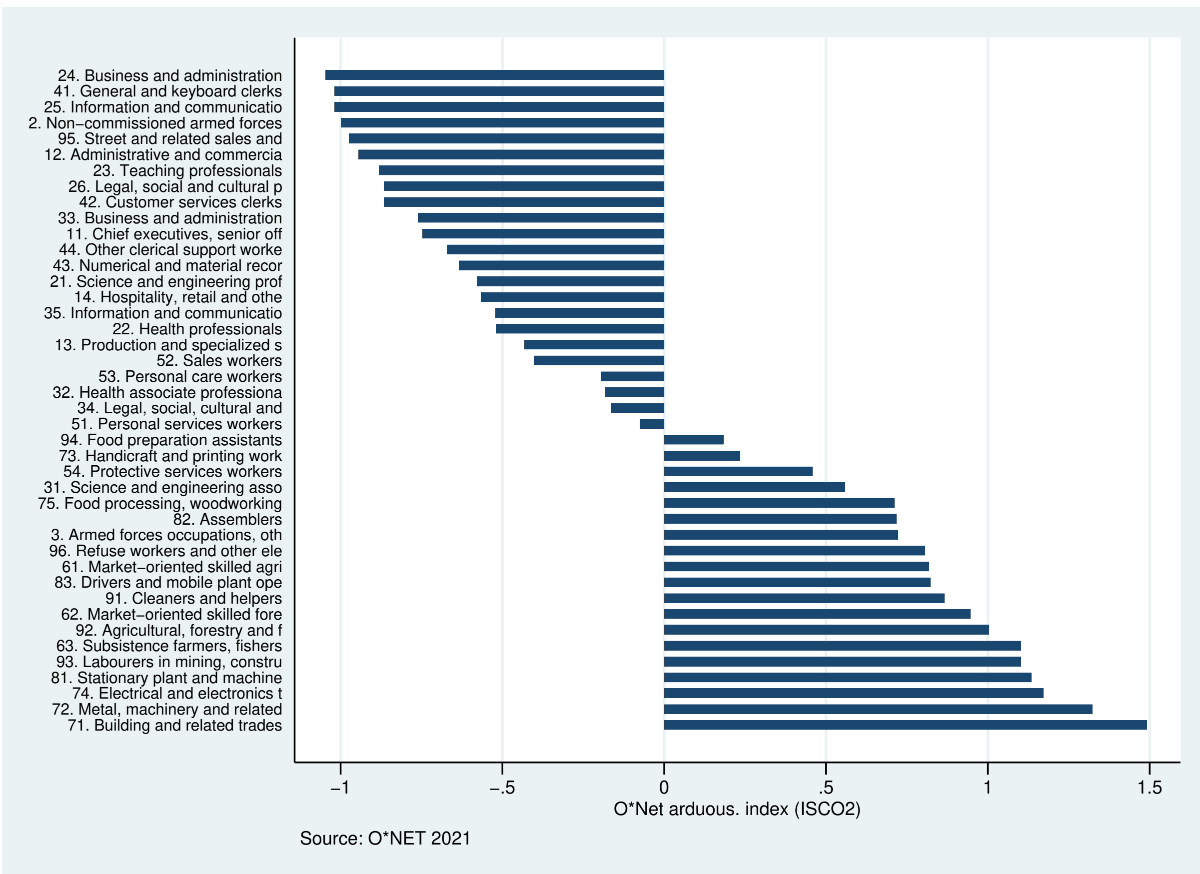

Figure 1: O*NET career arduousness index (ISCO2)

First Principal Component of items forming the O*NET *Work Context* module.

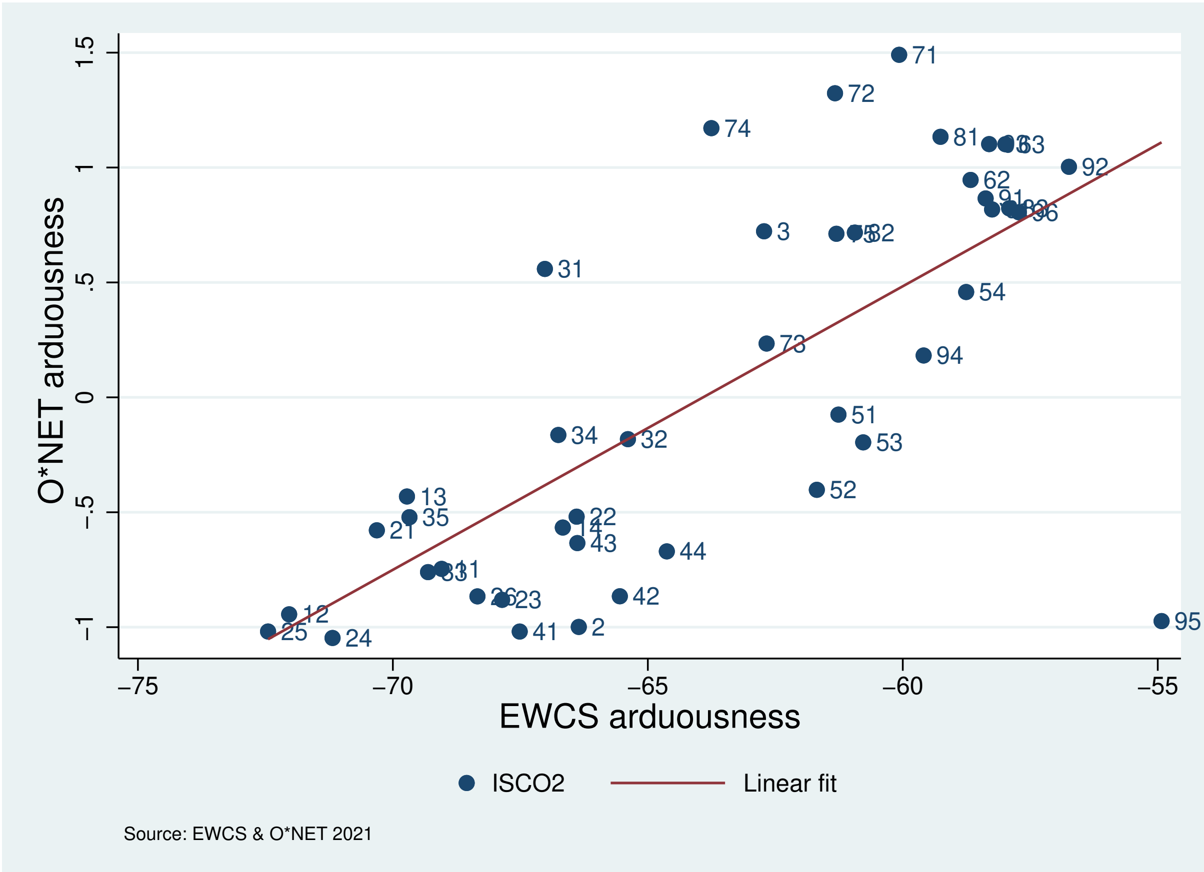

Figure 2: O*NET vs. EWCS ardousness indices at ISCO2 level

0 Armed forces occupations 1 Commissioned armed forces officers 2 Non-commissioned armed forces officers 3 Armed forces occupations, other ranks 10 Managers 11 Chief executives, senior officials and legislators 12 Administrative and commercial managers 13 Production and specialised services managers 14 Hospitality, retail and other services managers 20 Professionals 21 Science and engineering professionals 22 Health professionals 23 Teaching professionals 24 Business and administration professionals 25 Information and communications technology professionals 26 Legal, social and cultural professionals 30 Technicians and associate professionals 31 Science and engineering associate professionals 32 Health associate professionals 33 Business and administration associate professionals 34 Legal, social, cultural and related associate professionals 35 Information and communications technicians 40 Clerical support workers 41 General and keyboard clerks 42 Customer services clerks 43 Numerical and material recording clerks 44 Other clerical support workers 50 Services and sales workers 51 Personal services workers 52 Sales workers 53 Personal care workers 54 Protective services workers 60 Skilled agricultural, forestry and fishery workers 61 Market-oriented skilled agricultural workers 62 Market-oriented skilled forestry, fishery and hunting workers 63 Subsistence farmers, fishers, hunters and gatherers 70 Craft and related trades workers 71 Building and related trades workers (excluding electricians) 72 Metal, machinery and related trades workers 73 Handicraft and printing workers 74 Electrical and electronics trades workers 75 Food processing, woodworking, garment and other craft and related trades workers 80 Plant and machine operators and assemblers 81 Stationary plant and machine operators 82 Assemblers 83 Drivers and mobile plant operators 90 Elementary occupations 91 Cleaners and helpers 92 Agricultural, forestry and fishery labourers 93 Labourers in mining, construction, manufacturing and transport 94 Food preparation assistants 95 Street and related sales and services workers 96 Refuse workers and other elementary workers

3.3 Descriptive statistics

Table 2 contains the variables we have been able to assemble by merging SHARE career history data and O*NET or EWCS arduousness data. The first part of the table is about career arduousness, while the second describes the variables informing on career profile/instability. As to arduousness, most reported values are based on O*Net data unless specified otherwise. The very first column describes the respondents' *average* career arduousness. It is computed as the weighted average arduousness index of each of the successive occupations, where the weights correspond to the duration of the different jobs spells (themselves weighted to account for the part-time vs. full-time nature of the spell.[6] The next column describes the international "percentile" of respondents' average career arduousness. The third column presents the percentile of the average career arduousness estimated using European arduousness indices provided by EWCS. A quick examination of the country averages suggests that both the O*Net and the EWCS data convey similar information as to cross-country heterogeneity. That very tentative results will be confirmed by our regression and variance decomposition results further down. The next two columns correspond to the arduousness of (respectively) the first and the last job held by SHARE respondents. An interesting observation is that, on a country-by-country basis, arduousness is systematically higher for the first job than for the last job. This is the first illustration of something that we will document more extensively further: arduousness evolves over the courses of the career; and generally it diminishes. The next four columns report average arduousness across age bands (¡30; 30-39; 40-49; 50+). The values are in deviation from the overall average (column 1). Again, we verify that the younger years (¡30) usually synonymous with more arduousness, supporting the idea that arduousness goes down with age.

Table 3 presents the other variables used in this paper and that we use as controls. They include SHARE respondents' education (ISCED attainment), age, and gender. As mentioned above, they comprise items describing their health endowment. The second column presents the childhood ill-health on a 1-6 scale, where 5 corresponds to the worse status (and 6 to a health status that varied a lot). The next two columns report the death status of the parents. We consider whether parents are currently alive (1). And if they have died, we consider whether they died "prematurely" (2) (i.e. they died younger than the median age at death in the considered country) or not (3). This variable can be considered as a proxy of the "genetic" background of the respondent under the assumption of intergenerational transmission of health Trannoy et al., 2010.[7]

Finally, in Figure 3 we present a first, very preliminary, analysis of the relationship between our respondents (O*NET-based) career arduousness indices and their mental ill-

[6]Weight is .5 if people worked part-time, .75 is they shifted between part-time to full-time, and 1 otherwise.

[7]Note that the country average values reported in this table have no immediate interpretation.

health index at old age. The breakdown is by country and within each figure by gender. For the sake of clarity, we only plot the values for respondents aged 50-64. This visual inspection of the data reveals gender differences in terms of career arduousness (average career arduousness values are higher for male respondent), and also in terms of mental ill-health (women report more health issues than men). But concerning the key issue addressed by this paper, we find support for the existence of a positive association between career arduousness and mental health.

Table 1: SHARE: mental iil health items and indices[b]: individuals aged 50+. Country averages

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

Source: SHARE 2004-2017

[a]: No(0), yes(1)

[b]: First principal component of all items (the higher, the worse is people's health). Principal component analysis is carried with all countries pooled. Displayed values correspond to the predicted score values divided by standard deviation.

Table 2: SHARE, O*NET, EWCS: career arduousness and career profile

	Career Arduousness									Career Profile				
										Employment dur.			Number of	
	Car. av.	Car. av^a	Car. av^b	first job	last job	<30 ^{c}	30-<40 ^{d}	40-<50^e	50+^{f}	Cum. yrsl	FTE empl	Number of	6m gaps	redun.
AUT	0.04	50.81	47.38	0.18	0.03	0.06	-0.01	-0.01	-0.01	39.23	0.95	2.63	0.45	0.17
BEL	-0.19	43.32	42.62	-0.11	-0.22	0.04	0.00	-0.01	-0.02	37.44	0.94	2.67	0.38	0.36
CHE	-0.22	42.59	38.39	-0.03	-0.24	0.08	0.00	-0.01	-0.01	39.80	0.90	3.66	0.53	0.20
CZE	0.10	53.32	49.56	0.22	0.05	0.05	0.01	-0.02	-0.05	39.11	0.99	2.70	0.36	0.28
DEU	-0.03	48.72	44.70	0.14	-0.05	0.08	0.01	-0.02	-0.02	38.88	0.93	2.72	0.54	0.31
DNK	-0.28	40.66	38.61	-0.11	-0.31	0.11	0.02	-0.02	-0.04	37.32	0.93	3.87	0.63	0.52
ESP	0.33	58.69	59.55	0.37	0.30	0.04	0.00	-0.01	-0.02	43.21	0.98	2.22	0.37	0.20
EST	0.09	53.83	48.32	0.19	0.10	0.04	-0.01	-0.02	-0.00	39.88	0.99	3.45	0.50	0.39
FRA	-0.02	49.20	49.02	0.09	-0.06	0.03	-0.00	-0.02	-0.02	37.56	0.96	2.85	0.58	0.36
GRC	-0.04	48.09	50.55	0.03	-0.04	0.04	-0.01	-0.01	0.01	38.01	0.97	1.67	0.25	0.15
HRV	0.19	55.33	49.98	0.26	0.18	0.04	-0.01	-0.01	-0.00	36.50	0.99	2.10	0.31	0.25
HUN	0.21	56.85	50.40	0.31	0.20	0.02	-0.01	-0.00	-0.02	40.92	0.99	2.34	0.27	0.13
ISR	-0.19	43.91	38.78	-0.07	-0.19	0.04	-0.00	-0.01	-0.01	41.41	0.94	2.76	0.61	0.25
ITA	0.14	53.36	52.02	0.24	0.12	0.04	0.00	-0.01	-0.02	39.37	0.97	1.93	0.24	0.19
LUX	-0.05	47.69	44.42	-0.00	-0.05	0.02	0.00	-0.00	-0.00	38.19	0.96	2.36	0.26	0.16
POL	0.34	61.37	63.74	0.39	0.34	-0.01	0.00	-0.00	-0.01	35.88	1.00	2.48	0.34	0.21
PRT	0.45	63.39	59.49	0.49	0.42	0.05	0.02	-0.01	-0.03	43.08	0.99	1.95	0.24	0.17
SVN	0.06	51.20	47.34	0.16	0.06	0.04	-0.01	-0.01	-0.01	36.87	1.00	2.19	0.24	0.18
SWE	-0.14	45.72	41.48	0.01	-0.19	0.10	0.03	-0.02	-0.04	41.41	0.94	3.56	0.65	0.22

Source: SHARE 2004-2017, O*NET 2021, EWCS

[£]: Based on O*Net unless specified otherwise.

[a]: Percentile.

[b]: Percentile of EWCS-based index.

[c]: Deviation from career ardu. average when aged less than 30

[d]: Deviation from career ardu. average when aged 30-39

[e]: Deviation from career ardu. average when aged 40-49

[f]: Deviation from career ardu. average when aged 50+

[perc.] EWCS

Table 3: SHARE: other controls

	Education^{a}	Childhood health^{b}	Death status of father^{c}	Death status of mother^{c}	Age in years	Female
AUT	3.34	2.28	2.35	2.17	69.91	0.58
BEL	3.40	2.00	2.25	2.02	65.58	0.52
CHE	3.39	2.23	2.35	2.11	69.04	0.52
CZE	2.88	2.34	2.39	2.21	69.71	0.60
DEU	3.59	2.37	2.29	2.11	66.78	0.52
DNK	3.77	1.69	2.19	1.96	64.39	0.54
ESP	1.81	2.37	2.30	2.11	69.29	0.49
EST	3.42	2.77	2.44	2.24	69.94	0.62
FRA	2.81	2.19	2.30	2.00	67.78	0.56
GRC	2.82	1.57	2.32	2.14	66.21	0.43
HRV	2.69	1.90	2.36	2.15	65.79	0.51
HUN	3.16	2.22	2.33	2.12	68.47	0.48
ISR	3.35	1.99	2.39	2.22	70.85	0.52
ITA	2.20	1.99	2.29	2.00	66.50	0.46
LUX	2.86	2.18	2.29	2.04	66.23	0.51
POL	3.06	2.28	2.16	1.76	59.80	0.55
PRT	1.51	2.11	2.38	2.20	67.73	0.47
SVN	2.99	2.19	2.39	2.19	68.75	0.56
SWE	3.31	1.90	2.33	2.22	70.79	0.51

Source: SHARE 2004-2017

[a]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long].

[b]: Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.

[c]: Parent is currently alive (1); died early (2) died late (3) (i.e. they died younger than the median age at death in the considered country or not).

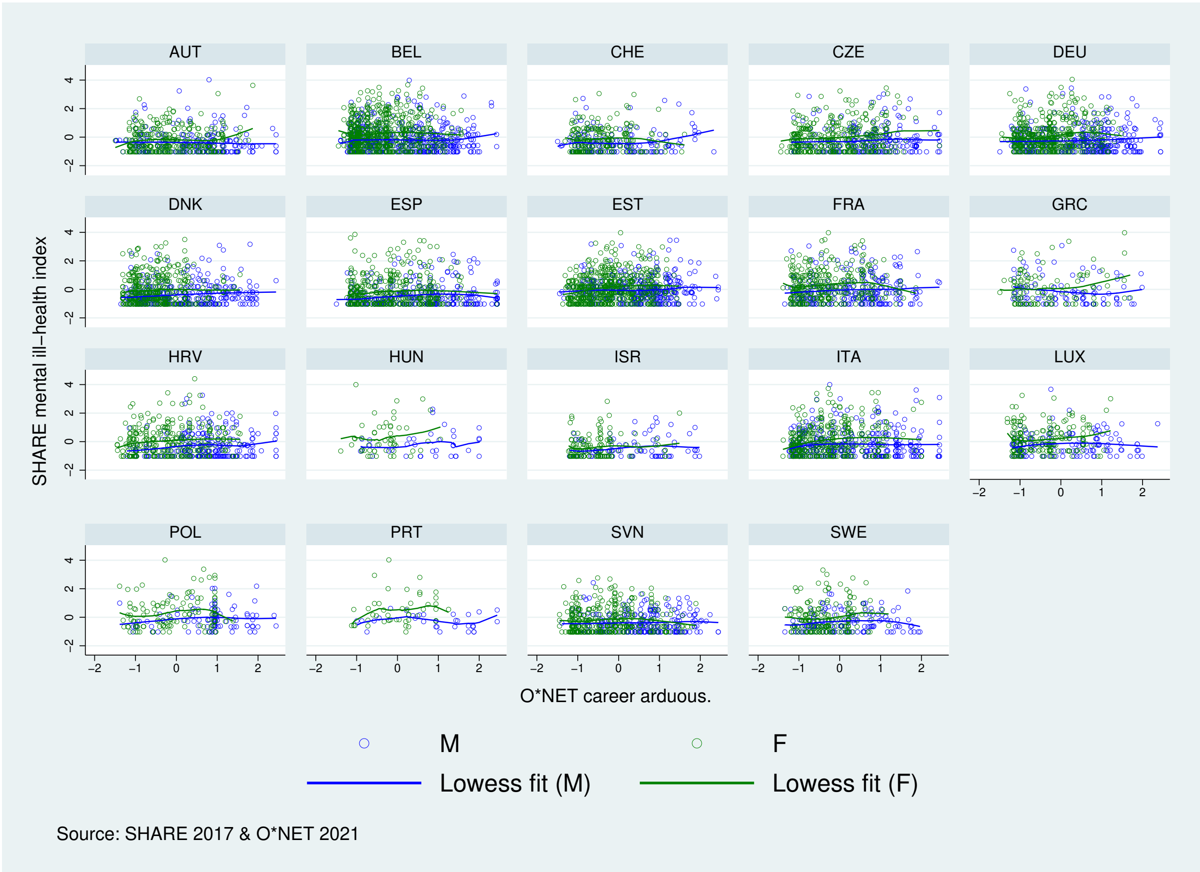

Figure 3: O*NET career arduousness (ISCO4) and SHARE mental ill-health index (respondents aged 50-64). Breakdown by country and gender

Lowess fit stands for locally weighted scatter plot smoothing. The basic idea is to create a new variable that, for each y_i, contains the corresponding smoothed value. The smoothed values are obtained by running a (local) regression by using only the data (x_i, y_i) and a few of the data near this point.

4 Results

4.1 Regression results

We begin our analysis of the relationship between health at old age and career history by considering the results of the OLS estimation of equation (1). Results are reported in Table 4. All estimated models comprise age and gender interacted dummies as baseline predictors of mental health. They also include the respondent's educational attainment and country fixed effects. These capture the contribution to mental health of country-level unobservables: the country's overall level of development, its quality of health care, but also its average level of career arduousness and instability, as by construction the inclusion of country fixed effects amounts to centring the other regressors on the country average.

The key coefficients are those corresponding to CAR^{ard} and CAR^{prof} equ. (1). In model 1 (M1), CAR^{ard} is computed as the weighted average arduousness value of each of the successive ISCO-4 occupation.[8]. Point estimate is .0425 and statistically significant, meaning that a more arduous career contributes to mental ill-health beyond the age of 50. In models 2 and 3 (M2, M3) we focus on the arduousness of the first and the last occupation, and we again find a positive association with mental ill-health. Points estimates are smaller (respectively .0289 and .0329).[9] In model 4 (M4), we explore the role of arduousness at different ages (< 30; 30-39, 40-49, 50plus). The estimated model comprises the overall average arduousness as the main regressor to which is added the arduousness deviation specific to each age band. None of the estimated coefficients for these deviations are statistically significant. This tentatively suggests that the way arduousness develops with age (and remember that our descriptive statistics of the previous section suggest it goes down with age) has no significant impact on late-life mental ill-health. Models 5 and 6 (M5, M6) reproduce the first model (M1) but with measures of the overall career arduousness expressed in percentiles. Model 5 uses the O*NET-based arduousness measure; while Model 6 uses the European measure from EWCS. Both points estimates are qualitatively similar: a one percentile rises of arduousness translates into a 0.0014 to 0.0016 increase of the mental ill-health index. The latter has been standardised internationally (i.e. a one-unit change of the index corresponds to one standard deviation), thus these point estimates suggest that 10 percentage points more arduousness translate into a 1.4 to 1.6 percent extra ill-health standard deviation..

The next set of interesting results relates to the career profile/instability CAR^{prof}, and are reported beneath in Table 4. They all point to the negative impact of career instability on mental health. People with a longer overall career (measured as the total number of years they have spent in paid employment, be it on a part- or full-time basis) have a lower ill-health index (point estimates range from -.005 to -.007 and are all statistically significant). What is more, the propensity to work full time (part time) correlates negatively(positively) with mental ill-health. And our point estimates show that this effect is relatively strong. Next come the estimates of the impact of the total number of jobs held by the respondent. These show that the higher that number, the higher is the mental ill-health index ceteris paribus. In the same vein, the larger the number of gaps of 6 months (or more) between two jobs, the

[8] As already explained, Weighing is done using the duration of the different jobs spells (themselves weighted to account for the part-time vs. full-time nature of the spell).

[9] Note that the point estimate for the last job is not statistically different from that for the first job (H0 equality has a p-value of .51).

worse people's mental health. And finally, the larger the number of times they have been made redundant, the worse their mental health past the age of 50. And it is interesting to note that it is for the latter variable that the point estimates are the largest: while an extra job leads to a .008 to .0137 rise of our standardised ill-health index, an extra redundancy translates into .0423 to .514 rise of that index.

Further down, in Table 4 are the results about the respondent's health endowment. Compared to someone who declares her childhood health to have been excellent, someone saying it was poor suffers a .303 to .408 rise of her ill-health index. That seems to be a powerful effect. The death status of parents also matters. Having a father who died early leads to a .04 to .05 rise of the ill-health index. And having a mother who died early translates into slightly lower increments, ranging from .0249 to 0.0312. The rest of Table 4 contains the coefficients highlighting the important contribution of educational attainment to late-life mental health. Compare to people with no education (our reference group), those with master-level attainment display an ill-health index that is -.35 to -.37 lower. The lowest part of the table contains the country fixed effects (ref. being Austria= AUT). The magnitude of some of these (e.g. Greece .34 to .35, or France .17 to .21) underlines the importance of the country you live in for mental health.[10]

[10]These fixed effects may capture the role of cultural factors, including how these drive the propensity of people to openly talk about their mental health issues (Gove and Geerken, 1977).

Table 4: Detailed results of regression analysis of mental ill=health SHARE index

	M1	M2	M3	M4	M5	M6
Ard. (car. av.)	0.0425***			0.0308***		
	(0.0066)			(0.0076)		
Ard. (first job av.)		0.0289***				
		(0.0064)				
Ard. (last job av.)			0.0329***			
			(0.0064)			
Ard. <30 (dev. from car. av.)				0.0039		
				(0.0165)		
Ard. 30-<40 (dev. from car. av.)				0.0316		
				(0.0279)		
Ard. 40-<50 (dev. from car. av.)				0.0049		
				(0.0331)		
Ard. 50+ (dev. from car. av.)				-0.0201		
				(0.0220)		
Ard. (car. av.) [perc.])					0.0014***	
					(0.0002)	
Ard. (car. av. EUR) [perc.]						0.0016***
						(0.0002)
Car. duration	-0.0070***	-0.0068***	-0.0069***	-0.0050***	-0.0070***	-0.0069***
	(0.0005)	(0.0005)	(0.0005)	(0.0010)	(0.0005)	(0.0005)
Propensity full-time[a]	-0.1080**	-0.1058**	-0.0967*	-0.1075*	-0.1069**	-0.0923*
	(0.0499)	(0.0514)	(0.0514)	(0.0606)	(0.0499)	(0.0499)
Numb. of jobs	0.0128***	0.0105***	0.0137***	0.0083**	0.0127***	0.0118***
	(0.0034)	(0.0036)	(0.0036)	(0.0037)	(0.0034)	(0.0034)
Numb. of 6m gaps	0.0373***	0.0385***	0.0356***	0.0406***	0.0370***	0.0359***
	(0.0077)	(0.0081)	(0.0081)	(0.0089)	(0.0077)	(0.0077)
Numb. of redun.	0.0437***	0.0514***	0.0423***	0.0465***	0.0435***	0.0446***

Table 4 – continued from previous page

	M1	M2	M3	M4	M5	M6
	(0.0087)	(0.0091)	(0.0092)	(0.0098)	(0.0087)	(0.0087)
Ch. health very good	0.0084	0.0082	0.0061	-0.0018	0.0083	0.0083
	(0.0125)	(0.0129)	(0.0129)	(0.0138)	(0.0125)	(0.0125)
Ch. health good	0.0929***	0.0972***	0.0927***	0.0802***	0.0927***	0.0921***
	(0.0132)	(0.0136)	(0.0136)	(0.0147)	(0.0132)	(0.0132)
Ch. health fair	0.2891***	0.2925***	0.2840***	0.2572***	0.2892***	0.2887***
	(0.0194)	(0.0200)	(0.0200)	(0.0218)	(0.0194)	(0.0194)
Ch. health poor	0.3972***	0.4026***	0.4084***	0.3029***	0.3969***	0.3967***
	(0.0306)	(0.0317)	(0.0315)	(0.0359)	(0.0305)	(0.0305)
Ch. heatlh varied a lot	0.1563**	0.1621**	0.1445*	0.1226	0.1563**	0.1581**
	(0.0783)	(0.0800)	(0.0805)	(0.0875)	(0.0783)	(0.0782)
Fath. died early	0.0567***	0.0574***	0.0583***	0.0418**	0.0563***	0.0564***
	(0.0182)	(0.0188)	(0.0189)	(0.0201)	(0.0182)	(0.0182)
Fath. died late	0.0090	0.0076	0.0033	-0.0038	0.0088	0.0095
	(0.0184)	(0.0190)	(0.0191)	(0.0202)	(0.0184)	(0.0184)
Moth. died early	0.0293**	0.0266*	0.0312**	0.0249	0.0290**	0.0287**
	(0.0141)	(0.0145)	(0.0146)	(0.0157)	(0.0141)	(0.0141)
Moth died late	-0.0068	-0.0060	-0.0022	-0.0061	-0.0068	-0.0070
	(0.0148)	(0.0153)	(0.0153)	(0.0164)	(0.0148)	(0.0148)
Primary	-0.1407***	-0.1418***	-0.1468***	-0.1307***	-0.1419***	-0.1409***
	(0.0310)	(0.0318)	(0.0315)	(0.0368)	(0.0310)	(0.0310)
Lower sec.	-0.2137***	-0.2215***	-0.2181***	-0.1981***	-0.2137***	-0.2118***
	(0.0309)	(0.0316)	(0.0314)	(0.0364)	(0.0309)	(0.0309)
Upper sec.	-0.2913***	-0.3022***	-0.3035***	-0.2748***	-0.2887***	-0.2812***
	(0.0307)	(0.0314)	(0.0312)	(0.0361)	(0.0307)	(0.0307)
Post sec.(non tertiary)	-0.3200***	-0.3397***	-0.3263***	-0.2933***	-0.3169***	-0.3025***
	(0.0367)	(0.0376)	(0.0374)	(0.0419)	(0.0367)	(0.0369)

Table 4 – continued from previous page

	M1	M2	M3	M4	M5	M6
Tertiary (1st stage)	-0.3422***	-0.3601***	-0.3519***	-0.3191***	-0.3373***	-0.3194***
	(0.0317)	(0.0324)	(0.0322)	(0.0372)	(0.0317)	(0.0320)
Tertiary (2nd stage)	-0.3667***	-0.3778***	-0.3815***	-0.3578***	-0.3583***	-0.3486***
	(0.0573)	(0.0592)	(0.0586)	(0.0640)	(0.0574)	(0.0573)
12. Germany	0.1330***	0.1184***	0.1294***	0.1183***	0.1325***	0.1344***
	(0.0257)	(0.0263)	(0.0265)	(0.0289)	(0.0257)	(0.0257)
13. Sweden	0.0445	0.0337	0.0326	0.0026	0.0444	0.0503*
	(0.0276)	(0.0282)	(0.0282)	(0.0298)	(0.0276)	(0.0276)
15. Spain	0.0170	0.0091	0.0075	-0.0012	0.0192	0.0159
	(0.0269)	(0.0274)	(0.0274)	(0.0303)	(0.0269)	(0.0269)
16. Italy	0.2168***	0.2102***	0.1962***	0.1750***	0.2192***	0.2195***
	(0.0278)	(0.0283)	(0.0283)	(0.0312)	(0.0278)	(0.0277)
17. France	0.3115***	0.3204***	0.3118***	0.3138***	0.3121***	0.3095***
	(0.0288)	(0.0303)	(0.0301)	(0.0332)	(0.0288)	(0.0288)
18. Denmark	0.0135	-0.0060	-0.0084	-0.0437	0.0143	0.0096
	(0.0298)	(0.0320)	(0.0321)	(0.0346)	(0.0298)	(0.0298)
19. Greece	0.3905***	0.3720***	0.3942***	0.3531***	0.3916***	0.3831***
	(0.0425)	(0.0435)	(0.0435)	(0.0492)	(0.0425)	(0.0424)
20. Switzerland	-0.0116	-0.0288	-0.0290	0.0146	-0.0106	-0.0088
	(0.0304)	(0.0314)	(0.0314)	(0.0348)	(0.0304)	(0.0304)
23. Belgium	0.2920***	0.2741***	0.2701***	0.2434***	0.2931***	0.2894***
	(0.0257)	(0.0265)	(0.0266)	(0.0291)	(0.0257)	(0.0257)
25. Israel	0.1646***	0.1484***	0.1506***	0.1680***	0.1652***	0.1691***
	(0.0311)	(0.0318)	(0.0318)	(0.0354)	(0.0311)	(0.0311)
28. Czech Republic	0.1077***	0.1040***	0.0961***	0.0662**	0.1073***	0.1138***
	(0.0250)	(0.0255)	(0.0255)	(0.0271)	(0.0250)	(0.0250)
29. Poland	0.3874***	0.3872***	0.3824***	0.4107***	0.3860***	0.3790***

Table 4 – continued from previous page

	M1	M2	M3	M4	M5	M6
	(0.0558)	(0.0578)	(0.0583)	(0.0656)	(0.0558)	(0.0558)
31. Luxembourg	0.2244***	0.2112***	0.1975***	0.2372***	0.2262***	0.2261***
	(0.0346)	(0.0358)	(0.0359)	(0.0410)	(0.0346)	(0.0346)
32. Hungary	0.4077***	0.3708***	0.3764***	0.3788***	0.4077***	0.4080***
	(0.0600)	(0.0663)	(0.0673)	(0.0740)	(0.0600)	(0.0600)
33. Portugal	0.3867***	0.3799***	0.3826***	0.3036***	0.3887***	0.3921***
	(0.0583)	(0.0601)	(0.0600)	(0.0680)	(0.0583)	(0.0583)
34. Slovenia	0.0693***	0.0463*	0.0517*	0.0116	0.0695***	0.0724***
	(0.0257)	(0.0264)	(0.0265)	(0.0294)	(0.0257)	(0.0257)
35. Estonia	0.3328***	0.3293***	0.3271***	0.3090***	0.3304***	0.3360***
	(0.0242)	(0.0250)	(0.0250)	(0.0269)	(0.0242)	(0.0242)
47. Croatia	0.2200***	0.2188***	0.2097***	0.1661***	0.2204***	0.2267***
	(0.0303)	(0.0308)	(0.0308)	(0.0355)	(0.0303)	(0.0303)
Constant	0.0463	0.0704	0.0527	-0.0369	-0.0300	-0.0569
	(0.0681)	(0.0699)	(0.0699)	(0.0856)	(0.0698)	(0.0699)
Age	X	X	X	X	X	X
Gender	X	X	X	X	X	X
Age$X$Gender	X	X	X	X		X
N	32,449	30,587	30,515	23,652	32,449	32,449

Source: SHARE 2004-2017, O*NET 2021, EWCS 1991-2015

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a]:]0,1] Propensity to work full-time is computed as the career duration in full-time-equivalent years (FTE) divided by that duration in years. For instance, someone who has always work full time will have a propensity equal to 1, while someone who always worked part-time will have a propensity equal to .5. People who always alternated part-time and full-time will have a propensity of .75. Standard errors in parentheses.

4.2 Endogeneity concerns

Delivering an unbiased estimate of the impact of career arduousness on mental health is challenging. There are several endogeneity/selection concerns. A significant correlation between occupation and long-term mental health can reveal a causal impact, but it may also stem from reverse causality/selection; with poor health constraining occupational choice (e.g. access to more demanding/stressful jobs). Such a constraint may intervene at the entrance of the labour market, or during the career, whereby the deterioration of health (i.e. mental health shocks) could lead people to abandon more demanding/stressful occupations. In health economics, this type of selection is known as the"healthy worker bias" and is mentioned in most papers as a potential source of bias towards zero in the results (Bassanini and Caroli, 2015). Endogeneity may also stem from other unaccounted factors: unobserved heterogeneity in terms of (risk) preferences can correlate both with mental health and occupational choice. Risk lovers, for instance, may be more susceptible to depression but pick more arduous/less stable jobs. The empirical literature always struggles to cope with either of these problems. It is challenging to find a plausible truly exogenous variation of occupation arduousness/instability. In this paper, we are not able to fully address the problem of unobserved heterogeneity in terms of preferences, but we believe we have a good chance of limiting the problem of the healthy worker bias.

First, we control for health until the age of 15; that means before people pick their first occupation and enter the labour market. Moreover, the inclusion of the parents' longevity/death status controls for the inherited part of people's initial health endowment, which is also, by definition, something that is set before people enter the labour market. Table A2 in the Appendix reports the result of the ancillary regression of the arduousness of the first job arduousness on the initial health endowment. The first two columns (M1, M2) show that, in particular, the longevity/death status of the parents is correlated with the arduousness of the first job. And we can see (M1) that respondents whose parents died early tend to self-select into more arduous jobs, even when conditioning of educational attainment (M2). Not accounting for that health endowment variable would translate into a biased estimation of the impact of career arduousness on late-life mental health. Gelbach (2016) reminds us of the well-known formula of the omitted variable bias and its relevance in this context. If we had estimated our model without controlling for health endowment $Hendow$, the value of the baseline estimated β^b would have deviated from the "true" β according to $\beta^b = \beta + \Pi\gamma$; where γ is the impact of health endowment on mental ill-health in equ (1) and Π is the correlation between health endowment and arduousness. The product of these two captures the effect of arduousness that operates via the health endowment. Note that the reasoning also applies to our point estimates of the impact of career instability. Including health endowment among the regressors leads to point estimates that have been netted out from the effect of career instability operating via the health endowment.

Second, regarding the deterioration of health during the career and its impact on arduousness, it is important to stress that we consider the impact of occupation on mental health beyond the age of 50. There is thus a significant *lag* between the moment of exposure to a certain job arduousness and the moment mental health is assessed. By construction, this eliminates some of the risk of bias compare to when arduousness and health are assessed simultaneously. Moreover, we assess the impact of job arduousness measured at distinct moments of the career (first vs. last job, age < 30 vs. age 50plus) (M2, M3, M4 in Table 4). And it seems reasonable to assume that the intensity of the healthy worker bias is stronger when using the arduousness of the last job, or that recorded over the 50plus age band. The point, however, is that we show in Table 4 that using the arduousness of the first vs. last job (M2, M3) does not matter for late-life mental health. We strongly reject the possibility that the two point estimates are unequal. And we reach a similar conclusion when we consider arduousness for different age bands (i.e. before the age of 30 or after 50).

Although this is more an addendum, it is interesting to examine the results of the ancillary regressions that we report in the Appendix (Table A2). The right-hand part of that table explores what influences the "gradient" of arduousness over the career, and in particular if initial health influences it. Note that our dependent variable is the arduousness gradient. This is because of the overall tendency of arduousness to be reduced as people progress in their career and get older. What matters for endogeneity is whether that trend differs due to pre-labour-entry health issues. Note that we do not know about the dynamic of health during the career (or about the occurrence of health shocks). We only know about health before people enter the labour market and proxies of the health endowment they might have inherited from their parents. But we believe it interesting to examine whether the arduousness trend correlates with these items. The arduousness gradient is computed first as the difference between the last and the first job, and then as the difference between the arduousness recorded over the 50+ and the <30 age bands. Both gradients are negative on average. This implies that negative (positive) point estimates reported in (Table A2) highlight variables that amplify(moderate) the reduction of arduousness over the course of the career. In both cases, we see positive and statistically significant point estimates for respondents whose parents died early, suggesting a slower reduction of arduousness. And note that we get this result when including the level of arduousness of the first/age< 30 job in the regression. These results do not validate the idea that initially less healthy people self-select into less arduous jobs for their career, to the contrary. Said differently, what we detect here in more an"unhealthy worker bias". This said, from an econometric point of view, these results are supportive of the idea that there is a risk of bias because of selection driven by people's health endowment. Hence, the importance of including variables describing that endowment if the aim is to properly estimate the net contribution of career arduousness or instability on late-life mental health.

4.3 Variance Decomposition

In Table 5 we display the results of the variance decomposition exposed in eq. (2), (3),(4). The underlying coefficients are from the OLS-estimated eq. (1) as reported in Table 4. And there is a perfect correspondence between the different variance decomposition results reported in the different columns of the table and the regression models (M1-M6). For the sake of clarity, we have computed the covariance shares for *blocks* of regressors combined using their OLS-estimated coefficients:

- Career ardu.: comprises the measurement(s) or arduousness (career weighted average, first/last jobs, career average plus age-band-specific deviation, European measurement of arduousness);
- Career prof.: regroups all the variables relative to the career profile/instability (duration of career, propensity to have worked full-time, number of jobs, breaks of 6 months+ or redundancies);
- Health endow. : regroups childhood health and parental longevity/death status.
- Educ: corresponds to the educational attainment categories (ISCED scale);
- Country: corresponds to the country fixed effects.

Note that the reported covariance share uses as denominator the non-demographic model-predicted variance. In other words, $\widehat{Mhealth}_{i,j}$ is computed using only the non-demographic variables and their corresponding OLS-estimated coefficients. And the reported shares (in % points) inform of the importance of the considered factor in explaining the mental health variance that exists beyond what can be ascribed to age, gender and the interaction between these two. Results are essentially threefold. First, career arduousness is a statistically significant, but relative small contributor to the variance of mental health. It accounts for 3.6 to 5.87% of the total variance considered. Second, the career instability matters more, with a contribution raging from 14.7 to 21.9%. This is confirmed by the ratios reported on the penultimate line of Table 5, ranging from .72 to .89. Said differently, the profile of a career and its instability account for between 75% and 90% of what all we can attribute to people's career. Third, health endowment, educational attainment and the country of the respondent matter a lot for mental health. Together, these three blocks of variables account for over 70% of the variance we consider.

Table 5: Variance decomposition analysis[a]

	M1	M2	M3	M4	M5	M6
Career ardu. [s1]	4.85***	2.63***	3.63	3.77***	5.87***	8.43***
	(0.865)	(0.515)	(1.851)	(0.221)	(0.730)	(0.852)
Career prof. [s2]	21.91***	21.99***	21.61***	14.70***	21.69***	21.48***
	(1.585)	(1.160)	(2.108)	(3.001)	(1.553)	(1.600)
Health endow.	25.01***	25.37***	25.76***	23.86***	24.87***	24.45***
	(2.854)	(3.838)	(3.802)	(1.824)	(2.807)	(2.637)
Educ	15.38***	16.62***	15.92***	14.13***	14.91***	13.55***
	(2.817)	(1.309)	(2.363)	(2.343)	(2.869)	(3.132)
Country	32.86***	33.38***	33.08***	43.30***	32.65***	32.09***
	(0.947)	(1.816)	(2.983)	(2.204)	(0.949)	(0.737)
Career prof. ratio [s2/(s1+s2)]	0.82***	0.89***	0.86***	0.80***	0.79***	0.72***
	(0.032)	(0.014)	(0.048)	(0.034)	(0.027)	(0.036)
N	32,449	30,587	30,515	23,652	32,449	32,449

Source: SHARE 2004-2017, O*NET 2021, EWCS 1991-2015
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Bootstrapped standard errors and p-values, with 1000 replications.
[a]: There is a perfect correspondence between the variance decomposition and the underlying regressions (M1-M6) presented in Table 4.

5 Conclusion

This paper explores the long-term consequences of career arduousness[11] and instability on mental health. It combines regression and variance decomposition methods to quantify the impact of these beyond the age of 50. The analysis is carried out simultaneously for 19

[11]The industrial relations literature often use the term *job demands* instead of arduousness.

European, but contrasted countries[12]: Austria- AUT, Belgium- BEL, Switzerland- CHE, Czech Rep.- CZE, Germany - DEU, Denmark- DNK, Spain- ESP, Estonia -EST, France-FRA, Greece- GRC, Croatia-HRV, Hungary-HUN, Israel-ISR, Italy-ITA, Luxembourg-LUX, Poland- POL, Portugal-PRT, Slovenia-SVN, Sweden-SWE.

The most significant finding of this paper is that whilst someone's career arduousness is a significant contributor to poor mental health at an older age, it appears still (quantitatively) a minor determinant. Career instability (i.e. the number of jobs held, long gaps of 6 months+, the number of redundancies...) matters more *ceteris paribus*. Our best estimate suggests that career instability is up to four times as important as job arduousness/demands for explaining the variance of mental health at an older age. The policy implications of that result are not to be underestimated. In most advanced economies, the regulatory apparatus aimed at fostering individuals' short- and long-term well-being is still primarily focused on improving workers' conditions, i.e. lowering the physiological and psychological demands put on them *while they work*, improving their work environment and the terms of their job. However, what our results suggest is that people's long-term mental health status might be more determined by the incidence of non-work episodes (those for which arduousness is apriori minimal as they are synonymous with *full leisure*), loose job attachment or the consequences of repetitive job displacement.

Another key finding is that pre-labour-market entry status matters a lot for mental health beyond 50; perhaps even more than the characteristics of the professional career (arduousness and instability confounded). Initial health endowment (proxied here by childhood health and the longevity of the respondent's parents) and educational attainment explain a larger part of mental health differences past the age of 50 *ceteris paribus*. Another important contributor is also simply the country of residence of the respondent. For public policy, these findings imply social policies aimed at promoting older people's mental health in the context of active ageing (including a postponement of the effective age of retirement) and health ageing strategy should also go beyond people's career stage and target social/health conditions early in childhood or foster the access to tertiary education.

This being said, is important to stress that the data, methods and results presented in this paper suffer limitations and call for additional research. First, SHARE does not include a repeated assessment of mental health during the career history. This a limitation if one is interested in exploring the dynamic relationship between the evolution of mental health and

[12] GDP per head data show an over 4 to 1 ratio between the wealthiest (Luxembourg-LUX) and the poorest (Croatia-HRV).

the unfolding of a career (Ravesteijn et al., 2018). Also, in SHARE, the participant's history is reported retrospectively and a long time since it happened (i.e. a SHARE respondent in 2017 must recall his work history since 1970 if he worked from the age of 20). This can lead to memory biases. Finally, as mentioned in the data section, the mental health variables in SHARE mostly measure depression/suicidality. This is already a lot better compared to what was available in most surveys a few years ago, but one may wonder what would be the outcome of our analysis using a "broader" definition of mental health, with — paralleling what is available for physical health — systematic information about specific conditions (schizophrenia, severe depression, severe bipolar disorders...).

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Appendix

Table A1: SHARE: waves and countries

	1	2	4	5	6	Total
AUT	0	5	96	399	1,730	2,230
BEL	2	3	6	205	2,409	2,625
CHE	0	2	10	56	1,312	1,380
CZE	0	1	94	257	2,568	2,920
DEU	0	2	0	165	2,337	2,504
DNK	0	1	1	90	1,453	1,545
ESP	2	6	22	479	2,143	2,652
EST	0	0	51	372	3,373	3,796
FRA	1	2	50	158	1,439	1,650
GRC	2	11	0	0	543	556
HRV	0	0	0	0	1,461	1,461
HUN	0	0	236	0	0	236
ISR	13	74	0	277	1,074	1,438
ITA	4	5	16	243	1,802	2,070
LUX	0	0	0	87	835	922
POL	0	2	12	0	273	287
PRT	0	0	20	0	259	279
SVN	0	0	14	102	2,474	2,590
SWE	2	2	12	162	1,823	2,001
Total	26	116	640	3,052	29,308	33,142
N	33,142					

Source: SHARE 2004-2017, O*NET 2021, EWCS 1999-2015

Table A2: Ancillary regression: the determinants of first-job arduousness and its evolution between the age of 30- and 50+

	First job ardu.		Evolution of job ardu.			
			Last - first job		Aged 50+ - aged < 30	
	M1	M2^a	M1	M2	M3	M4
Ardu. first job			-0.354***	-0.465***		
			(0.004)	(0.005)		
Ardu. age <30					-0.217***	-0.286***
					(0.004)	(0.005)
Poor childhood health^b	0.003	0.006	-0.001	-0.004	-0.002	-0.004
	(0.017)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)
Moth. died early^c	0.121***	0.043***	0.046***	0.028***	0.029***	0.020***
	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
Fath. died early^c	0.081***	0.039***	0.037***	0.024***	0.019***	0.012*
	(0.011)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
Primary		0.067**		0.009		0.023
		(0.029)		(0.024)		(0.024)
Lower sec.		-0.138***		-0.095***		-0.023
		(0.028)		(0.024)		(0.024)
Upper sec.		-0.512***		-0.292***		-0.144***
		(0.028)		(0.024)		(0.024)
Post sec.(non tertiary)		-0.612***		-0.350***		-0.201***
		(0.034)		(0.029)		(0.028)
Tertiary (1st stage)		-0.939***		-0.522***		-0.293***
		(0.029)		(0.025)		(0.024)
Tertiary (2nd stage)		-1.353***		-0.674***		-0.404***
		(0.053)		(0.045)		(0.042)

Table A2 – continued from previous page

	First job ardu.		Evolution of job ardu.			
			Last - first job		Aged 50+ - aged < 30	
	M1	M2[a]	M1	M2[a]	M3	M4[a]
N	30,784	30,587	29,304	29,112	24,662	24,501
Age		X		X		X
Gender		X		X		X
Age$X$Gender		X		X		X
Country(FE)		X		X		X

Source: SHARE 2004-2017, O*NET 2021, EWCS 1991-2015

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses.

[a]:Comprises Age, Gender, Age$X$Gender dummies and country FE.

[b]:Binary version: 1= varied a lot, poor fair; 0= good, very good, excellent.

[c]:Binary version: 1= parent died early, 0= parent still alive, died late.