Career Arduousness and Instability.

Both Matter for Health Beyond 50

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Vincent Vandenberghe*

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Abstract

This paper explores the long-term consequences of career arduousness and career instability for both physical and mental health in the European context. One of its strengths is to link what happens during the entire career and the health status at an older age. The paper 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 and physical ill health, but also evidence that career instability (i.e. career gaps, job insecurity, displacements, unemployment spells) could matter as much as arduousness *per se*. And this has implications for pension policy *inter alia*.

Keywords: Career Arduousness and Instability, Pre-Labour Determinants of Late-Life Health, Regression, Variance Decomposition

JEL Codes: J81, J24, I10, J26

*Economics School of Louvain (ESL), IRES-LIDAM, Université catholique de Louvain (UCL), 3 place Montesquieu, B-1348 Belgium. Corresponding author: vincent.vandenberghe@uclouvain.be

1 Introduction

This paper aims at contributing to the economic literature on the long-term health consequences[1] of career arduousness but also `career instability`. The still widespread view – probably inherited from a not-so-distant past where most workers were executing manual/physically demanding tasks – is that work is predominantly arduous and that its accumulation is by definition detrimental to health. But the observation of modern economies suggests that such a monolithic vision of work and its impact on health needs to be enriched. In this paper, we posit that people's mental and physical health might also be determined by the incidence of `non-work episodes` (those for which arduousness is a priori minimal as they are synonymous with rest or leisure), loose job attachment or the consequences of repetitive job changes/displacements, in short: career instability.

One of the key contributions of the paper to the literature stems from our ability to link what happens during the entire career and the health status at an older age. To explore the respective role of career arduousness and instability, this paper exploits unique, and so far untapped retrospective European SHARE[2] data on careers that simultaneously document occupational arduousness and instability, and rich data on physical and mental health measured on a sample of individuals when they are aged 50+; thus after what we call their career throughout this paper.[3] Also, this paper assesses the `relative` importance of pre-labour determinants[4] in driving the risk of poor health in late years (Trannoy et al., 2010), and how much they matter for late-life health compared to career arduousness and instability. In doing so, our goal is not such much to establish that these pre-labour factors play a role (something that the literature reviewed below has established), but to get an idea of how much they matter compared to career/work-related determinants.

Several policy questions are related to such a research agenda. The first one is the way to account for career heterogeneity in pensions, singularly when policymakers, as in Europe now, raise the age of retirement. One concern is whether such a policy is fair, as some elderly workers may lack the capacity to work longer because of health problems. The standard view is that those who are the most at risk are those who worked for many years in arduous occupations. And the usual policy recommendation is to differentiate the retirement age according to the arduousness of the career (Ayuso et al., 2016; Leroux

[1] Beyond the age of 50.

[2] Survey of Health, Ageing and Retirement in Europe (SHARE) (Börsch-Supan et al., 2013).

[3] Health is measured at the moment of the interview, among individuals whose age range from 50 to 75 and more. Health is thus measured when respondents are retired and, in any case, after the period used to compute career arduousness and instability.

[4] Inherited or emerging during childhood, before people start working

et al., 2015).[5] There is the issue of the feasibility of such a policy, which is examined for example in Vandenberghe (2021b) or Baurin et al. (2022). Our point here is more about the relevance of such a policy if other aspects of a career also matter a lot. Should the right to retire early be solely granted to those who had an arduous career? Or should it also (and perhaps primarily) be granted to individuals who experienced an unstable one? This paper contains evidence that today, in Europe, career instability could matter as much as arduousness for the risk of late-life ill health, and thus that a fair retirement age policy should deal with more than career arduousness.

The second policy question is how best to prevent/minimize the risk of late-life ill health. If that risk is only a matter of career arduousness, then the only focus should be on instruments reducing the incidence and duration of arduous work; e.g. stricter health and safety or working-time regulations aimed at lowering the physiological and psychological demands put on individuals while they work. But if the risk is also driven by career instability, then the instruments to be mobilised (and prioritised if instability turns out to matter a lot) are different. They comprise replacement income schemes (unemployment insurance), basic/unconditional income (Van Parijs, 2017); or active labour market programmes that provide coaching, mentoring, job placement, or job-related training. Also from a prevention point of view, our focus in this paper on quantifying the relative contribution of the pre-labour market entry determinants of long-term health status may usefully inform policymakers.[6] If people's initial health endowment (proxied hereafter by childhood health and the longevity of the respondent's parents) or educational attainment explain a larger part of mental or physical health differences past the age of 50, then policies aimed at promoting older people's health and well-being should more systematically go beyond people's career stage, and target in priority social/health conditions early in childhood.

The contribution of this paper to the literature on arduous/unstable occupations and late-life health (Vermeer et al., 2016; Vandenberghe, 2021b; Wise, 2017; Vandenberghe, 2021c) is essentially fourfold.

First, we attempt to account for the role of `career arduousness`. Conceptually, hereafter, arduousness relates to how that concept is defined in the job demands and job quality literature (Bakker and Demerouti, 2007; Chen et al., 2017). A more arduous/demanding

[5] Related proposals recommend differentiating contributions or replacement rates.

[6] As will become clear in the literature review, our paper is certainly not the first to identify the existence of a link between initial/childhood health and late-life health, but it delivers numeric results on how important pre-labour determinants are compared to career/work-related ones.

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. The point is that the job demands literature has abundantly shown that occupations are not equally stressful or physically demanding and that they may affect individuals' job performance and health. What differentiates our approach from most of the job demands literature is that 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 quantify the arduousness throughout someone's career. With these data, we can account for the duration of these occupations and, as people change occupations, how these changes contribute to the cumulative 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 health is something new in the economic literature.

Second, we simultaneously assess the role of `career instability`. A career is not just a succession of more or less arduous (full-time) jobs. That vision might have been valid in the past when the vast majority of people were toiling in manual/non-mechanised jobs. In modern economies, there is a need to go beyond arduousness. Work by Bassanini and Caroli (2015) has highlighted that what is detrimental to health is not so much work per se but, for instance, the gap which may exist between the actual and the desired amount of work. In this paper, we have no way to assess the health consequences of constrained vs. chosen work, but we can assess those of work instability vs. arduousness. People may indeed work part-time, alternate part-time and full-time jobs, experience spells of non- or unemployment, and 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 (in)stability.

And there is evidence that instability contributes to ill health. Vodopivec et al. (2021) for instance, use administrative longitudinal data to assess the risk of cardiovascular disease (CVD) for men aged 50-65 with a history of distant unemployment – that occurred during the past 6–10 and 11–15 years. Estimating a hazard model, they show that past unemployment significantly affects the hazard of CVDs. Estimated coefficients that are statistically significant imply hazard ratios of 1.10 to 1.26, reflecting the elevation of hazard rates associated with unemployment in the past 6–10 or 11–15 years compared to hazard rates of permanently employed workers. The Bassanini and Caroli (2015) paper is a review of the economic literature on work and health. Regarding the link between unemployment/job loss and health, the authors conclude that the impact found is generally negative. No article ever finds a positive health effect of becoming unemployed. Using the 2010 European Working Conditions Survey (EWCS), Caroli and Godard (2016) find that job insecurity —defined as the perceived risk of job loss — has a negative effect on a few health outcomes, including suffering from headaches or eye strain and skin problems.

This paper intends to assess simultaneously the contribution of career arduousness and career (in)stability. There are many works on the link between job arduousness and health (Bassanini and Caroli, 2015). There are also many works on the relationship between job instability and (mostly mental) health (Barnay, 2016). They focus on unemployment or job insecurity and subjective well-being (see Chadi and Hetschko (2021) for a recent review); some on mental health *per se*. 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 of individual workers in five countries (Australia, Canada, Korea, Switzerland and the United Kingdom), OECD (2012) also confirms that mental health suffers when individuals move from employment to unemployment or inactivity. Our point is that there are few papers, at least by economists, that look simultaneously at arduousness `and` career instability, although both aspects can undermine physical and/or mental health cumulatively over the life course (Lindeboom, 2012). We aim to fill that void and quantify their relative contribution to the risk of late-life ill health.

Third, we try to account for what epidemiologists call people's `health endowment` and other pre-labour[7] determinants of late-life physical and mental health. Regarding mental health, epidemiologists (Kessler et al., 2005) show that 50% of all mental disorder lifetime cases start at age 14, and 75% by age 24. Hakulinen et al. (2019) show that these have a detrimental impact on educational attainment and labour market status. Hoven et al. (2017) find that early "adversity" is linked with early retirement. There is also the life course literature that stresses the long-lasting effects of family and social background (including educational attainment) on general health status in adulthood. Recent empirical contributions comprise Mazzonna (2014) or Antonova et al. (2017) using SHARE wave 3 data[8]; and also the recent paper by Zhu and Liao (2021), using data from the Chinese equivalent of SHARE, the China Health and Retirement Longitudinal Study (CHARLS). 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

[7]Decided or determined before people enter the labour market.

[8]That wave of SHARE collected retrospective information on respondents' family backgrounds during their childhood similar to the one collected via Wave 7 that we use here. But wave 3 did not contain retrospective information about people's careers.

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. A large body of literature equally acknowledges the role played by the social determinants of health (Marmot and Wilkinson, 2005). As far as we know, the job arduousness literature has overlooked the possibility of a link between early life/pre-labour factors and health in adulthood or old age. This paper aims to remedy that situation by delivering estimates of the health-deteriorating role of career arduousness (or instability) from which the contribution of health endowment has been netted out. Our data on health endowment comprise the health status during childhood[9] and also information about the death status of parents (more on this below in Section 2). From an econometric point of view, these variables represent a source of selection bias. They must be considered to measure correctly the net effect of professional occupation on the risk of ill health. The point 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 impact of people's careers on their long-term health.

Fourth, we pay equal attention to `physical and mental health` beyond the age of 50. Mental health has so far received slightly less attention, at least by economists. Notable exceptions comprise the work of Catalano et al. (1999); Lu et al. (2009); Cutler and Wise (2009); OECD (2012); Frijters et al. (2010); Frijters et al. (2014); Vandenberghe (2021a). In particular, Maclean et al. (2015) find a negative relationship between self-assessed adverse labour market events (problems with coworkers, employment changes, financial strain) and mental health. Still, our paper can be seen as a response to invitations to pay more attention to mental health in economics (Layard, 2013).

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.[10] We can identify each respondent's last and first occupation, and all those occupied in between. SHARE informs on the number of job 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 career instability proxies. Second, although SHARE provides a lot

[9]Before the respondent turns 15.

[10]SHARE wave 3 also contained retrospective employment modules, but not with the degree of detail available in wave 7. For example, job history in wave 3 is only available at ISCO 1 digit while is it at ISCO 4 digits in wave 7.

of information about people's careers, it falls short of informing about the arduousness of successive jobs.[11] 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 the data Section 2, 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. Then, as we do in this paper, these indices can be imported into SHARE and applied to each job spell forming SHARE respondents' careers, using the ISCO code as a merge variable. More on this in Section 2.2.

Another specificity of the paper is that it uses a variance decomposition method to assess the relative importance of career arduousness vs. instability as determinants of ill health past the age of 50; or that of professional career vs. early-life/pre-labour determinants. Traditionally, to assess the importance/relevance of factors, economists rely on the direct comparison of (standardised) regression coefficients. But this approach has limitations. 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 or educational attainment? Also, how to assess the importance of groups of variables, some of whom might be continuous and others categorical? To overcome this non-comparability/grouping problem, we propose using (alongside the traditional standardization of regression coefficients) the method pioneered by Fields (2004) in labour economics and used more recently by Jusot et al. (2013) in health economics. It implies supplementing the regression analysis with a decomposition of the variance of the outcome variable explained by the estimated model.[12] As will become clear in Section 3, the decomposition extensively uses the model-predicted values of health, and the estimated coefficients.[13] It thus is a direct extension of the regression analysis rather than a separate exercise. Fields (2004) shows how regression models can be supplemented by these decompositions to quantify the relative importance of different explanatory factors. In pure regression analyses, the emphasis is on the estimated coefficients and their statistical significance. When combined with variance decomposition, it is on the information content of the variables in question. In short, the idea is to consider the variance of health explained by the different groups of variables of the model, singularly those quantifying respondents' career arduousness and instability; and compute the respective shares that can be attributed to each group.

[11] Other shortcomings comprise the lack of retrospective data on wages and wealth. But these can be partially compensated by other SHARE data on work-related income/pensions. More on this in the data section.

[12] The importance of that model-explained variance is traditionally measured by the R^2.

[13] In Stata, this amounts to using the [predict] function

Finally, it is worth stressing that we quantify the impact of career arduousness or instability on health simultaneously for 26 European countries + Israël, using a fully harmonised data set. Compared to works using only national data, the advantage is that we analyse wider distributions of health and arduousness/instability. And this is a prior good for identification. At the same time, the presence of 27 quite contrasted countries risks biasing our estimates due to country-level unobserved heterogeneity.[14] We will explain below how we mitigate that risk.

The rest of this paper is organised as follows. The data on mental and physical health, career arduousness by ISCO occupation or career instability used in this paper are presented in Section 2. In Section 3, we present our method of analysis. Section 4 presents the main results of the paper as well as our discussion of endogeneity issues. Section 5 summarises the findings and discusses their policy implications.

2 Data

2.1 SHARE

As stated above, this paper makes extensive use of the 7th wave of the Survey on Health, Ageing and Retirement in Europe (SHARE). This wave was conducted in 2017 across 28 European countries plus Israel. The 7th wave contains several "retrospective" modules that provide detailed data about the respondent's history. Extensive information is provided about 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 37,035 wave-7 respondents, from only 27 out of the 29 participating countries (Table 1): Austria (AUT), Belgium (BEL), Bulgaria (BGR), Switzerland (CHE), Cyprus (CYP), Czech Rep. (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), Greece (GRC), Croatia (HRV), Hungary (HUN), Israel (ISR), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Sweden (SWE).

Our first variables of interest are physical and mental health i.e. our outcome variables. Both are measured at the moment of a SHARE interview, which means at an age that varies from 50 to 75 and more, depending on the age of the respondent. This means that

[14] Country-specific factors, like the quality of health care, or health and safety legislation, correlated with both the health and the career variables.

we will need to account for age heterogeneity in our analysis. Also, for all respondents included in the analysis, health is measured after the period corresponding to what we call their career (more on the latter below). Mental health is not available in Wave 7.[15] So we had to collect it from the adjacent waves 6 and 8 (see in Appendix, Table 14). We decided to do the same for physical health to ensure simultaneity of measurement for all our health outcomes.[16] As we explain in Section 4.3.1, this data limitation has its advantages when it comes to limiting a special version of the Common Method variance problem, namely the *justification bias* (Baker et al., 2004). This happens when survey respondents report values of health that are driven by what they say about their labour-market status, their job or occupation. The typical concern in labour/health economics is that un- or under-employed individuals report a lower level of health to justify their absence or lack of employment. A variant of this problem here would be that people modify (to some extent) what they say about their health given what they have just told the interviewers about their job history.

In SHARE, there are numerous items documenting respondents' physical health. In Table 3 we present those we have retained to build our physical ill health index. Most physical health items in SHARE are self-reported/subjective but many (that we prioritised here) explicitly refer to conditions diagnosed by health professionals (heart attack, hypertension, cholesterol, stroke, diabetes, lung disease, cancer,. . .) or directly measured by the SHARE interviewers like the maximum grip strength of respondents. In SHARE, mental ill health essentially means depression/suicidality: melancholy, diminished interest, sleep disorders or suicidal thoughts. . . The detailed list of items we use to build our mental ill health index is reported in Table 2. 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). Note that we also include (diagnosed) Alzheimer's disease and dementia to compute our mental ill health index. Both our mental and physical ill health indices are computed as first principal component of all items listed in Tables 3; 2. The principal component analysis is carried out with all countries pooled. The retained values are predicted score values divided by standard deviation. We report the statistical moments of the score distributions at the bottom of Tables 2 and 3.

Our next variables of interest are those describing the respondent's job history. In the 7$^{\text{th}}$ wave of SHARE, respondents are asked to retrace their complete job history by providing

[15] Wave 7 was used to collect many lifetime/history information from respondents. Due to time constraints, they were administered a simplified version of the standard rolling SHARE questionnaire.

[16] We do the same for our GDP measure.

the starting/ending year of each of their successive jobs/occupations, and whether these were done on a full- or part-time basis. A participant's history is reported retrospectively and thus a long time after work 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. The Life History Calendar (LHC) method uses a calendar-like matrix to map out life events, providing visual cues to both the interviewer and interviewee regarding the onset, duration, sequencing, and co-occurrence of events. The calendar includes rows, which are categories of life events; these might include schools attended, jobs, living arrangements, dating relationships, and so on. There are numerous innovations of the LHC that provide benefits relative to data collection through traditional questionnaires. The LHC's columns encourage recall at the temporal level, while the rows encourage recall at the thematic level. The LHC has been tested extensively with respondents of varying ages and cultural backgrounds, including those with unstable lives and cognitive difficulties (DeHart, 2021). The LHC 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/occupations 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 2.2). 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 ill health.

Table 4 presents the variables used in this paper as controls. They all come from the same waves (and thus are measured/self-reported a the same moment) as our health outcomes ie. waves 6 and 8. They comprise the age of the respondent. This variable allows us to estimate the baseline relationship between ill health and age. Unfortunately, SHARE contains no information about the history of income that we would have liked to include in the analysis alongside the career variables highlighted above. But in every wave (incl. waves 6 and 8) SHARE informs about people's work-related earnings. For the people who still work this corresponds to their salary or revenue as self-employed. For the others (ie. the majority of respondents included in the analysis) it corresponds to their pension. To maximize comparability across 27 countries (with quite different levels of average income, and also different currencies), we resort to the country$\times$wave income decile. This variable should be seen as a proxy of the income history of people. In most European countries, people who finish their career with a relatively high/low wage tend to have had such a (relative) level of income during their career. Also, the (relative) level of a pension – in countries that have predominantly inherited from the contributory/Bismarckian model of pensions – should be indexed on the level of earnings at each stage of people's careers.[17] Another control is SHARE respondents' education (ISCED attainment[18]).

Also in terms of controls, one strength of this paper is that it exploits SHARE information on respondents' initial health endowment (Table 4). Using one of the wave 7 retrospective modules, we can control for the (self-reported) health status of the individual up to the age of 15. In each wave, SHARE respondents also say if their parents are currently alive and declare the age at which they died. The lower part of Table 4 provides descriptive statistics on childhood ill health on a 1-6 scale, where 5 corresponds to the worst status (and 6 to a health status that varied a lot). The next two lines report the death status of the parents. We consider whether the 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).

[17]The other dimension is the duration of the career.

[18]International Standard Classification of Education (ISCED).

Table 1: SHARE: Wave 7 respondents aged 50+. Count by country and gender

	Male	Female	Total
Austria (AUT)	800	1,099	1,899
Belgium (BEL)	1,184	1,281	2,465
Bulgaria (BGR)	273	402	675
Switzerland (CHE)	659	701	1,360
Cyprus (CYP)	106	109	215
Czech Rep. (CZE)	1,063	1,615	2,678
Germany (DEU)	1,188	1,290	2,478
Denmark (DNK)	685	822	1,507
Spain (ESP)	1,126	1,111	2,237
Estonia (EST)	1,329	2,240	3,569
Finland (FIN)	392	437	829
France (FRA)	676	858	1,534
Greece (GRC)	315	246	561
Croatia (HRV)	772	805	1,577
Hungary (HUN)	123	177	300
Hungary (HUN)	518	600	1,118
Italy (ITA)	1,040	858	1,898
Lithuania (LTU)	285	543	828
Luxembourg (LUX)	431	463	894
Latvia (LVA)	108	167	275
Malta (MLT)	188	160	348
Poland (POL)	559	647	1,206
Portugal (PRT)	355	373	728
Romania (ROU)	317	283	600
Slovakia (SVK)	340	388	728
Slovenia (SVN)	1,148	1,470	2,618
Sweden (SWE)	926	984	1,910
Total	16,906	20,129	37,035

Source: SHARE 2004-2020 (Wave 7).

Table 2: SHARE: mental ill health items and indices^{c}: individuals aged 50+. Descriptive statistics

	mean	sd	min	max
Depression^{a,b}	0.39	0.49	0.00	1.00
Pessimism^{a}	0.17	0.37	0.00	1.00
Suicidality^{a}	0.05	0.22	0.00	1.00
Guilt^{a}	0.08	0.27	0.00	1.00
Sleep^{a}	0.37	0.48	0.00	1.00
Interest^{a}	0.10	0.29	0.00	1.00
Irritability^{a}	0.27	0.44	0.00	1.00
Appetite^{a}	0.09	0.28	0.00	1.00
Fatigue^{a}	0.35	0.48	0.00	1.00
Concentration^{a}	0.15	0.36	0.00	1.00
Enjoyment^{a}	0.12	0.32	0.00	1.00
Tearfulness^{a}	0.22	0.41	0.00	1.00
Alzheimer, dementia, senility^{a}	0.18	0.38	0.00	1.00
Mental health index ^{c}	-0.05	0.94	-1.04	4.49

Source: SHARE 2004-2020 (Wave 6,8 responses of Wave 7 respondents).
[a]: No(0), yes(1)
[b]: Exact question asked is: "In the last month, have you been sad or depressed"
[c]: First principal component of all items (the higher, the worse people's health). Principal component analysis is carried out with all countries pooled.
Displayed values correspond to the predicted score values divided by standard deviation.

Table 3: SHARE: Physical ill health items and indices^a: individuals aged 50+. Descriptive statistics

	mean	sd	min	max
Long-term illness ^{b}	2.79	1.99	1.00	5.00
Limited because of health^c	2.36	0.74	1.00	3.00
Numb. of limits (daily living)^d	0.23	0.81	0.00	6.00
Numb. of limits (instrum. act. daily living)^e	0.47	1.39	0.00	9.00
Hart attack^b	0.12	0.33	0.00	1.00
Hypertension^b	0.45	0.50	0.00	1.00
Cholesterol^b	0.25	0.43	0.00	1.00
Stroke^b	0.04	0.20	0.00	1.00
Diabete^b	0.14	0.35	0.00	1.00
Lung disease^b	0.06	0.24	0.00	1.00
Cancer^b	0.05	0.23	0.00	1.00
Ulcer^b	0.04	0.18	0.00	1.00
Parkinson^b	0.01	0.09	0.00	1.00
Cataract^b	0.09	0.29	0.00	1.00
Hip fracture^b	0.02	0.13	0.00	1.00
Other fractures^b	0.21	0.41	0.00	1.00
Mobility, arm function & fine motor limits^f	1.64	2.33	0.00	10.00
Max. of grip strength measure$g$	32.93	11.36	2.00	90.00
Hospital past 12 months	0.16	0.37	0.00	1.00
Poor phys. health index	0.05	1.02	-1.68	6.25

Source: SHARE 2004-2020 (Wave 6,8 responses of Wave 7 respondents)
[a]: 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.
[b]: No(0), yes(1)
[c]: Limited in activities because of health [3(no)-1(severely) scale scale].
[d]: Number of limitations with activities of daily living (0-6 scale).
[e]: Number of imitations with instrumental activities of daily living (0-9 scale).
[f]: Number of limitations (measured by interviewer) (0-10 scale)
[g]: 0-100 (measured by interviewer)

Table 4: SHARE: Health endowment and other controls. Descriptive statistics

	mean	sd	min	max
Age in years	67.98	9.45	50.00	102.00
Income prox. (dec)[a]	4.02	3.24	1.00	10.00
ISCED level[b]	3.07	1.41	0.00	6.00
Childhood health [c]	2.19	1.08	1.00	6.00
Death status of father [d]	2.39	0.61	1.00	3.00
Death status of mother [d]	2.22	0.73	1.00	3.00

Source: SHARE 2004-2020 (Wave 7)
[a]: Country × wave decile of work-related earnings (ie. salary or self-employed earnings if the person still works or (most of the time in SHARE) pension if retired. [b]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long].
[c]: Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.
[d]: Parent is currently alive (1); died early (2) died late (3) [i.e. they died younger(2)/older(3) than the median age at death in the considered country].

2.2 O*NET & EWCS

SHARE wave 7 provides a lot of information about people's careers (including info to gauge the latter's degree of instability). But, as mentioned above, it falls short of providing information about the arduousness of successive jobs/occupations. To overcome that limitation, we turn to O*NET from the US, and 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 *Work context* module. Items composing this module have been collected in 2021,[19] and are related to 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/managerial relationship at work (e.g. contact with others, responsibility for other's health and safety, face-to-face discussions). We use a principal component (PC) analysis to get a summary indicator of occupation arduousness. More information (1st and 2nd principal components, eigenvalues and loading factors) is reported in the Appendix (Table 15). Only the 1st PC is used in the paper to quantify each occupation's arduousness. We show in that table that it correlates with working conditions items associated with arduousness (e.g. "Exposed to Contaminants", "Pace (of work) determined by the speed

[19]For some O*NET occupations, the last update was made in 2020.

of Equipment", "Sounds noise levels are distracting or uncomfortable"...). We also show that the 2nd Principal component correlates more with managerial vs. non-managerial work content: a dimension that is a priori less relevant in an exercise centred on the health impact of arduousness. In the Appendix, Figure 6 presents our O*NET 1st principal component (PC) at ISCO 2 level. We see that typical manual/outdoor occupations (e.g. building and related trades works) translate into high arduousness PC values, while more intellectual/indoor occupations (e.g. Business and Administration) display much lower values.

It is important to stress what we do with these occupation-specific arduousness data. Once injected into SHARE, they are used 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 self-reported in SHARE wave 7. The weights reflect the duration (in years) of the successive occupation spells. Note that the years have been multiplied by .5 if the occupation was declared to be always part-time, 1 if always full-time and .75 when variable. Hereafter, we mostly use the entire (average) career arduousness index. But we also consider the cumulative arduousness to assess the role of the total amount of arduousness people have been exposed to. We also use the arduousness index corresponding to the first job vs. the last job, or for the jobs held 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 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.[20] Each of these 6 job quality indices is measured on a scale from 0 to 100. We inverse the sign of each

[20]Note the similarity with the dimensions forming the O*NET "Work Context module" visible in Appendix, Table 15.

of these indices because we are interested in arduousness (while these indices quantify the "quality" of jobs) and compute their average by occupation. A limitation with EWCS is that respondents' occupation is only available at the 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 systematically includes EWCS-based measures of career arduousness to see if these deliver results that deviate from O*NET-based ones. A first, purely descriptive, comparison of O*NET and EWCS is reported in the Appendix, Figure 7. 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 differences for some ISCO 2 occupations.

2.3 Career arduousness and (in)stability

The upper part of Table 5 contains the variables we have been able to compute by merging SHARE career history data and O*NET or EWCS arduousness data. The lower part of that table describes the SHARE wave 7 variables informing on career (in)stability. As to arduousness, most reported values are based on O*NET data unless specified otherwise. The first line describes the respondents' *average* career arduousness. It is computed as the weighted[21] average arduousness index of each of the successive occupations (reported in SHARE wave 7). The next line corresponds to the same average arduousness but based on (a priori less accurate) ISCO 2 O*NET arduousness PC scores by occupation.[22] The third line presents the cumulative arduousness as the sum of (weighted) O*NET occupation indices. The fourth line is the average career arduousness estimated using European arduousness indices provided by EWCS (at ISCO 2 level only). The next two lines correspond to the O*NET-based measure of the arduousness of (respectively) the first and the last job held by SHARE respondents. The next four columns report O*NET-based average arduousness across age bands (<30; 30-39; 40-49; 50+). The values are in deviation from the overall average (row 1).[23]

[21]Where the weights correspond to the duration of the different job spells (themselves weighted to account for the part-time vs. full-time nature of the spell. Weight is .5 if people worked part-time, .75 is they shifted between part-time to full-time, and 1 otherwise.

[22]In Section 4.3.1, we use this less precise measure of arduousness to assess biases arising from aggregation.

[23]In Section 4.3.1, we use these to assess the risk of the so-called healthy-worker bias.

Table 5: SHARE, O*NET, EWCS: career arduousness and career (in)stability. Descriptive statistics

	mean	sd	min	max
Ardu. (car. av.)[a]	0.06	0.99	-1.67	2.73
Ardu. (car. av.) (ISCO2)[a]	0.06	1.00	-1.29	1.84
Ardu. (car. cumul.)[b]	0.09	0.99	-5.99	8.55
Ardu. car. av. (EU-EWCS ISCO2)[c]	-16.48	1.04	-18.73	-14.20
Ardu. (first job)	0.16	1.05	-1.67	2.73
Ardu. (last job av.)	0.04	1.03	-1.67	2.73
Ardu. <40 (dev. from car. av.)[d]	0.02	0.24	-3.12	3.19
Ardu. >=40 (dev. from car. av.)[e]	-0.02	0.25	-2.96	3.65
Cum. yrs empl.	34.72	11.14	0.50	131.50
Propensity to work FT (Max=1)	0.96	0.10	0.01	1.00
Number of jobs	2.76	1.86	1.00	20.00
Number of 6m gaps	0.46	0.80	0.00	12.00
Number of redundancies	0.30	0.64	0.00	7.00

Source: SHARE 2004-2020 (Wave 7), O*NET 2021, EWCS 2015
: Based on O*NET (ISCO4) unless specified otherwise.
[a]: Average career arduousness (weighted)
[a]: Cumulative career arduousness (weighted)
[c]: Average career arduousness (weighted) (EU/EWCS-based index.)
[d]: Deviation from aver. career ardu. when aged less than 40
[e]: Deviation from aver. career ardu. when aged 40+

3 Method

This paper aims to analyse the link between career arduousness or career (in)stability and ill health at an older age while accounting for the latter's pre-labour determinants. Let us consider $IHealth_{i,j}^{k}$, a measure of current mental ($k = M$) or physical ($k = P$) ill health of elderly individual i in the country j who participated in the SHARE survey (measured in 2015 or 2019). We consider that $IHealth_{i,j}^{k}$ is a function that can be written as follows:

$$\begin{aligned} IHealth_{i,j}^{k} = \alpha^{k} + \beta_1^{k}\, CAR_{i,j}^{ard} + \beta_2^{k}\, CAR_{i,j}^{inst} + \gamma^{k}\, X_{i,j} + \\ \delta_j^{k} + \sum_a \eta^{k,a}\, \mathbb{1}\{AGE_{i,j} = a\} + \epsilon_{i,j}^{k} \qquad (1) \\ k = M, P \end{aligned}$$

where CAR^{ard} is the respondent's career arduousness. The career (in)stability (overall duration, breaks, redundancies…) is CAR^{inst}. Together, these two variables reflect the respondent's job history. Our model also systematically comprises controls X (work-related income proxy, educational attainment and health endowment) plus country fixed effect δ. Finally, it comprises age dummies η^a (where age is measured at the moment health is assessed by SHARE). As we pool respondents who vary a lot in terms of age (all SHARE respondents aged 50+), this part of the model plays a key role. It represents the baseline relationship between age and (presumably) declining health[24] that is common to all respondents whatever the arduousness and instability of their career. In other words, the estimated coefficients for our arduousness and instability variables must be interpreted as deviations from the age/health baseline relationship. Note also that we will be estimating this model separately for physical and mental health. We will also run separate regressions for each gender, capitalising on a long literature on labour and health economics that suggests that occupations, arduousness, work or health (but also the relationship between work and health) potentially differ between men and women (Case and Paxson, 2005; Goldin, 2015). Finally, to better account for the (potentially important) cross-country heterogeneity in factors affecting simultaneously the health and the arduousness/instability of careers, we estimate the above model separately for 3 groups of countries based on the level of GDP per head (see Appendix, Figure 8).

The first part of the analysis consists of estimating the above model using different definitions of career arduousness (i.e. mean value over an entire career, cumulative arduousness, arduousness of first job or last job, of the job held before the age of 40 vs. the one(s) done past that age...) together with variables capturing the (in)stability of careers and variables proxying respondents' health endowment. The second part is the one where we analyse the relative importance of career arduousness versus instability (and also other blocks of variables present in the model). One common way of assessing the "importance" of a right-hand side (continuous) variable is to estimate its coefficient using standardized Y and X. Note that such standardization has been applied to all the continuous variables used in this paper. Thus, all the individual coefficients we report can be interpreted as the impact of one standard deviation of X in terms of units of Y (where a "unit" also equals one standard deviation). But this approach has its limits, particularly when one is interested in gauging the importance of `groups of variables` (with some variables continuous and others categorical). This is why we resort instead to a decomposition of the (model-predicted) outcome variance. This is a method pioneered by Shorrocks (1982) and used by Fields (2004) in labour economics and Jusot et al. (2013) in health economics. It amounts to a linear regression post-estimation exercise with two stages. At stage 1, using equation (1), we predict the respondent's ill health based on the (block of) regressors and the corresponding estimated coefficients:

[24] At least physical health.

$$
\begin{aligned}
\widehat{IHealth}_{i,j}^{k,CAR^{ard}} &\equiv \widehat{\beta_1^k}\, CAR_{i,j}^{ard} \\
\widehat{IHealth}_{i,j}^{k,CAR^{inst}} &\equiv \widehat{\beta_2^k}\, CAR_{i,j}^{inst} \\
\widehat{IHealth}_{i,j}^{k,X} &\equiv \widehat{\gamma^k}\, X_{i,j} \\
\widehat{IHealth}_{i,j}^{k,\delta^k} &\equiv \widehat{\delta_j^k} \\
\widehat{IHealth}_{i,j}^{k,AGE} &\equiv \eta^{\widehat{k,AGE_{i,j}}} \\
k = M, P &
\end{aligned}
\tag{2}
$$

In stage 2, we use the variance of the (model-explained) ill health (the one that corresponds to the $R2$ of the estimated model[25]) as a reference. To quantify the contribution of each (block of) variable(s), we compute the covariance between the part of the outcome predicted by each (block of) regressor(s) and the outcome predicted by the entire list of regressors. The sum of these co-variances is equal to the model-predicted outcome variance.

$$
\begin{aligned}
\sigma^2\left(\widehat{IHealth^k}_{i,j}\right) = \sigma\left(\widehat{IHealth^k}_{i,j}, \widehat{IHealth}_{i,j}^{k,CAR^{ard}}\right) + \\
\sigma\left(\widehat{IHealth^k}_{i,j}, \widehat{IHealth}_{i,j}^{k,CAR^{inst}}\right) + \\
\sigma\left(\widehat{IHealth^k}_{i,j}, \widehat{IHealth}_{i,j}^{k,X}\right) + \\
\sigma\left(\widehat{IHealth^k}_{i,j}, \widehat{IHealth}_{j}^{k,\delta^k}\right) + \\
\sigma\left(\widehat{IHealth^k}_{i,j}, \widehat{IHealth}_{i,j}^{k,AGE}\right) \\
k = M, P
\end{aligned}
\tag{3}
$$

We then estimate the relative importance of a particular variable (or block of variables) simply as the ratio (expressed in %-points hereafter) of its covariance divided by the total model-explained ill health variance. We refer to these ratios as covariance shares s. They add up to 100 hereafter. For instance, for career arduousness

[25] Thus the decomposition used here is equivalent to a $R2$ decomposition method

$$s[CAR^{ard}]^k \equiv \frac{\sigma\left(\widehat{IHealth}^k_{i,j}, \widehat{IHealth}^{k,CAR^{ard}}_{i,j}\right)}{\sigma^2\left(\widehat{IHealth}^k_{i,j}\right)} \times 100 \qquad (4)$$

$$k = M, P$$

4 Results

4.1 Regression results

We begin our analysis of the relationship between ill health at old age and career history (arduousness/instability) by considering the results of the OLS estimation of equation (1). We report here, in Tables 6,7, the results for female respondents. All other regression results are reported in the Appendix (Section 6.2). All estimated models comprise age dummies as baseline predictors of ill health. They also include the respondent's (proxied) work-related income decile, her educational attainment and country fixed effects. These capture the contribution to ill 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 (in)stability, as, by construction, the inclusion of country fixed effects amounts to centring the other regressors on the country average. As a robustness check, to better account for the potential role of the degree of economic development (and by extension, the degree of social protection) we also estimate the above model separately by GDP category. Using Penn World Table data (see Appendix, Figure 8) we distinguish countries with a low, medium, and high level of GDP per head.

The key coefficients are those corresponding to CAR^{ard} and CAR^{inst} in eq. (1). In model M1, CAR^{ard} is computed as the weighted average arduousness value of each of the successive ISCO-4 occupation.[26] In Table 6, point estimate[27] is .0463 and statistically significant, meaning that +1-standard-deviation of arduousness raises the risk of ill health beyond the age of 50 by 4.63% of a standard-deviation. In model M2 we focus on the impact of cumulative arduousness (i.e. the one accumulated over the entire career). The standardized coefficient is 0.0348 and statistically significant, thus of similar (limited) magnitude as for M1. In models M3, M4, we focus on the arduousness of the first and the last occupations, and we again find a positive association with female mental ill health. Our point estimates

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

[27] As our variables have been standardised, that estimate can be read as a standardised beta coefficient.

(respectively .0412 and .0345) are very similar to those found for average career arduousness (0.0463).[28] In models M5, M6, we explore the role of arduousness at different ages (< 40; 40+). The estimated model comprises the overall average arduousness as the main regressor (same as in M1) to which is added the arduousness deviation specific to each age band. The estimated coefficients for these deviations are not statistically significant. This tentatively suggests that the way arduousness develops with age has no significant impact on late-life female mental ill health. Model 6 (M6), like M1, is about average arduousness but uses the European measure from EWCS. It delivers a (statistically significant) point estimate of .0464 which is remarkably similar to its O*NET US equivalent (.0463). Finally, model M7 reproduces M1 but excludes the respondents older than 75, to assess the consequences of earlier death among individuals who experienced the most arduous careers.[29] Again, the point estimate at .0480 appears to be quite close to the .0464 estimate we get when considering all ages.

The next set of interesting results relates to the career (in)stability CAR^{inst}, and are reported beneath in Table 6. For female respondents, 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 -.0058 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 are the estimates of the impact of the total number of jobs held by the respondent. These show that the higher that number, the higher the risk of 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 worse people's mental health. And finally, the larger the number of times they have been made redundant, the worse their mental health is 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 .013 to .019 rise in our standardised ill health index, an extra redundancy translates into a .044 to .047 rise in that index.

Table 7 shows the results for females' risk of physical ill health. They are qualitatively very similar to those obtained for mental ill health. But the magnitude of the point estimates is generally slightly larger. For instance (M1), a +1-standard-deviation increment of average career arduousness translates into +0.0752 standard deviation of physical ill health (the

[28]Note that the point estimate for the last job is not statistically different from that for the first job.

[29]Also, the potential bias due to under-coverage of people with the worst health (physical or mental) who live in institutions.

equivalent value of mental ill health is +.0464). Results about career instability, generally suggest it hurts physical health. Women with a longer overall career[30] have a lower ill health index (point estimates range from -.0064 to -.0081 and are all statistically significant). Also, those who held more jobs and experienced more redundancies are more exposed to the risk of ill health. But in contrast with mental health, the propensity to work full time no longer reduces the risk of ill health in a statistically significant way. Similarly, the number of gaps of (at least) 6 months between jobs stops being statistically positively linked to ill health.

The results for male respondents are reported in Appendix, Section 6.2 in Tables 16,17. They all confirm the existence of a positive (and statistically significant) link between career arduousness and both mental and physical ill health. But the magnitude of the coefficients is smaller compared to their female equivalent. For instance, point estimates for average career arduousness are 0.0216 and 0.0381 for males' mental and physical health, whereas they are respectively 0.0464 and 0.0752 for their female counterparts. Another male/female difference is that point estimates for each of our proxies of career (in)stability are generally larger for male respondents. This said, we also find that, for males, not all proxies of career (in)stability are statistically significant when it comes to physical ill health; whereas they are for mental ill health. This hints at a more pronounced role of career instability when it comes to old-age mental health compared to physical health.

In the Appendix, Section 6.2 (Tables 18-29), the reader will find the regression results when separating countries based on their level of GDP, still by gender and distinguishing mental and physical health. The remarkable thing is that they largely align with the above results when all countries are pooled, suggesting that the inclusion of fixed effects suffice to account for the presence of unobserved heterogeneity.

[30]That we interpret as a sign of stability

Table 6: Detailed results of regression analysis of **mental ill health (female)**

	M1	M2	M3	M4	M5	M6	M7
Ardu. (car. av.)	0.0463***				0.0465***		0.0480***
	(0.0094)				(0.0105)		(0.0106)
Ardu. (car. cumulative)		0.0348***					
		(0.0107)					
Ardu. (first job av.)			0.0412***				
			(0.0091)				
Ardu. (last job av.)				0.0345***			
				(0.0090)			
Ardu. <40 (dev. from car. av.)					0.0197		
					(0.0372)		
Ardu. 40+ (dev. from car. av.)					-0.0069		
					(0.0367)		
Ardu. (car. av. EU-EWSE)						0.0461***	
						(0.0078)	
Cum. yrs empl	-0.0059***	-0.0058***	-0.0059***	-0.0058***	-0.0065***	-0.0058***	-0.0070***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0006)	(0.0007)
Propensity to work full-time (1=max)[a]	-0.1233**	-0.1183**	-0.1121*	-0.1102*	-0.0151	-0.1104*	-0.1395**
	(0.0584)	(0.0585)	(0.0605)	(0.0603)	(0.0656)	(0.0584)	(0.0648)
Numb. of jobs	0.0151***	0.0129**	0.0137**	0.0187***	0.0153***	0.0142***	0.0150***
	(0.0052)	(0.0052)	(0.0055)	(0.0055)	(0.0054)	(0.0052)	(0.0057)
Numb. of 6m gaps	0.0352***	0.0369***	0.0428***	0.0329***	0.0315***	0.0339***	0.0297***
	(0.0101)	(0.0101)	(0.0107)	(0.0107)	(0.0110)	(0.0101)	(0.0109)
Numb. of redun.	0.0445***	0.0449***	0.0453***	0.0475***	0.0468***	0.0452***	0.0472***
	(0.0119)	(0.0119)	(0.0127)	(0.0128)	(0.0127)	(0.0119)	(0.0127)
constant	0.2579***	0.2623***	0.2333***	0.2619***	0.2187**	0.9888***	0.1422
	(0.0845)	(0.0847)	(0.0875)	(0.0871)	(0.0975)	(0.1450)	(0.0981)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educ.[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child health[c]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental death	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,129	20,129	18,749	18,711	16,375	20,129	15,659

Source: SHARE 2004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.
[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; [b]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long]; [c]: Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6; [d]: 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).

Table 7: Detailed results of regression analysis of **physical ill health (female)**

	M1	M2	M3	M4	M5	M6	M7
Ardu. (car. av.)	0.0752***				0.0716***		0.0633***
	(0.0089)				(0.0099)		(0.0095)
Ardu. (car. cumulative)		0.0531***					
		(0.0102)					
Ardu. (first job av.)			0.0673***				
			(0.0087)				
Ardu. (last job av.)				0.0635***			
				(0.0086)			
Ardu. <40 (dev. from car. av.)					0.0513		
					(0.0352)		
Ardu. 40+ (dev. from car. av.)					0.0431		
					(0.0346)		
Ardu. (car. av. EU-EWSE)						0.0609***	
						(0.0074)	
Cum. yrs empl	-0.0065***	-0.0064***	-0.0065***	-0.0065***	-0.0086***	-0.0064***	-0.0081***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0006)	(0.0007)
Propensity to work full-time (1=max)[a]	-0.0305	-0.0233	-0.0510	-0.0431	0.0481	-0.0150	-0.0666
	(0.0555)	(0.0557)	(0.0574)	(0.0573)	(0.0620)	(0.0556)	(0.0583)
Numb. of jobs	0.0204***	0.0171***	0.0165***	0.0175***	0.0195***	0.0190***	0.0196***
	(0.0049)	(0.0049)	(0.0052)	(0.0052)	(0.0051)	(0.0049)	(0.0051)
Numb. of 6m gaps	0.0085	0.0112	0.0129	0.0123	-0.0031	0.0073	0.0058
	(0.0096)	(0.0096)	(0.0102)	(0.0102)	(0.0104)	(0.0096)	(0.0098)
Numb. of redun.	0.0185	0.0192*	0.0297**	0.0246**	0.0214*	0.0196*	0.0171
	(0.0113)	(0.0114)	(0.0121)	(0.0121)	(0.0120)	(0.0113)	(0.0114)
constant	-0.2454***	-0.2359***	-0.2476***	-0.2247***	-0.2365**	0.7287***	-0.2571***
	(0.0804)	(0.0806)	(0.0831)	(0.0828)	(0.0921)	(0.1380)	(0.0882)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educ.[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child health[c]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental death	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,129	20,129	18,749	18,711	16,375	20,129	15,659

Source: SHARE 2004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
[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; [b]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long]; [c]: Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6; [d]: 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).

4.2 Assessing the importance of regression coefficients using Variance Decomposition

We now turn to what is perhaps the most important set of results of this paper. They correspond to our decomposition of the (model-explained) ill health variance. As shown in eq. (2),(3),(4), this decomposition consists of using the regression results to assess the capacity of groups of variables to predict ill health beyond 50: e.g. that of career arduousness vs. (in)stability, or vs. the other categories of determinants. Paralleling what we have done for regression results, we report here in Tables 8,9 the variance decomposition results for females. Those for males and those (for both genders) distinguishing GDP categories are reported in the Appendix (Section 6.3). The underlying coefficients are from the estimated eq. (1) that are reported, for example, in Tables 6,7. And there is a perfect correspondence between the different variance decomposition results reported in the different columns of Tables 8,9 and the regression models (M1-M7).

For the sake of clarity, we have computed the (covariance) shares for the following 6 blocks of variables (referred to hereafter as s1 to s6)

- `Career ardu.` [s1]: comprises the measurement(s) or arduousness (career weighted average, first/last jobs, career average plus age-band-specific deviation, European measurement of arduousness);
- `Career (in)stab.` [s2]: regroups all the variables relative to the career (in)stability (duration of career, propensity to have worked full-time, number of jobs, breaks of 6 months+ or redundancies);
- `Health endow.` [s3]: regroups childhood health and parental longevity/death status.
- `Income prox.` [s4]: equals our income proxy variable (work-related earnings/pension).
- `Educ.` [s5]: corresponds to the educational attainment categories (ISCED scale);
- `Country` [s6]: corresponds to the country fixed effects.

Note that the reported shares ([s1]...[s6]) correspond to eq. (4). Each share is computed as a fraction. The numerators consist of the covariances between the model-predicted outcome and the part of that outcome predicted by the considered block of regressors. The (common) denominator is the non-demographic model-predicted ill health variance. In other words, we exclude from that denominator the contribution of age: $\widehat{IHealth}_{i,j}^{k}$ is computed using only the other variables and their corresponding estimated coefficients.

And the reported shares (that add up to 100) inform of the importance of the considered factor in explaining the ill health variance that exists beyond what can be ascribed to age.

The important results are essentially fivefold. First, career arduousness [s1] is a statistically significant, but relatively small, contributor to mental and physical ill health. For female mental ill health (Table 6), it accounts only for 3 to 8% of the total outcome variance considered. Second, by comparison, career (in)stability [s2] accounts for at least double that percentage. The second line of Table 6 shows values ranging from 16 to 22%. Thus, career (in)stability matters more. This is confirmed by the ratios reported on the penultimate line of Table 6, ranging from 0.68 to 0.84. Said differently, in the case of females (mental health) career (in)stability accounts for between 68% and 84% of the contribution of career arduousness and (in)stability combined. Third, compared to career (in)stability, the initial health endowment [s3] (proxied here by childhood health and the longevity of the respondent's parents) explains a larger part of mental or physical health differences past the age of 50 *ceteris paribus*. We estimate its contribution to range from 20.7 to 23.4%. Fourth, beyond arduousness, instability and health endowment, (proxied) earnings [s4] still matter. We estimated their contribution to ill health to range from 5.5 to 7.5%. Fifth, taken together our 3 non-labour (blocks of) variables (i.e. health endowment, educational attainment and the country of the respondent [s3],[s5],[s6]) matter a lot for female mental ill health. These account for over 70% of the model-explained outcome. We find very similar results for female physical health (Table 7), and for males (both physical and mental health), or when replicating the analysis by category of GDP per head (see Appendix, Section 6.3 for the detailed results).

What we consider as the key results of the paper (i.e. the greater contribution of career instability) can be visualized synthetically in Fig 1 and Fig 2. Unlike Tables 6,7 and those in Appendix, Section 6.3) these figures only report [s1] and [s2] and their relative value: [s2]/[s1]+[s2]. Figures 2,4 report the results when the sample is split into three groups of countries, based on the level of GPD (Appendix, Figure 8). In all cases, we see that the share that variance decomposition ascribes to career arduousness dominates. Beyond, two interesting nuances emerge. First, career instability matters more when it comes to mental health than physical health, both for male and female respondents. That is visible when comparing the upper and the lower panels of Figures 1,2. And Figures 3,4 suggest that countries with medium to high GDP per head drive this result. Second, a more detailed analysis reveals that, in low GDP countries, both career arduousness and instability matter less than in richer countries while education seems to play a far bigger role.

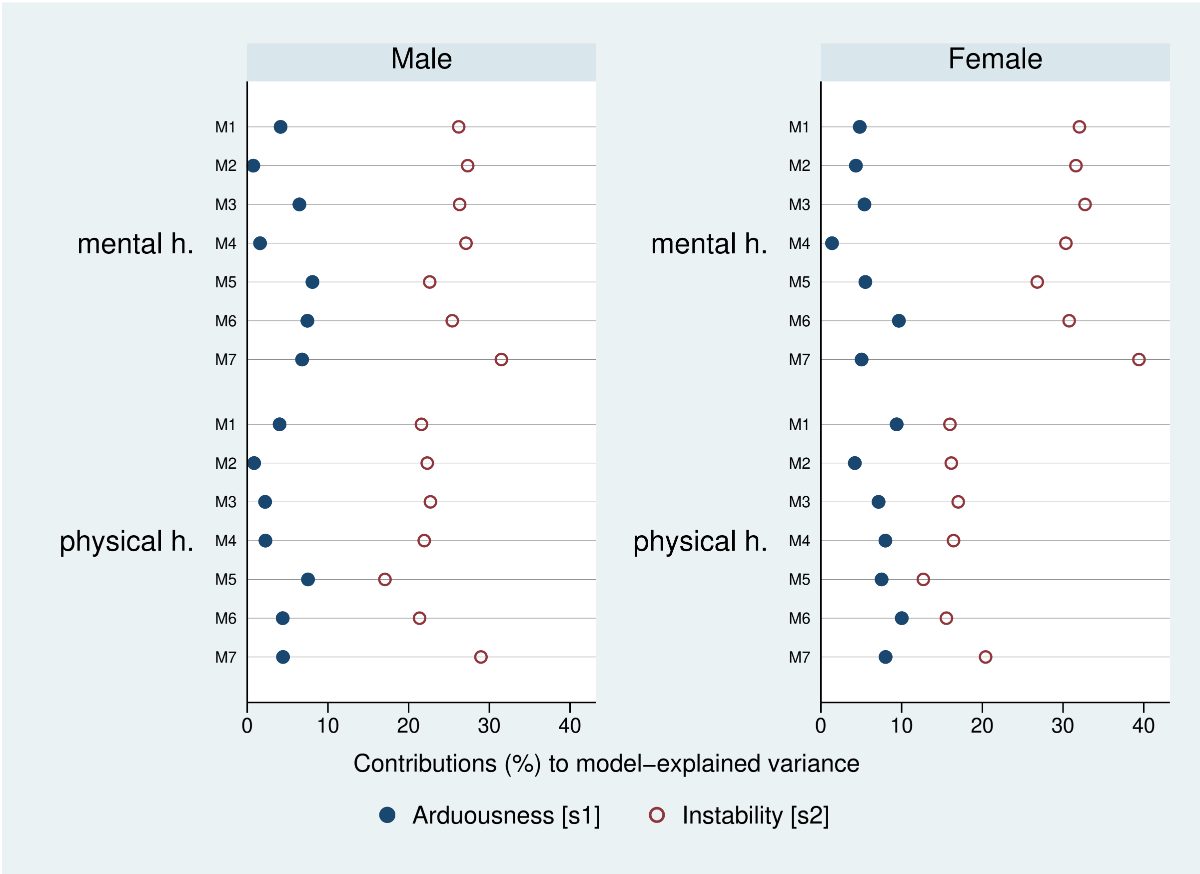

Figure 1: Contribution to model-predicted variance: career arduousness [s1] & instability [s2] shares. Reported contributions [s1], [s2] use regression coefficients from models M1 to M7. In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.

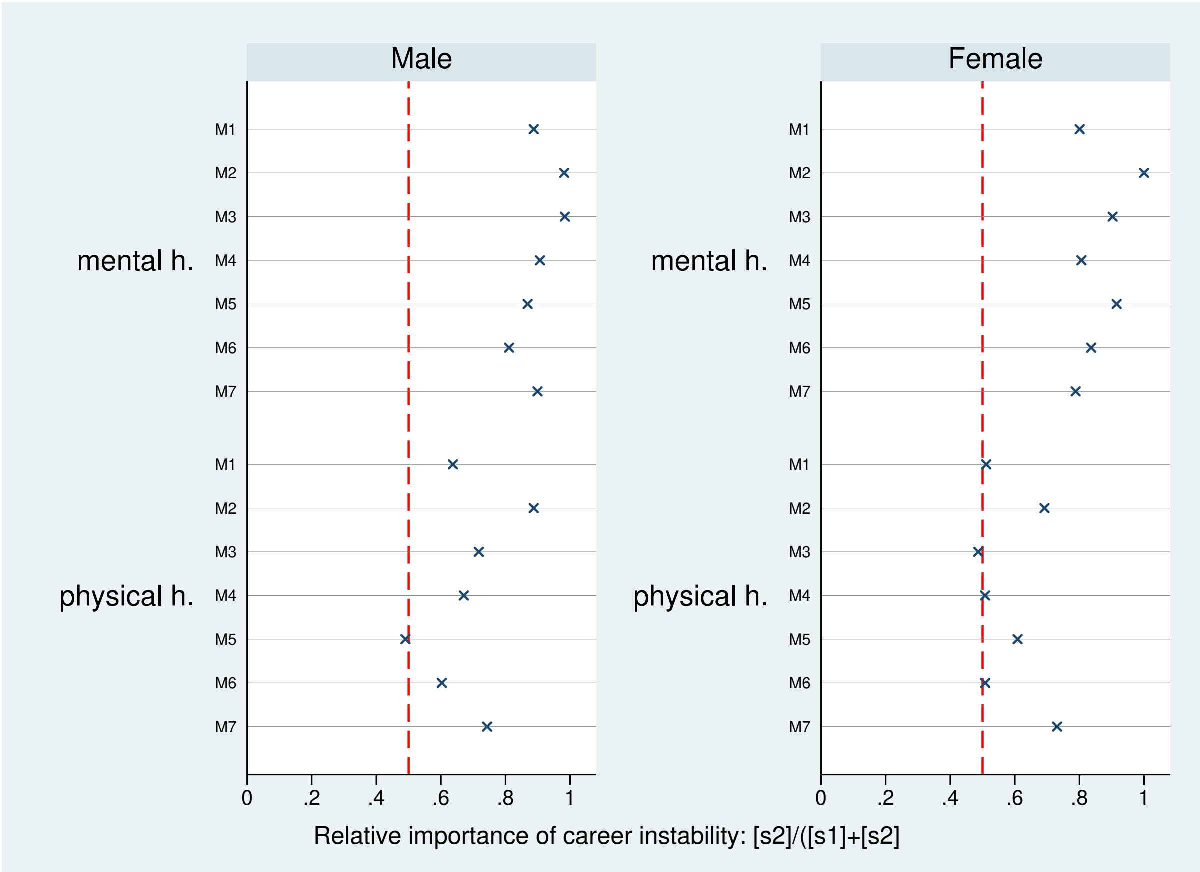

Figure 2: Contribution to model-predicted variance:c career instability's relative share s2/([s1] + [s2]. Reported contributions [s1], [s2] use regression coefficients from models M1 to M7. In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.

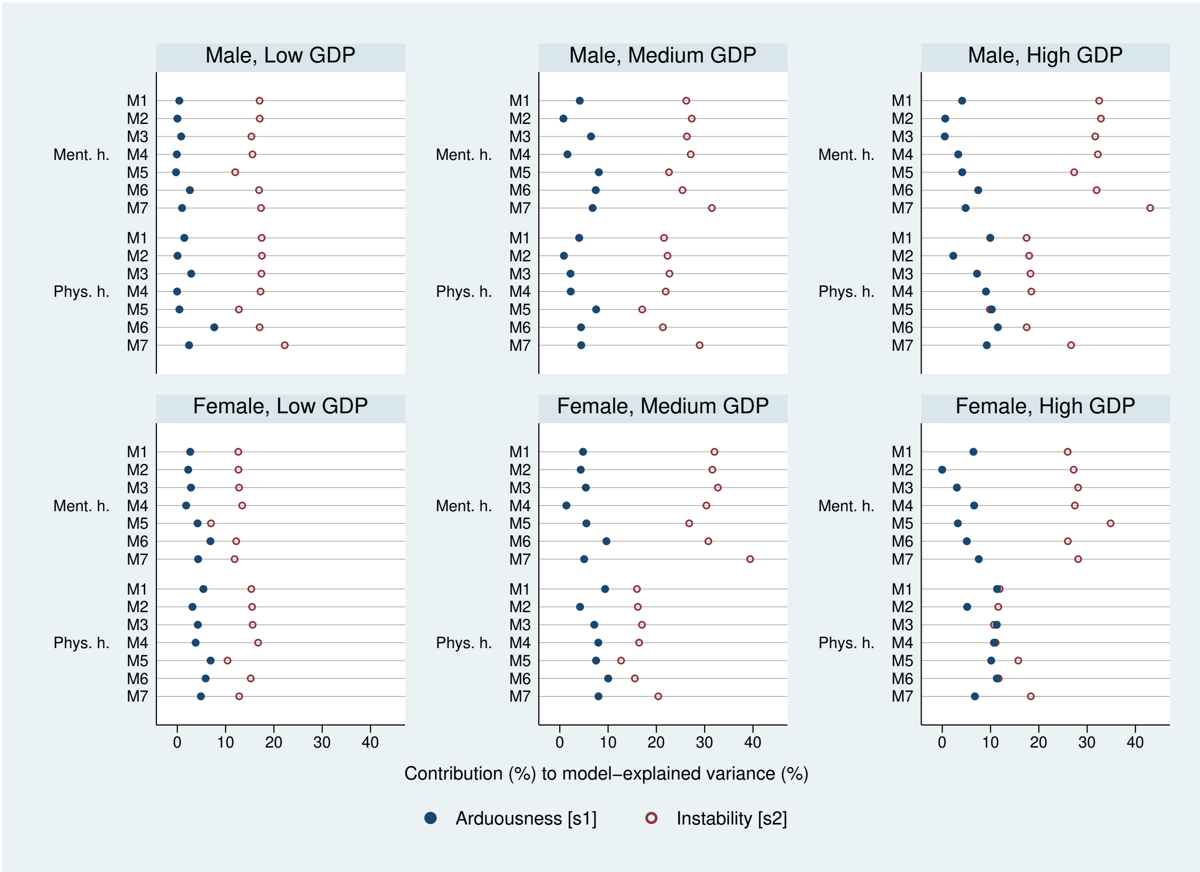

Figure 3: Contribution to model-predicted variance: career arduousness [s1] & instability [s2] shares. Breakdown by level of GDP (see Appendix, Figure 8). Reported contributions [s1], [s2] use regression coefficients from models M1 to M7. In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; $40+$). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.

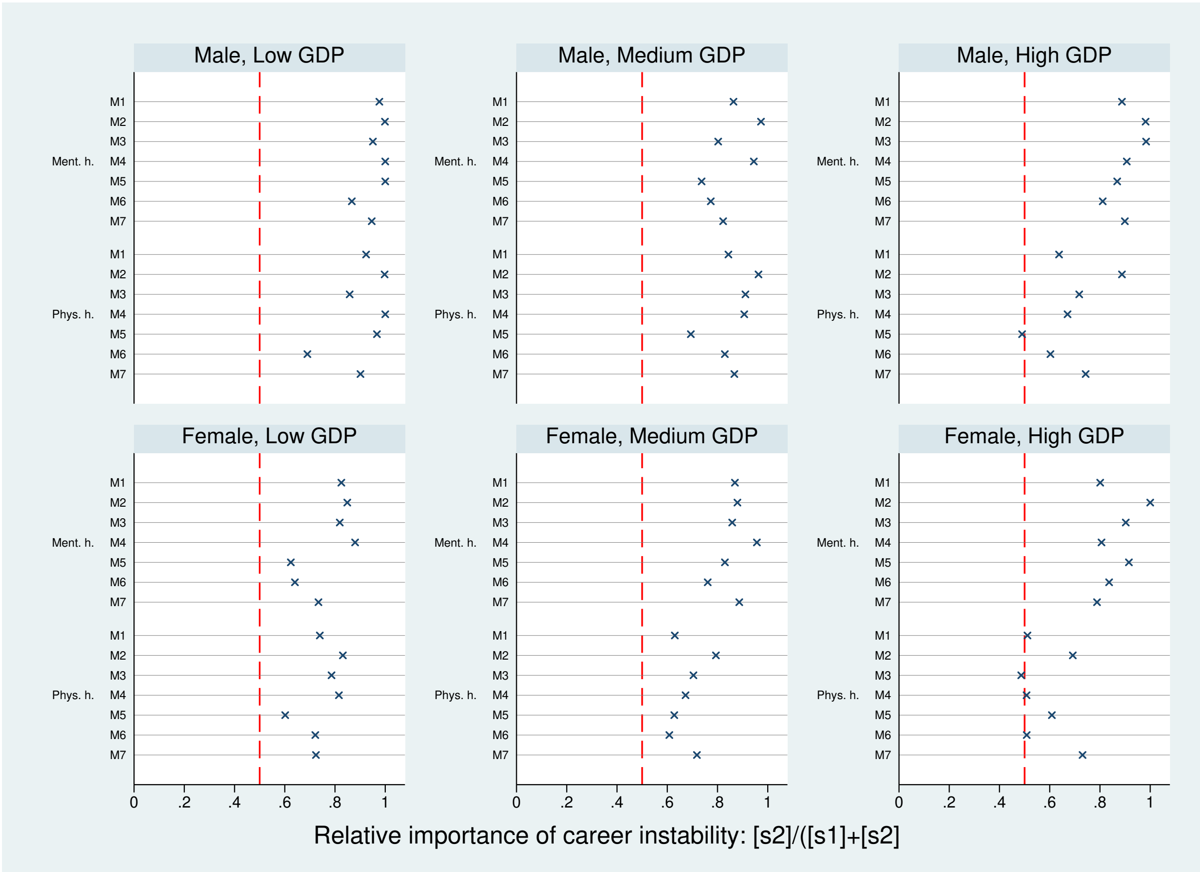

Figure 4: Contribution to model-predicted variance:c career instability's relative share [s2/([s1] + [s2]]. Breakdown by level of GDP (see Appendix, Figure 8). Reported contributions [s1], [s2] use regression coefficients from models M1 to M7. In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.

Table 8: Variance decomposition analysis: **Mental ill health (female)**

	M1	M2	M3	M4	M5	M6	M7
Career ardu. [s1]	5.79***	3.13***	4.93***	4.22*	5.66**	7.96***	6.66***
	(1.478)	(0.884)	(1.507)	(2.203)	(2.338)	(0.840)	(1.300)
Career (in)stab.^{a}[s2]	17.01***	16.92***	17.60***	17.68***	16.58***	16.55***	22.37***
	(2.120)	(2.123)	(1.717)	(1.644)	(2.371)	(2.126)	(2.802)
Health endow.^{b}[s3]	22.50***	22.84***	22.69***	23.48***	21.82***	22.27***	20.71***
	(2.101)	(2.183)	(2.076)	(2.597)	(3.178)	(2.097)	(2.682)
Income prox. [s4]	5.72***	5.85***	5.86***	5.74***	5.53***	5.57***	7.52***
	(1.141)	(1.127)	(0.987)	(1.544)	(1.394)	(1.112)	(2.323)
Educ.^{c} [s5]	11.97***	13.66***	12.03***	12.33***	10.56***	11.05***	9.01***
	(2.943)	(2.713)	(2.384)	(1.277)	(1.950)	(2.493)	(1.876)
Country [s6]	37.02***	37.61***	36.88***	36.54***	39.86***	36.60***	33.73***
	(2.652)	(2.816)	(2.858)	(3.257)	(2.648)	(2.774)	(4.690)
Career inst. ratio [s2/(s1+s2)]	0.75***	0.84***	0.78***	0.81***	0.75***	0.68***	0.77***
	(0.058)	(0.036)	(0.057)	(0.079)	(0.084)	(0.032)	(0.047)
N	20,129	20,129	18,749	18,711	16,375	20,129	12,691

Source: SHARE 2004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; bootstrapped standard errors and p-values, with 1000 replications.
In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.
Underlying regression results in Table 6.
[a]: Cumulative years in employment, propensity to work full-time, Number of jobs held, Number of 6m+ gaps, Number of redundancies. [b]: Childhood health (respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.) & Parental death status (Parent is currently alive (1); died early (2) died late (3) [i.e. they died younger(2)/older(3) than the median age at death in the considered country]. [c]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long].

Table 9: Variance decomposition analysis: **Physical ill health (female)**

	M1	M2	M3	M4	M5	M6	M7
Career ardu. [s1]	9.43***	4.52***	8.20***	8.17***	9.25***	9.06***	7.11***
	(1.775)	(1.171)	(1.987)	(1.470)	(1.035)	(1.144)	(1.247)
Career (in)stab.[a][s2]	9.55***	9.49***	9.59***	9.88***	10.26***	9.40***	13.89***
	(1.162)	(1.189)	(1.537)	(0.703)	(1.604)	(1.202)	(1.754)
Health endow.[b][s3]	30.36***	31.22***	30.77***	29.72***	29.75***	30.43***	29.58***
	(1.776)	(1.829)	(1.694)	(2.731)	(2.875)	(1.821)	(3.398)
Income prox. [s4]	7.71***	7.97***	7.41***	7.80***	7.53***	7.65***	9.05***
	(1.002)	(1.011)	(1.435)	(1.599)	(1.417)	(0.951)	(1.014)
Educ[c] [s5]	9.80***	12.12***	10.55***	10.25***	10.08***	9.55***	10.06***
	(1.337)	(1.443)	(1.285)	(1.574)	(1.782)	(1.308)	(1.845)
Country [s6]	33.15***	34.68***	33.47***	34.18***	33.13***	33.90***	30.31***
	(1.522)	(1.498)	(0.966)	(2.874)	(2.096)	(1.296)	(3.766)
Career inst. ratio [s2/(s1+s2)]	0.50***	0.68***	0.54***	0.55***	0.53***	0.51***	0.66***
	(0.062)	(0.064)	(0.078)	(0.036)	(0.058)	(0.052)	(0.052)
N	20,129	20,129	18,749	18,711	16,375	20,129	12,691

Source: SHARE 2004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; bootstrapped standard errors and p-values, with 1000 replications.
In (M1), CAR^{ard} is computed as the weighted aver. arduousness of successive ISCO-4 occupations. In (M2) CAR^{ard} is cumulative arduousness (i.e. over the entire career). In (M3, M4), we focus on the arduousness of the first and the last occupations. In (M5), we explore the role of arduousness at different ages (< 40; 40+). (M6) is about average arduousness but uses the European measure from EWCS. (M7) reproduces M1 but excludes the respondents older than 75.
Underlying regression results in Table 7.
[a]: Cumulative years in employment, propensity to work full-time, Number of jobs held, Number of 6m+ gaps, Number of redundancies. [b]: Childhood health (respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.) & Parental death status (Parent is currently alive (1); died early (2) died late (3) [i.e. they died younger(2)/older(3) than the median age at death in the considered country]. [c]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long].

4.3 Identification issues

The results above (regressions and model-explained ill-health variance decomposition) are valid only as long as we properly identify the relationship between ill health and career arduousness and instability. In what follows, we discuss and assess the magnitude of problems that might bias the above results. We first look at those related to the way arduousness is measured. We then discuss endogeneity issues.

4.3.1 Health Calendar Differences, Arduousness Time Gap & Measurement Error, Justification Bias

A first measurement issue stems from the use of information about `health` collected in two different waves that are up to 6 years apart. To assess the impact of this health-calendar-time heterogeneity, we re-estimate model M1 with SHARE wave fixed effects. Results in Tables 10, 11 (M1 vs M8) suggest a quasi absence of impact on the arduousness and instability coefficients or co-variance shares $[s1], [s2]$.

Regarding `arduousness`, we distinguish three measurement issues: the "arduousness time gap", the "arduousness measurement error" and the "justification bias". The time-gap problem refers to the duration that has elapsed between the moment SHARE respondents worked, and the moment arduousness is evaluated.[31] Contemporary O*NET/EWCS indices (i.e. estimates of the arduousness of occupations as they were in the early 2000s) may underestimate the actual arduousness of past occupations (i.e. as they were when SHARE respondents worked). More precisely, there might be some unobserved heterogeneity in the way arduousness by occupation has evolved between the moment of treatment (i.e. work) and the moment of the measurement of the intensity of the treatment (i.e. the year O*NET/EWCS data were collected). Assuming that the ranking of occupations by the degree of arduousness has not fundamentally evolved; but the overall level of arduousness has declined, time-gap unobserved heterogeneity can be modelled as cohort fixed effects. In our results, these are likely to be captured by the age fixed effects (equ.(1)). In other words, the coefficients we estimated for these age fixed effects confound the (natural) impact of ageing on health and the (unobserved) propensity of past arduousness to be higher than those quantified via O*NET or EWCS. There is no straightforward solution to that problem. What we suggest is to compare the results when pooling all age groups with those for the "old-olds" (aged > 60), or with those for the "young-old" (aged $<= 60$) SHARE respondents. By construction, the time gap (and the magnitude of the fixed effect corresponding to the gap between the O*NET arduousness index and the actual arduousness the respondent was exposed to) must be smaller for the young-olds. The point is that results reported in Tables 10, 11 (M1 vs M9 or M9 vs M10) deliver point estimates that are barely affected by the change of age group.

The second issue is the treatment/arduousness measurement error as such: with our method, people get assigned the "average" arduousness level for the occupation they had. But the actual arduousness might have been lower or higher given the specific working conditions of their job within what remains a broad and potentially heterogeneous category of jobs. And this may translate into an aggregation bias. The way we assess the magnitude of that problem is by comparing the coefficients we get using arduousness data at ISCO 4 vs ISCO 2 level. We posit that the risk of measurement error is a priori larger when using ISCO 2 data than ISCO 4 data.[32] The point is that the results, reported in Tables 10,11 (M1 vs M11), are not supportive of an aggregation bias when using ISCO 2 data to quantify

[31] There is no similar concern about instability, as it exclusively corresponds to historical information.

[32] Note that the comparison can only be done using O*NET as EWCS only reports job quality/arduousness at the ISCO 2 level.

arduousness.

The third problem is known as "justification bias".[33] Labour and health economists using survey data refer to a particular version of that problem that they call the "ill health justification bias" (Baker et al., 2004) i.e. the fact that you worsen the description of your health status to justify your problematic labour market (here your professional career) status. But with SHARE we must rely on pre- or post-wave 7 answers to assess people's health. Wave 7 (2017) was dedicated to the collection of historical/career information. The consequence was that only a summary questionnaire was used to collect the other usual SHARE items. In particular, no mental health items were collected. As is visible in Appendix, Table 14, we use only wave 6 and 8 data to assess respondents' mental and physical health. De facto, this means that at least two years have elapsed between the moment people told about their employment history and the moment they talked about their health.[34] We think that this data feature significantly limits the risk of justification bias.

[33] A version of the "common method variance" problem, i.e. variance that is attributable to the measurement method rather than to the constructs the measures represent.

[34] Most of the time, analysts try to deal with this "justification bias", within a survey, by avoiding asking about health or well-being immediately after having interviewed people about work/arduousness.

Table 10: Assessing the risk of Time Gap and Measurement-Error Bias using O*NET/EWCS: mental and physical health (Female)

	Mental ill health					Physical ill health				
	M1	M8	M9	M10	M11	M1	M8	M9	M10	M11
Ardu. (car. av.) ISCO4	0.0463***	0.0465***	0.0688***	0.0347***		0.0752***	0.0749***	0.0570***	0.0781***	
	(0.0094)	(0.0094)	(0.0195)	(0.0107)		(0.0089)	(0.0089)	(0.0162)	(0.0105)	
Ardu. (car. av.) ISCO2					0.0467***					0.0683***
					(0.0090)					(0.0086)
Cum. yrs empl	-0.0059***	-0.0059***	-0.0104***	-0.0051***	-0.0058***	-0.0065***	-0.0064***	-0.0105***	-0.0059***	-0.0064***
	(0.0006)	(0.0006)	(0.0015)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0012)	(0.0007)	(0.0006)
Propensity to work full-time (1=max)	-0.1233**	-0.1244**	-0.2922**	-0.0205	-0.1219**	-0.0305	-0.0274	-0.0880	0.0195	-0.0293
	(0.0584)	(0.0585)	(0.1140)	(0.0680)	(0.0584)	(0.0555)	(0.0556)	(0.0948)	(0.0670)	(0.0556)
Numb. of jobs	0.0151***	0.0151***	0.0068	0.0166***	0.0150***	0.0204***	0.0204***	0.0172*	0.0205***	0.0202***
	(0.0052)	(0.0052)	(0.0107)	(0.0059)	(0.0052)	(0.0049)	(0.0049)	(0.0089)	(0.0058)	(0.0049)
Numb. of 6m gaps	0.0352***	0.0353***	0.0347*	0.0359***	0.0353***	0.0085	0.0083	0.0094	0.0089	0.0089
	(0.0101)	(0.0101)	(0.0195)	(0.0118)	(0.0101)	(0.0096)	(0.0096)	(0.0162)	(0.0116)	(0.0096)
Numb. of redun.	0.0445***	0.0446***	0.0641***	0.0340**	0.0433***	0.0185	0.0181	0.0189	0.0163	0.0169
	(0.0119)	(0.0119)	(0.0217)	(0.0143)	(0.0119)	(0.0113)	(0.0114)	(0.0180)	(0.0141)	(0.0114)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educ.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child health	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave	No	Yes	No	No	No	No	Yes	No	No	No
Variance decomposition analysis										
$[s1]$	5.79	5.80	5.34	4.43	6.75	9.43	9.39	5.30	10.00	9.34
$[s2]$	17.01	17.07	25.35	12.49	16.78	9.55	9.42	16.91	7.87	9.42
$[s2/(s1+s2)]$	0.75	0.75	0.83	0.74	0.71	0.50	0.50	0.76	0.44	0.50
N	20,129	20,129	4,633	15,496	20,129	20,129	20,129	4,633	15,496	20,129

Source: SHARE 2004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
In (M1), CAR^{ard} is computed as the arduousness (weighted average) of successive ISCO-4 occupations. In (M8) we add at to M1 SHARE wave dummies. In (M9) we re-estimate M1 with respondents aged <=60. In (M10) we re-estimate M1 with respondents aged >60. (M11) reproduces M1 using ISCO2 O*NET arduousness index.

Table 11: Assessing the risk of Time Gap and Measurement-Error Bias using O*NET/EWCS: mental and physical health (Male)

	Mental ill health					Physical ill health				
	M1	M8	M9	M10	M11	M1	M8	M9	M10	M11
Ardu. (car. av.) ISCO4	0.0216***	0.0211***	0.0395**	0.0161**		0.0381***	0.0371***	0.0446***	0.0362***	
	(0.0069)	(0.0069)	(0.0156)	(0.0077)		(0.0075)	(0.0075)	(0.0148)	(0.0086)	
Ardu. (car. av.) ISCO2					0.0207***					0.0447***
					(0.0072)					(0.0079)
Cum. yrs empl	-0.0088***	-0.0086***	-0.0162***	-0.0075***	-0.0088***	-0.0122***	-0.0117***	-0.0187***	-0.0112***	-0.0123***
	(0.0008)	(0.0008)	(0.0020)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0019)	(0.0010)	(0.0009)
Propensity to work full-time (1=max)	-0.4324***	-0.4171***	-1.0333***	-0.2306	-0.4303***	-0.4125***	-0.3766***	-0.7318***	-0.3115*	-0.4128***
	(0.1328)	(0.1329)	(0.2743)	(0.1518)	(0.1328)	(0.1449)	(0.1450)	(0.2614)	(0.1703)	(0.1449)
Numb. of jobs	0.0142***	0.0143***	0.0106	0.0151***	0.0141***	0.0176***	0.0178***	0.0174*	0.0172***	0.0178***
	(0.0042)	(0.0042)	(0.0096)	(0.0047)	(0.0042)	(0.0046)	(0.0046)	(0.0091)	(0.0052)	(0.0046)
Numb. of 6m gaps	0.0370***	0.0363***	0.0245	0.0359***	0.0369***	0.0039	0.0023	-0.0386*	0.0139	0.0034
	(0.0109)	(0.0109)	(0.0222)	(0.0126)	(0.0109)	(0.0119)	(0.0119)	(0.0211)	(0.0141)	(0.0119)
Numb. of redun.	0.0117	0.0105	-0.0114	0.0195	0.0117	-0.0114	-0.0143	-0.0168	-0.0101	-0.0120
	(0.0111)	(0.0111)	(0.0220)	(0.0129)	(0.0111)	(0.0122)	(0.0122)	(0.0209)	(0.0145)	(0.0122)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educ.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child health	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave	No	Yes	No	No	No	No	Yes	No	No	No
Variance decomposition analysis										
$[s1]$	3.20	3.13	3.86	2.44	3.01	5.34	5.10	4.86	5.12	6.56
$[s2]$	24.20	23.37	32.33	19.43	24.25	18.43	16.89	20.83	16.43	18.47
$[s2/(s1+s2)]$	0.88	0.88	0.89	0.89	0.89	0.78	0.77	0.81	0.76	0.74
N	16,906	16,906	3,264	13,642	16,906	16,906	16,906	3,264	13,642	16,906

Source: SHARE 20004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
In (M1), CAR^{ard} is computed as the arduousness (weighted average) of successive ISCO-4 occupations. In (M8) we add at to M1 SHARE wave dummies. In (M9) we reestimate M1 with respondents aged <=60. In (M10) we re-estimate M1 with respondents aged >60. (M11) reproduces M1 using ISCO2 O*NET arduousness index.

4.3.2 Endogeneity, Selection, Omitted Variable Bias

A correlation between occupation and long-term ill health can reveal a causal impact, but it may also stem from (non-random) selection into treatment; with (pre-existing) health influencing occupational arduousness.[35] Inherited poor health or its deterioration (i.e. health shocks) could lead people to abandon more demanding/stressful occupations or, to the contrary, strand them in these occupations. The direction of the induced bias is hard to predict: while some selection mechanisms (e.g., worse health forcing people to stay in more arduous jobs) point to an overestimation of the true adverse effect of hazardous conditions; other mechanisms (referred to as the healthy worker survivor effect in the literature[36]) leads to an attenuation of the true causal link (Belloni et al., 2022). Endogeneity may also stem from other unaccounted/omitted factors: unobserved heterogeneity in terms of (risk) preferences can correlate both with health and occupational choice. Risk lovers, for instance, might be more susceptible to depression but pick more arduous/less stable jobs. The empirical literature always struggles to cope with either of these problems. Finding a plausible, truly exogenous, variation of occupation arduousness/instability is challenging. 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 problems we regroup under the label selectivity.

We posit that selectivity may happen after, during and before people are present in the labour market.

After the presence of the labour market, it corresponds to death attrition. In the European context, it (mostly) occurs after retirement and is potentially correlated with high arduousness/high instability, causing a risk of underestimation. To gauge the magnitude of this problem, we suggest looking at how our key results are affected when considering only the "young-olds": those aged less than 60 (models M9 Tables 10,11), or those aged less than 75 (model M7 in Tables 6, 7). By definition, these respondents are less affected by death attrition. But we see that our results for them do not deviate significantly from the results obtained when we include older cohorts.[37]

Turning to selectivity during people's careers, SHARE allows us to assess the impact of job arduousness at distinct moments of these careers (first vs. last job, age $<$ 40 vs.

[35] Also known as reverse causality (Ravesteijn et al., 2018.)

[36] with healthy workers being able to increase or just maintain their workplace exposure to physically more demanding jobs.

[37] Death attrition and the arduousness measurement time gap discussed above are both synonymous with a risk of underestimation. And we posit that both phenomena are less important with the "young olds".

age 40+) (M3, M4, M5 in Tables 6,7 for females, or similar tables for males in Appendix, Section 6.2). And it seems reasonable to assume that the intensity of the (positive or negative) selectivity bias is stronger when using the arduousness of the last job, or that recorded over the 40+ age band. The point, however, is that we show for example in Tables 6,7 that using the arduousness of the first vs. last job (M3, M4) does not matter econometrically. We strongly reject the possibility that the two point estimates are unequal. And we reach a similar conclusion (about arduousness) when we consider how much it deviates from the average before and after the age of 40.

To account for selectivity at (or before) the entrance of the labour market, SHARE also offers interesting opportunities. It informs on educational attainment but also health until the age of 15 (childhood health status). These are endowment items whose level is determined before people pick their first occupation and enter the labour market. Moreover, SHARE informs about the parents' longevity/death status, which we use to control for the more inherited part of people's initial health endowment. In Tables 12,13 we illustrate how much the inclusion of these pre-labour market entry controls matters for the estimation of the contribution of career arduousness/instability to late-life mental and physical ill health.[38] The first column (Baseline) reports the point estimates when these pre-labour controls are excluded. The last column (Full) displays the point estimates for the full model (i.e. equivalent to model M1). We also report point estimates for intermediate models (Int1, Int2, Int3) to give an idea of the contribution of each (block of) control variable(s). For female mental ill health (Table 12), the inclusion of education, health endowment (i.e. child health + parental dead status) and country fixed effects lowers the point estimate of average career arduousness from 0.103 to 0.046. In Table 13 one observes a similar reduction in the magnitude of our point estimates for female physical ill health. We also verify that each of our controls incrementally leads to a reduction of the point estimates. Our estimates for the (relative) importance of arduousness [s1] vs. instability [s2] change too. In the lower part of Table 12 one can see that the inclusion of controls leads to a rise of the relative importance or career instability (e.g. from .60 to .75 for female ill health).

In short, SHARE offers various ways to assess the magnitude of selection biases. It also

[38]Gelbach (2016) reminds us of the well-known formula of the omitted variable bias and its relevance to assess the contribution of observed controls to its reduction. If we had estimated our model without controlling for health endowment, the value of the baseline estimated β^b would have deviated from the true/full β^f according to $\beta^b = \beta^f + \rho\gamma$; where γ is the direct impact of health endowment on ill health in eq. (1) and ρ is the correlation between health endowment and career arduousness. For instance, in the case of childhood ill health (one of the components of our health endowment vector) we have $\gamma > 0$ (poor childhood health correlates positively with old-age ill health) and $\rho > 0$ (a positive correlation between childhood ill health and degree of the arduousness of the career.

provides observables (ie. good pre-labour control variables) to directly control for health-driven selection biases. Sceptics might argue that there could still be some selection on unobservables (in other words, an omitted variable bias). A common approach to evaluating robustness to omitted variable bias is to observe coefficient movements after the inclusion of controls (Oster, 2019). If a coefficient is stable after the inclusion of controls, this is taken as a sign that the (remaining) omitted variable bias is limited. Note that this approach is the one underpinning what we report in Tables 12,13. And we see that, in particular, our arduousness coefficient is not stable: it goes down for each (block of) control(s) we include. One interesting idea is that the bias arising from our *observed* controls (and that the Gelbach (2016) formula emphasises) is informative about the bias that arises from a hypothetical full set of controls. At the bottom of tables 12,13 we report the unobserved control bias-adjusted values of the arduousness/instability coefficients proposed by (Oster, 2019). They are computed as $\beta^{adj} = \beta^f - (\beta^b - \beta^f) * (R2^{max} - R2^f)/(R2^f - R2^b)$ assuming *i)* that unobserved & observed controls are equally related to career arduousness/instability *ii)* the relative contribution of each observed control to career arduousness/instability equals its (relative) contribution to ill health, *iii)* $R2^{max} = 1.3\ R2^f$ where $R2^{max}$ is the $R2$ that one would compute when including unobserved controls and 1.3 is a value recommended by Oster (2019) because it is consistent with randomised treatment analysis outcomes. Results suggest that, if anything, we could not exclude the arduousness coefficient being equal to zero if we were to include non-observable controls. By contrast, the instability coefficients that turn out to be different than zero would remain so with the inclusion of a full list of controls. This tentatively reinforces one of the key results of the paper: career arduousness appears to be less of a contributor to late-life ill health than generally assumed, whereas career instability could be a more potent determinant and deserve more attention by analysts and policymakers.

Table 12: Sensitivity of Arduousness/Instability Coefficients to Observable and Unobservable Controls: Mental ill health (female)

	Mental ill health					Physical ill health				
	Baseline	Int1	Int2	Int3	Full(M1)	Baseline	Int1	Int2	Int3	Full(M1)
Ardu. (car. av.) ISCO4	0.1060***	0.0983***	0.0678***	0.0614***	0.0463***	0.1493***	0.1387***	0.1149***	0.1051***	0.0752***
	(0.0084)	(0.0084)	(0.0092)	(0.0092)	(0.0094)	(0.0081)	(0.0081)	(0.0089)	(0.0088)	(0.0089)
Cum. yrs empl	-0.0069***	-0.0062***	-0.0057***	-0.0057***	-0.0059***	-0.0066***	-0.0056***	-0.0054***	-0.0053***	-0.0065***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Propensity to work full-time (1=max)	0.0330	0.0534	0.0649	0.0379	-0.1233**	0.2202***	0.2484***	0.2460***	0.2067***	-0.0305
	(0.0553)	(0.0552)	(0.0552)	(0.0548)	(0.0584)	(0.0532)	(0.0531)	(0.0531)	(0.0524)	(0.0555)
Numb. of jobs	0.0103**	0.0118**	0.0146***	0.0104**	0.0151***	0.0201***	0.0222***	0.0238***	0.0178***	0.0204***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0052)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0049)
Numb. of 6m gaps	0.0326***	0.0313***	0.0303***	0.0295***	0.0352***	0.0100	0.0081	0.0072	0.0068	0.0085
	(0.0102)	(0.0102)	(0.0101)	(0.0101)	(0.0101)	(0.0098)	(0.0098)	(0.0098)	(0.0096)	(0.0096)
Numb. of redun.	0.0709***	0.0691***	0.0650***	0.0633***	0.0445***	0.0515***	0.0490***	0.0428***	0.0401***	0.0185
	(0.0120)	(0.0120)	(0.0120)	(0.0119)	(0.0119)	(0.0116)	(0.0115)	(0.0116)	(0.0114)	(0.0113)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Educ.[a]	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Health end.[b]	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Country	No	No	No	No	Yes	No	No	No	No	Yes
Variance decomposition analysis										
[$s1$]	40.17	31.81	19.16	11.67	5.79	60.45	45.02	35.27	18.94	9.43
[$s2$]	59.83	48.44	39.31	24.42	17.01	39.55	29.42	26.37	13.53	9.55
[$s2/(s1+s2)$]	0.60	0.60	0.67	0.68	0.75	0.40	0.40	0.43	0.42	0.50
Nobs	20,129	20,129	20,129	20,129	20,129	20,129	20,129	20,129	20,129	20,129
Unobserved control bias-adjusted value of the arduousness coef. (Oster, 2019)[c]										
Ardu. (car. av.) [adj]					0.0131					-0.0202
Cum. yrs empl [adj]					-0.0054					-0.0064
Prop. to work full-time (1=max) [adj]					-0.2104					-0.3534
Numb. of jobs [adj]					0.0177					0.0209
Numb. of 6m gaps [adj]					0.0177					0.0209
Numb. of redun. [adj]					0.0298					-0.0240

Source: SHARE 20004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

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

[b]: Childhood health (Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.) & Parental death status (Parent is currently alive (1); died early (2) died late (3) [i.e. they died younger(2)/older(3) than the median age at death in the considered country]. [c]: computed as $\beta^{adj} = \beta^f - (\beta^b - \beta^f) * (R2^{max} - R2^f)/(R2^f - R2^b)$ assuming *i)* that unobserved & observed controls are equally related to career arduousness *ii)* the relative contribution of each observed control to career arduousness equals its (relative) contribution to ill health, *iii)* $R2^{max} = 1.3\, R2^f$ where $R2^{max}$ is the $R2$ that one would compute when including unobserved controls and 1.3 is a value recommended by Oster (2019).

Table 13: Sensitivity of Arduousness/Instability Coefficients to Observable and Unobservable Controls: Physical ill health (female)

	Mental ill health					Physical ill health				
	Baseline	Int1	Int2	Int3	Full(M1)	Baseline	Int1	Int2	Int3	Full(M1)
Ardu. (car. av.) ISCO4	0.0610***	0.0572***	0.0342***	0.0298***	0.0216***	0.0956***	0.0896***	0.0628***	0.0559***	0.0381***
	(0.0061)	(0.0061)	(0.0068)	(0.0067)	(0.0069)	(0.0068)	(0.0067)	(0.0074)	(0.0074)	(0.0075)
Cum. yrs empl	-0.0092***	-0.0091***	-0.0100***	-0.0096***	-0.0088***	-0.0132***	-0.0131***	-0.0139***	-0.0133***	-0.0122***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)
Propensity to work full-time (1=max)	-0.4866***	-0.4761***	-0.4389***	-0.4280***	-0.4324***	-0.3948***	-0.3780**	-0.3736**	-0.3584**	-0.4125***
	(0.1342)	(0.1339)	(0.1337)	(0.1330)	(0.1328)	(0.1477)	(0.1471)	(0.1470)	(0.1457)	(0.1449)
Numb. of jobs	0.0138***	0.0144***	0.0174***	0.0155***	0.0142***	0.0195***	0.0203***	0.0234***	0.0205***	0.0176***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0042)	(0.0045)	(0.0045)	(0.0045)	(0.0044)	(0.0046)
Numb. of 6m gaps	0.0536***	0.0522***	0.0476***	0.0438***	0.0370***	0.0205*	0.0183	0.0136	0.0092	0.0039
	(0.0110)	(0.0110)	(0.0109)	(0.0109)	(0.0109)	(0.0121)	(0.0120)	(0.0120)	(0.0119)	(0.0119)
Numb. of redun.	0.0231**	0.0200*	0.0176	0.0173	0.0117	0.0065	0.0017	-0.0026	-0.0036	-0.0114
	(0.0112)	(0.0112)	(0.0112)	(0.0111)	(0.0111)	(0.0123)	(0.0123)	(0.0123)	(0.0122)	(0.0122)
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income prox.	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Educ.[a]	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Health end.[b]	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Country	No	No	No	No	Yes	No	No	No	No	Yes
Variance decomposition analysis										
[$s1$]	24.37	18.80	9.33	6.21	3.20	37.34	26.24	16.71	10.92	5.34
[$s2$]	75.63	62.33	53.25	37.03	24.20	62.66	47.49	44.74	29.23	18.43
[$s2/(s1+s2)$]	0.76	0.77	0.85	0.86	0.88	0.63	0.64	0.73	0.73	0.78
Nobs	16,906	16,906	16,906	16,906	16,906	16,906	16,906	16,906	16,906	16,906
Unobserved control bias-adjusted value of the arduousness coef. (Oster, 2019)[c]										
Ardu. (car. av.) [adj]					-0.0017					-0.0325
Cum. yrs empl [adj]					-0.0086					-0.0110
Prop. to work full-time (1=max) [adj]					-0.4005					-0.4343
Numb. of jobs [adj]					0.0144					0.0153
Numb. of 6m gaps [adj]					0.0144					0.0153
Numb. of redun. [adj]					0.0050					-0.0334

Source: SHARE 20004-2020 (Wave 7, health items from waves 6,8), O*NET 2021, EWCS 2015
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
[a]: ISCED1997 classification of educational attainment [0:no degree 6: tertiary long].
[b]: Childhood health (Respondents report their health on a 5-item scale: Excellent 1, Very Good 2, Good 3, Fair 4, Poor 5, Varied a lot 6.) & Parental death status (Parent is currently alive (1); died early (2) died late (3) [i.e. they died younger(2)/older(3) than the median age at death in the considered country]. [c]: computed as $\beta^{adj} = \beta^f - (\beta^b - \beta^f) * (R2^{max} - R2^f)/(R2^f - R2^b)$ assuming *i)* that unobserved & observed controls are equally related to career arduousness *ii)* the relative contribution of each observed control to career arduousness equals its (relative) contribution to ill health, *iii)* $R2^{max} = 1.3\, R2^f$ where $R2^{max}$ is the $R2$ that one would compute when including unobserved controls and 1.3 is a value recommended by Oster (2019).

5 Summary of Results and Policy Implications

Exploiting unique (and so far untapped) retrospective data on entire careers,[39] together with data on the arduousness of occupations, plus rich data on physical and mental health beyond the age of 50, this paper explores the long-term health consequences of career arduousness[40] and instability.[41] It combines regression and decomposition of the (model-explained) ill health variance to quantify the impact of these beyond 50. The analysis is carried out simultaneously for 27 developed but still contrasted mostly European countries.[42]

The key finding of this paper is that whilst someone's career arduousness is a significant contributor to mental or physical ill health at an older age, it appears (quantitatively) a minor determinant. Career instability (i.e. the number of jobs held, long gaps of 6 months+, the number of redundancies…) could matter as much if no more *ceteris paribus*. This result holds for male and female respondents, mental or physical health,[43] and across countries with rather contrasted GDP levels and degrees of social protection. Of course, it would be good if future research, using different data, could confirm it, and also identify the detailed mechanisms connecting career instability to poor health in the long run. Also, that result (although not directly comparable) aligns with those of Vodopivec et al. (2021) who stress the long-term negative health impact of unemployment spells.[44]

We also believe that our results can be useful for policymakers.

First for those in charge of pensions, who are currently trying to account for the heterogeneity of careers by differentiating the (rising) retirement age.[45] Should the right to retire early be solely granted to those who have had a long and arduous career? Or should it also be granted to those who had an unstable one? If we believe the results of this paper, probably to both profiles of prospective retirees. However, in practice, this would make such a differentiated retirement policy even more complicated to implement: it would increase the amount of (reliable) information needed by pension officers to properly account for individual heterogeneity.[46]

[39]Not just the current occupation or job.

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

[41]As far as we know, this is the first paper that exploits the SHARE wave 7 very detailed (ISCO 4 digits) work history data.

[42]GDP per head data show over 4 to 1 ratio between the wealthiest (Luxembourg-LUX) and the poorest (Bulgaria-BGR) countries.

[43]This paper finds little evidence that career arduousness and instability (but also the other variables considered) contribute differently, for men vs. women to mental vs. physical ill health beyond the age of 50.

[44]We say "not directly comparable" because that paper does not combine arduousness and instability. Also, it focuses on adulthood health whereas we consider late-life health.

[45]Or related pension parameters, like the contribution or replacement rates.

[46]For a discussion of the role of (the lack of) information in implementing retirement age differentiation see Vandenberghe (2021b).

Our results could also help achieve better prevention policies. They support a relatively more intensive use of instruments susceptible to reducing career instability, reinforcing job attachment or limiting their negative consequences (if we consider that job mobility is there to stay or a desirable trait of labour markets). These instruments differ from those used to combat arduous and hazardous working conditions. The latter are inherited from the 19$^{\text{th}}$ and early 20$^{\text{th}}$ centuries and focused on improving workers' conditions, i.e. lowering the physiological and psychological demands put on individuals while they work, improving the work environment and raising pay.[47] However, our results suggest that people's long-term mental and physical health status might as much be determined by the incidence of non-work episodes (for which arduousness is a priori minimal). Examples of policies that are better suited for addressing that specific risk comprise employment protection and unemployment insurance but also fully-fledged and more generously funded active labour market programmes (ALPM) that provide coaching, mentoring, job placement or job-related training. Also, alternative income support policies with a less contributory component[48] might be worth considering. For example, a guaranteed income in the form of a negative income tax (Friedman, 1962) or a basic income (Van Parijs, 2017).

Also, in terms of prevention, our finding that pre-labour status matters a lot for mental or physical health – perhaps more than the characteristics of the professional career (arduousness and instability confounded) – has policy implications. 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 or physical health differences past the age of 50 *ceteris paribus*. That result aligns with what the life-course literature has long posited (Trannoy et al., 2010). For public policy, this tentatively suggests that policies aimed at promoting older people's health and well-being should go beyond people's career stage, and target social/health conditions early in childhood.

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[47]For instance, the EU Charter of Fundamental Rights states that: "1. Every worker has the right to working conditions which respect his or her health, safety and dignity. 2. Every worker has the right to limitation of maximum working hours, to daily and weekly rest periods and an annual period of paid leave".

[48]A feature of many unemployment schemes that favours people with a strong labour-market attachment.

10.6103/SHARE.w2.710, 10.6103/SHARE.w4.710, 10.6103/SHARE.w5.710,
10.6103/SHARE.w6.710, 10.6103/SHARE.w7.711, 10.6103/SHARE.w8cabeta.001),
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Finally, this paper used data from the European Foundation for the Improvement of Living and Working Conditions. (2020). European Working Conditions Survey Integrated Data File, 1991-2015. [data collection]. 8th Edition. UK Data Service. SN: 7363,
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6 Appendix

Tables & Figures forming the Appendix are to be found here [click].