



HAL
open science

I Can't Forget About U: Lifetime Unemployment and Retirement Well-being

Andrew E. Clark, Anthony Lepinteur

► **To cite this version:**

Andrew E. Clark, Anthony Lepinteur. I Can't Forget About U: Lifetime Unemployment and Retirement Well-being. 2024. halshs-04788992

HAL Id: halshs-04788992

<https://shs.hal.science/halshs-04788992v1>

Preprint submitted on 18 Nov 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



WORKING PAPER N° 2024-55

**I Can't Forget About U: Lifetime
Unemployment and Retirement Well-being**

**Andrew E. Clark
Anthony Lepinteur**

JEL Codes: J21, J63, I31

Keywords: Unemployment, Retirement, Scarring, Well-Being, SHARE.



I Can't Forget About U: Lifetime Unemployment and Retirement Well-being

ANDREW E. CLARK
Paris School of Economics – CNRS

ANTHONY LEPINTEUR
University of Luxembourg

This version: November 2024

Abstract

It is well-known that unemployment leaves scars after re-employment, but does this scarring effect persist even after retirement? We analyse European data on retirees from the SHARE panel, and show that the well-being of the retired continues to reflect the unemployment that they experienced over their working life. These scarring effects are somewhat smaller for older retirees, but larger for those who arguably had higher expectations regarding the labour market when they were active. The lower well-being from lifetime unemployment does not reflect lower retirement income. This long-run scarring for those who have left the labour market underlines that contemporaneous correlations significantly under-estimate the well-being cost of unemployment.

Acknowledgements

We are very grateful to the Editor, Henry Overman, and four anonymous referees for detailed and constructive comments. Andrew Clark acknowledges financial support from the EUR grant ANR-17-EURE-0001.

JEL Codes: J21, J63, I31.

Keywords: Unemployment, Retirement, Scarring, Well-Being, SHARE.

1. Introduction

Does unemployment leave indelible marks? A large body of literature has underscored that unemployment is associated with contemporaneously lower well-being (Clark and Oswald, 1994, Winkelmann and Winkelmann, 1998, Dolan *et al.*, 2008, and Stutzer and Frey, 2010, are some of only many examples). In addition to the lower well-being experienced during unemployment, there is also evidence of scarring on the labour market after the unemployment spell is over. Initially analysed with respect to earnings in the post-unemployment job (Ruhm, 1991, Jacobson *et al.*, 1993, Stevens, 1997, Arulampalam, 2001, von Wachter and Bender, 2006, Oreopoulos *et al.*, 2008, and De Fraja *et al.*, 2021), scarring has more-recently been investigated with respect to post-unemployment subjective well-being (Clark *et al.*, 2001, Bell and Blanchflower, 2011, Knabe and Rätzel, 2011, Clark *et al.*, 2018, Clark and Lepinteur, 2019, and Hetschko *et al.*, 2019). This well-being scarring has been found when holding the earnings in the new job constant, so that the negative consequences of past unemployment are not only pecuniary.

This existing work on scarring has most often considered relatively-recent unemployment (often over the past few years). We here expand the temporal scope of the analysis to its maximum, and consider the relationship between well-being during retirement (which is an absorbing state for most individuals) and their lifetime experience of unemployment. By doing so, we hope to establish the extent to which unemployment, over a period of many decades, may continue to leave a mark on individuals' well-being even after they have left the labour market.

Our empirical analysis uses SHARE data, which records all of the labour-market experiences of over 45,000 individuals from 29 different European countries, as well as their current level of well-being as measured via the CASP index. We first find that any past unemployment experience is associated with significantly-lower well-being post-retirement. This association does not

qualitatively depend on the estimation technique (OLS, median regression or ordered probit) and cannot plausibly be reversed in sign. We deal with endogeneity issues by first taking an instrumental variable approach and then only considering unemployment due to layoff or plant/office closure: in both cases past unemployment experiences causally reduce well-being post-retirement.

As such, the retired do not forget the unemployment that they have experienced. We consider three potential mediators of this lifetime-scarring effect: income, family and health. All of these have appeared as consequences of unemployment in the shorter-run analysis of scarring: see Arulampalam (2001) for earnings, Lester (1996) and Tumin and Qian (2017) for the family, and Stauder (2019) for health. Unemployment may also have a direct effect on well-being that is plausibly of a psychological nature (such as lower self-confidence, or social stigma). In our analysis below we will show that the direct effect of past unemployment is stronger than the indirect effect that passes via these three mediators.

If the memory of unemployment fades over time, then the most-recent unemployment experiences will be the most salient. This is not what we find, with the estimated coefficient on prime-age unemployment (between the ages of 30 and 50) being more negative than that at older or younger ages. The smaller effect of unemployment after age 50 may partly mask early retirement or that labour-market earnings in later life are less important for the building-up of capital.

The well-being of the retired thus continues to reflect the unemployment that they have experienced: as such, unemployment has permanent effects throughout life. These effects are, however, somewhat moderated by age, being smaller for older retirees. On the contrary, this scarring is greater for those who arguably had higher expectations from the labour market when they were active: men and the better-educated. Last, we take advantage of the cross-country

dimension of SHARE and estimate well-being scarring separately by country. Despite the substantial variation in culture and labour-market institutions over the 29 countries, we do not uncover any significant country differences.

The remainder of the paper is organised as follows. Section 2 presents a literature review on the scarring effect of unemployment, Section 3 the data, and Section 4 the estimation sample and empirical strategy. The main results, robustness checks and heterogeneity analyses appear in Section 5. Last, Section 6 concludes.

2. The Literature on the Scarring Effect of Unemployment

In Ellwood's (1982) terminology, 'scars' refer to the long-term effects left by adverse experiences on individuals. In the context of unemployment, the jobless are considered to be scarred if they continue to experience repercussions from the experience even after they have returned to work.

The Economics literature has largely concentrated on the scarring effects of unemployment on earnings. De Fraja *et al.* (2021) recently developed a theoretical model, in a Mincerian framework, to encapsulate the notion of scarring in the context of wages. There has been a substantial amount of empirical work that has quantified this scarring effect with respect to earnings, with findings that are consistent across geographical areas, data types and identification approaches: past unemployment casts a shadow over future earnings. Some examples are Ruhm (1991), Jacobson *et al.* (1993), Stevens (1997), Arulampalam (2001), von Wachter and Bender (2006), Oreopoulos *et al.* (2008), and De Fraja *et al.* (2021).

Other related work has focused on the impact of past unemployment on future job stability. Narendranathan and Elias (1993) and Arulampalam *et al.* (2000) use British data to show that the

risk of future unemployment is higher following an initial job loss; Nilsen and Reiso (2014) find the same result in Norwegian data. The result from the meta-analysis in Filomena (2024) is that a past unemployment spell is associated with 3% lower current labour earnings and a 5.5% fall in the probability of current employment. Expanding this analysis across individuals, Clark and Lepinteur (2019) reveal evidence of unemployment transmission across generations, so that the scars of unemployment can extend beyond individuals to affect the outcomes of their children.

As von Wachter (2020) emphasises, the scarring effects of unemployment are not confined to labour-market outcomes. In Currie and Schwandt (2014), Hofmann *et al.* (2017) and Di Nallo and Lipps (2023) unemployment affects fertility decisions well beyond the initial job loss period. Equally, Lester (1996), Jalovaara (2003), Hansen (2005), Sayer *et al.* (2011) and Tumin and Qian (2017) uncover long-term negative consequences of unemployment on marital stability, and Stauder (2019) shows similar results for health.

Regarding subjective well-being, past unemployment continues to have an effect on current life satisfaction. In Clark *et al.* (2001), unemployment over the past three years reduces current life satisfaction in German panel data, even controlling for current labour-force status. Similar findings appear in Bell and Blanchflower (2011), Knabe and Rätzl (2011), Clark *et al.* (2018), Clark and Lepinteur (2019) and Hetschko *et al.* (2019). The psychological toll of unemployment is then both significant and long-lasting.

However, much of this existing scarring work has concentrated on relatively-recent unemployment, tracking outcomes for only a few years after the unemployment has ended. As noted above, the existing literature tends to find persistent effects over this period. But what about over a longer-run? We here extend the temporal scope of analysis to consider the well-being impact of unemployment during retirement, a point at which most individuals have left the labour market

for good. By focusing on the relationship between well-being in retirement and the total experience of unemployment throughout the working life, we aim to establish whether unemployment over a period of many decades continues to affect well-being even beyond the individual's association with the labour market.

3. Data

Our empirical analysis is based on data from the Survey of Health, Ageing and Retirement in Europe (SHARE: <https://share-eric.eu/>). This is an almost biennial panel survey that started in 2004 and has covered 28 European countries and Israel.¹ At the time of writing, there are nine SHARE waves (the last of which was collected between 2021 and 2022). The target population of SHARE is individuals aged 50 or above at the time of the survey with a regular domicile in one of the SHARE countries. Refreshment samples have been included in every wave (apart from Wave 3), and the partners of SHARE respondents are also interviewed, irrespective of their age.

The SHARE questionnaire covers various topics such as demographics, social networks, health, employment and pensions, childhood background and expectations. Waves 3 and 7 focus on respondents' life histories, with a special module on the working life. Brugiavini *et al.* (2019) have combined the retrospective information from these two waves to create the SHARE Job Episode Panel. This describes the various labour-force statuses (working - either employed or self-employed, unemployed, in education, out of the labour force or retired) that SHARE respondents experienced throughout their life. The data in this job-episode panel indicates the respondents' main labour-force status at each age a (defined in the SHARE data as the year t in which the

¹ Not all countries appear in all waves: see <https://share-eric.eu/data/data-documentation/waves-overview>.

respondent had their a^{th} birthday). SHARE respondents were asked to indicate the beginning and end year of each employment spell, and any unemployment spells of six months or more that they experienced (i) between the end of full-time education and the first employment spell and (ii) between two employment spells.² As such, we do not know the exact length of any reported unemployment spell (whereas this information is available in the British Cohort Study data analysed in Clark and Lepinteur, 2019, for example), and unemployment spells of under six months do not appear. For each employment spell, the respondent also reports the reason why the spell in question ended. We will make use of this latter information in Section 5.3 below.

The SHARE survey includes questions that are used to calculate the CASP-12 score (Control, Autonomy, Self-realisation and Pleasure scale), which is one of the most-common international measures of quality of life and well-being at older ages. The 12 CASP questions are listed in Appendix Table B1 (for example, “I look forward to each day” and “I feel left out of things”), with the responses to each being “Often”, “Sometimes”, “Rarely” or “Never”. Assigning values of one, two, three and four respectively to these responses (reverse coding for the negative questions) and summing over the 12 questions yields the CASP-12 score. This score ranges from 12 to 48, with higher scores corresponding to a better quality of life. Oliver *et al.* (2021) provide an extensive discussion of the validity and reliability of the CASP-12 score.

² The SHARE Job Episode Panel assigns one labour-force status to each respondent age. This assignation gives priority to employment, in that the labour-force status in the year in which the respondent had their a^{th} birthday is recorded as employment if any employment spell covered any part of this year. In our calculation of lifetime unemployment exposure, we have amended this assignation protocol to ensure that we pick up all unemployment spells (of six months or more). More details on the construction of labour-force episodes appear in Appendix A.

4. Estimation Sample and Empirical Strategy

To understand how unemployment during the working life affects well-being after retirement, we consider an estimation sample of retirees who are aged over 65, with valid working-life history and CASP-12 information, who have spent at least one year active in the labour market, and for whom retirement is an absorbing state (*i.e.* they are not observed to return to the labour market). This yields an estimation sample of 141,084 observations on 47,795 individuals. Our analysis will cover all 29 of the SHARE countries.

The descriptive statistics for this estimation sample appear in Table 1. Average age is around 74 and the sample is almost perfectly gender-balanced.³ About 9% of our sample observations refer to individuals who experienced at least one episode of unemployment of six months or more during their active life. The average CASP-12 score (on a scale from 12 to 48) is just over 37, with a standard deviation of 6.2; the median value is 38. Figure 1 plots the CASP-12 distribution in the sample. This is somewhat left-skewed, but not drastically so (with a skewness figure of -0.52). These figures are comparable to those in the CASP-12 score distributions in other aging population surveys, such as the UK ELSA survey, and indeed to the distribution of psychological well-being as measured by the GHQ, another multi-item scale, in the UK population.⁴

Figure 2 depicts the distribution of employment and unemployment by respondent age. Unemployment is more prevalent at younger ages, with its incidence steadily decreasing thereafter. The employment percentage is on the contrary hump-shaped, rising from age 15 to roughly 30, then plateauing up to age 50 and finally dropping towards zero due to retirement. Note that our

³ The descriptive statistics at the individual, rather than the observation, level appear in Appendix Table B2. This shows that 10% of retired individuals in the SHARE dataset experienced at least one episode of unemployment of six months or more.

⁴ See <https://www.understandingsociety.ac.uk/wellbeing-dashboard/>.

sample also includes respondents above age 80 (who are not shown in Figure 2), but the percentages of individuals working or unemployed at these ages are close to zero. Very few respondents in our estimation sample retired after age 80; excluding these late retirees from our analysis does not change the results. Last, Figure 3 plots the distribution of individuals in our estimation sample by the number of experiences of unemployment they reported, conditional on having reported at least one unemployment spell.⁵ One third of those who report past unemployment experienced only one spell. A non-negligible proportion of individuals report ten or more such spells: all of our empirical results are robust to excluding this group.

We evaluate retirees' well-being scarring from unemployment by estimating the following regression:

$$CASP_{ict} = \beta_1 Unemp_i + \beta_2 Childhood_{it} + \beta_3 Adulthood_{it} + \beta_4 Duration_i + \mu_c + \lambda_t + \epsilon_{ict}. \quad (1)$$

Here $CASP_{ict}$ is the CASP-12 score of individual i living in country c in year t . In our main model, $Unemp_i$ is a dummy for the individual reporting at least one six-months or longer unemployment spell in the Job Spell Panel of SHARE.⁶ Shorter unemployment spells are not recorded in the data. As such, we cannot directly interpret $Unemp_i$ as capturing the influence of unemployment as

⁵ The distribution of observations (rather than individuals) according to the number of past unemployment spells is almost exactly identical.

⁶ It is possible that it is the more-unpleasant unemployment experiences that are more salient, and therefore more likely to be remembered. However, the question in the SHARE survey used to create labour-force episodes is neutral, in that it asks individuals to list all employment episodes in sequence, and to indicate their labour-force status during any gaps of six months or more between these episodes. Second, our measure of lifetime unemployment is extensive (a dummy for the individual reporting at least one six-months or longer unemployment spell). Forgotten unemployment will only change this extensive variable for individuals with no reported long unemployment spell. In addition, memory bias may be more likely for shorter unemployment spells than for those of half a year or longer. A last point here is that the sign of any bias from forgetting cannot be established *a priori*. This bias depends on first the number of individuals with all unemployment spells of six months or more forgotten relative to the number of individuals with at least one remembered unemployment spell of six months or more, and second the relative size of the well-being impacts of these two types of unemployment relative to no unemployment spells of six months or more (remembered or forgotten).

compared to employment, but rather that of longer-term unemployment as against employment and short-term unemployment. For simplicity, we will refer henceforth to the effect of past unemployment when discussing the estimates of β_1 , although this actually refers to unemployment spells of over six months. Note that in Equation (1) above, $Unemp_i$ is time-invariant as we only model the $CASP_{ict}$ scores of those who are retired.

Although unemployment is arguably involuntary in most cases, it does not occur randomly. Clark and Lepinteur (2019) use British birth-cohort data to show that unemployment up to age 30 depends on a number of childhood characteristics that also affect well-being directly. We address this issue by controlling for $Childhood_{it}$, a vector of exogenous characteristics (gender, age and age-squared, and a cohort fixed-effect) and variables that pre-date entry into the labour market (years of education, childhood health, childhood Maths ability, and a dummy for high parental SES – proxied by the occupational position of the parents during childhood). We last include country (μ_c) and year (λ_t) dummies.⁷ Together, these variables help to address the influence of confounders that could affect both an individual’s unemployment experiences and their post-retirement well-being. Along the same lines, in Section 5.3 we will also take an Instrumental Variable approach and focus on arguably ‘more-exogenous’ variations in unemployment.

It is a mainstay in the literature that the contemporaneous correlation between subjective well-being and unemployment is negative. The scarring literature to date has considered only relatively short periods after the end of the unemployment spell. What is not known is whether this scarring eventually fades away. We here present a lifetime analysis of this question, and ask whether unemployment during the whole active life continues to be correlated with well-being even during

⁷ Replicating the analysis using country*cohort fixed effects does not change the nature of the conclusions. These results are available upon request.

retirement. If retirement protects the individual from their past unemployment, then we should find that β_1 is zero; with a continued detrimental effect of lifetime unemployment even after retirement, β_1 will be negative.

There are a number of reasons why unemployment spells may continue to reduce well-being even after they have ended (both in the short- and longer-run). First, unemployment has a persistent effect on a variety of objective individual characteristics. It is well-known that past unemployment casts a shadow over earnings once the individual returns to work (Arulampalam, 2001, among others), and this unemployment wage penalty may continue to affect retirement income. Unemployment also reduces the probability of having a partner (Lester, 1996, and Tumin and Qian, 2017) and of good health (Stauder, 2019), both of which may well persist over many years. The second pathway is more psychological: unemployment may enduringly reduce well-being via its effect on self-esteem or the social stigma that the individual may suffer. Winkelmann and Winkelmann (1998) distinguish between the material and psychological effects of unemployment on well-being (with both being measured simultaneously), and conclude that the latter is much larger. We here follow this approach by including the vector $Adulthood_{it}$ in Equation (1). This contains a number of variables that are measured contemporaneously with $CASP_{ict}$: a dummy for having a partner in the household, household size, the individual's number of chronic diseases, and household annual net income (this is expressed in real Euros adjusted for purchasing power parity (PPP), and appears in logs). Although we cannot claim that $Adulthood_{it}$ covers all of the objective mediators of past unemployment, it does include a number of the most-prominent candidates. As such, the estimated coefficient on β_1 holding these variables constant will provide a rough measure of the psychological consequences of past unemployment. In order to distinguish

the total from the mediated effect of past unemployment, we will estimate Equation (1) first without and then with the *Adulthood*_{it} variables.

We also control for *Duration*_i, the duration of the working life in years, as this might be thought to be mechanically correlated with both unemployment experience and subjective well-being. Although we have multiple observations per individual, we cannot introduce individual fixed effects as lifetime unemployment experience is time-invariant for retirees. All standard errors in our analysis will be clustered at the individual level.

The robustness checks will consider alternative estimators (quantile regressions and ordered probit estimation) and a variety of different measures of unemployment exposure. We will also estimate a Two-Stage Least Squares version of Equation (1) in order to address the potential endogeneity of *Unemp*_i.⁸

5. Results

5.1. Main Results

To provide an initial overview of the correlation between unemployment experiences and well-being, we first present the distribution of CASP-12 scores based on respondents' unemployment histories. Figure 4 shows the CASP-12 score distribution for two groups: those who experienced unemployment for at least 6 consecutive months and those who did not. Individuals with any history of longer-term unemployment have lower CASP-12 scores on average, as can be seen in the leftward shift for the “Ever unemployed” group. The mean CASP-12 score for those who had

⁸ We do not weight our observations. However, to ensure that our conclusions are robust to differences in country population sizes, we conducted additional analyses using population size weights based on average UN estimates from 1960 to 2023. These weighted results are in line with the unweighted findings, and are available upon request.

longer-term unemployment is 36.08, as opposed to a (statistically-higher) figure of 37.36 for those who did not.

Table 2 moves on from the initial evidence in Figure 4 by carrying out a regression analysis. All of the continuous variables in these regressions are standardised, to allow for the simple comparison of the estimated coefficients.

The first column includes only the dummy variable for having had at least one unemployment spell, the duration of the working life, and country and year of interview dummy variables. Lifetime unemployment seems to throw a shadow over retirement well-being, in that the estimated coefficient on unemployment experience is negative and significant. The size of the estimated effect here is 0.183 of a standard deviation, which corresponds (using the figure in Table 1) to around 1.15 points (a figure that is very similar to the difference in the means in the raw data). Adding the exogenous variables and childhood-background variables in column (2) has little material effect on the estimated coefficient, which falls to 0.145 (corresponding to a drop of around a point on the CASP-12 scale).

Column (3) of Table 2 then introduces the potential objective mediator variables of household size, the presence of a partner in the household, the number of chronic diseases and household net annual income (in logs). There is only marginal mediation, with the estimated coefficient falling from -0.145 to -0.125. This relatively small effect from a number of the main objective consequences of unemployment is consistent with the scarring effect of lifetime unemployment being mostly psychological. In column (3) of Table 2, the effect of past unemployment is associated with a drop in well-being that is of the same size as not having a spouse in the household at the time of the interview. From the estimated income coefficient in Table 2, a 74% rise in annual

net household income would be required to compensate for past unemployment ($= \exp(0.069/0.125) - 1$).

5.2. Robustness Checks and Additional Results

This section presents a series of robustness tests, the results of which appear in Table 3 and Appendix Table B3. The first column of these two Tables reproduces the coefficient on unemployment experience in the mediated specification in column (3) of Table 2 for comparison purposes.

We first address the linearity of the dependent variable. The summary CASP-12 score is on a range from 12 to 48, and it might be thought that non-linear estimation might be more appropriate (given the ordered nature of the replies to each of the 12 questions). The ordered probit results appear in column (2) of Table 3. The estimated coefficient on unemployment experience during working life remains negative and significant (ordered logit estimation yields the same conclusion).

The critique of Schröder and Yitzhaki (2017) and Bond and Lang (2019) regarding sign-reversals in regressions with ordered dependent variables applies to the total CASP-12 score, as each component item is measured on a four-point Likert scale. We have carried out two tests to consider this issue. We first adopt the approach proposed by Chen *et al.* (2022) and re-estimate our model via median regression. This produces results that are similar to those from OLS. Second, we check the non-reversal condition in Kaiser and Vendrik (2023), and find that under some conditions a positive monotonic transformation of the CASP-12 scale can reverse the effect of unemployment experience. However, the necessary transformation of the scale is too extreme to be credible. This is in line with the results in Kaiser and Lepinteur (2024), where the coefficients that are the most

difficult to reverse plausibly from linear well-being regressions are those on exogenous variables (e.g. age, sex, and those resulting from policy changes) and those that are defined well before the date at which well-being is measured (such as past poverty).

It is possible that some respondents may not have fully engaged with the survey and, as a result, provided the same response to all of the CASP-12 questions. We thus re-ran our main regressions, excluding respondents who gave the same answer to all 12 items (which leads to a 2.4% smaller sample). The results, shown in Column (4) of Table 3, remain unchanged.

The CASP-12 scale comprises four sub-dimensions: control, autonomy, self-realisation, and pleasure. To see whether these dimensions are differentially affected by past unemployment, we replicate the main specification for each sub-dimension. The results in Columns (2) to (5) of Appendix Table B3 show that all dimensions are significantly negatively associated with past unemployment. The estimated coefficients are mostly relatively similar in terms of size: the exception is the autonomy score, where the correlation is larger.

The SHARE survey also contains other evaluative measures, such as the EURO-D depression scale and self-assessed health. Although these variables do not measure well-being *per se* (as they each focus on one particular aspect of life), we can consider them as dependent variables (although the EURO-D does not appear in SHARE Wave 3) as a test of convergent validity. The CASP-12, EURO-D and self-reported health scores are positively correlated with each other, with correlations ranging between 0.42 and 0.52 (Appendix Table B4), as expected if they measure aspects of health and well-being that tend to move in the same direction. However, the correlation coefficients are well below one, so that the measures are also distinct from each other. The last two columns of Appendix Table B3 list the estimated unemployment coefficients with the EURO-

D and self-reported health as the dependent variables. As for the CASP-12, past unemployment experience is associated with lower well-being post-retirement.⁹

We have so far reduced an individual's past unemployment experience to a dummy variable for having had at least one unemployment spell of over six months. Although we do not have information on shorter-duration unemployment spells, we do know how many episodes of long-term unemployment SHARE respondents experienced. In column (5) of Table 3, we replace the ever-experienced unemployment dummy by a categorical variable for (i) no experience of unemployment (the reference category), (ii) one spell, (iii) two spells, and (iv) three or more spells. All of the estimated coefficients are negative, with the scarring effects of three or more unemployment spells being statistically the largest. We also experimented with a continuous measure of unemployment: the proportion of time spent in long-term unemployment relative to the duration active in the labour market. The results from this continuous measure appear in Column (6) of Table 3 and show that a greater percentage of time spent in unemployment is associated with a lower CASP score.

Column (7) of Table 3 asks whether events that are farther in the past are less salient, splitting unemployment up by the age at which it was experienced (inspired by Figure 2, we split age up into under 30, 30 to 50, and after age 50). Column (7) carries out this exercise for the "ever unemployed" dummy. The estimated coefficients on all three unemployment dummies are negative: retirement does not erase the detrimental effect of past unemployment. There is in addition no evidence of the slope that would be consistent with more-distant events being increasingly forgotten, with the largest negative coefficient being found for the peak working ages

⁹ The results of the robustness checks for these new dependent variables appear in Appendix Tables B5 and B6. The results continue to hold for almost all specifications.

of 30-50. We can carry out the same exercise considering the categorical variable for number of unemployment spells that we used in Column (5), now defined as the number of spells experienced within each age category. We find that unemployment in prime age is equally harmful, independent of the number of spells, whereas more-frequent unemployment has a notably larger effect at the beginning or end of the career. These results are available upon request.

While our results show that unemployment is not forgotten during retirement, this is an average effect over all retirees. One obvious factor is how long the individual has been retired, and the individual's retirement date is indicated in the SHARE Job Spell Panel. Column (8) of Table 3 tests whether time spent in retirement attenuates the effect of past unemployment, with an interaction between the dummy for ever having been unemployed and a dummy for having been retired for over five years (as well as the main effect of the latter). The estimated coefficient on this interaction variable is positive, and suggests that the scarring effect of lifetime unemployment is about 43% ($0.081/0.188$) lower after at least five years of retirement. An alternative interaction between ever having been unemployed and a continuous years of retirement variable did not produce significant estimates, so that the attenuation of retirement duration seems to be more like a step function.

5.3. Addressing endogeneity

A central concern in estimating the scarring impact of unemployment on well-being is the potential endogeneity of this unemployment. Unemployment is unlikely to be purely random, and may reflect unobserved individual characteristics or life circumstances that are themselves correlated with post-retirement well-being. Specifically, omitted-variable biases arise if pre-existing traits, such as earlier-life mental health, impact both job stability and CASP-12 scores. If these factors

are not fully accounted for, our estimates of the effect of unemployment on well-being may be biased.

Our main specification already includes a series of early-life characteristics that are likely to influence both labour-force trajectories and later well-being. These include childhood health, cognitive skills at age 10, and parental SES. We also incorporate cohort and country fixed effects to account for any unobserved time-invariant cultural or institutional influences that may vary across birth cohorts and countries.

Despite these controls, there is always the risk of some remaining endogeneity. We therefore now take two approaches designed to identify variations in unemployment that are more likely to be exogenous. We first estimate an instrumental variable (IV) regression with peer unemployment as an instrument. Here individual unemployment experience is instrumented by the average unemployment experience of all other individuals born in the same country up to two years before or after the respondent, of the same gender, and the same level of education.¹⁰ The idea here is that peer-group unemployment reveals external labour-market movements and so provides information on the probability of unemployment that is independent of the individual's own characteristics. As such, the IV regression relies on the individual changes in unemployment that come from exogenous macroeconomic conditions.

Second, we obtain information on arguably exogenous unemployment spells by focusing on involuntary job loss. The SHARE survey asks respondents to specify the reason for the unemployment spells that they list, allowing us to identify distinguish involuntary reasons ('I was

¹⁰ To check for the robustness of these IV results to small cell sizes, we re-estimated the model excluding cells with fewer than 5, 10, 25, or 50 peers. The estimated effect of unemployment on well-being remains consistent in all of these specifications: these results are available upon request.

laid off' or 'my plant or office closed down') from the other reasons ('I resigned', 'by mutual agreement', 'I retired', 'A temporary job had been completed' and 'Other reason'). As the separate reasons for involuntary job loss are relatively infrequent, we combine layoffs and plant closures into a single 'involuntary unemployment' dummy variable. These unemployment spells are more likely to be unrelated to individual characteristics.

The IV and involuntary job-loss results appear in the final two columns of Table 3. The standard errors are clustered at the country*cohort*gender*education level in the IV specification (clustering at the individual level produces standard errors of similar value), and the Kleibergen-Paap rk Wald F-statistic of over 1000 reveals that the instrument is not weak. The point estimates in these last two columns, relying on unemployment that is more likely to be exogenous, are negative and significant. They are both a little larger than the benchmark estimate (-0.125), with values of -0.214 and -0.133 respectively. The larger effect is consistent with involuntary unemployment having a more pronounced impact on well-being.

5.4. Heterogeneity Analyses

The lifetime scarring effect of unemployment may differ by socio-demographic characteristics, as well as by retirement duration. We examine potential moderation from purely-exogenous variables (age and gender) and those that pre-date labour market entry (education and the SES of the main

family breadwinner).¹¹ We split the sample in two and estimate separate regressions for each heterogeneity variable, splitting at the country median of the continuous variables.¹²

Columns (1) and (2) in Table 4 list the results for retirees below and above the national median age (in our sample) respectively. The negative effects of past unemployment are stronger for younger respondents, consistent with the retirement-duration analysis in Table 3. Columns (3) and (4) refer to gender as a moderator of the effect of past unemployment. Our sample median birth year is 1942, and we might expect respondents' gender norms to be fairly traditional, with unemployment mattering more for men: this is indeed what we find (although the difference between the two estimated coefficients is only small). In the next two columns, the effect of past unemployment is larger for the more-educated, which is consistent with the educated having higher labour market aspirations. Last, we find no evidence of any heterogeneity with respect to the SES of the respondent's parents in the last two columns of Table 4.

Despite these various differences across groups, it should be underlined that lifetime unemployment experience is (conditional on all of the control variables) associated with lower post-retirement well-being for all of the eight separate groups in Table 4.

Last, as SHARE is multi-country we can estimate a separate effect of past unemployment in each sample country. The results are depicted in Figure 5. The black dots refer to the estimated coefficient in the given country, and the solid and dotted grey lines in the background to the overall estimate and confidence intervals from the pooled analysis of all countries. Our sample countries

¹¹ We also assess whether the effect of experiencing at least one episode of unemployment differs for SHARE respondents who were not born in the country in which they were interviewed. These respondents may have been exposed to different institutional contexts prior to migration, potentially affecting the impact of unemployment. There are no statistically-significant differences: the estimated coefficients on interactions between the 'ever unemployed' variable and dummy variables for being foreign-born or for migrating at age 18 or older are all insignificant. Results are available upon request.

¹² Using interaction terms rather than separate samples produces qualitatively-similar results.

differ in many ways, such as their labour-market institutions (e.g. employment protection legislation and unemployment benefits) and culture. Even so, the differences between countries in Figure 4 are not particularly striking. Most estimated coefficients are negative, and the relatively-small country samples (see Table B7 in the Appendix) produce fairly-wide confidence intervals so that the country-effect of past unemployment experience is never significantly different from either the average effect in the whole sample or that in any other country. While larger samples may produce some significant differences in this respect, the visual inspection of Figure 4 suggests that post-retirement scarring from lifetime unemployment is a general phenomenon across Europe.

To formally test whether certain country characteristics moderate post-retirement scarring, we take data from a number of sources. Time-series data on social expenditures (1980–2022) and replacement rates after one year of unemployment (2001–2023) were obtained from the OECD. For GDP (1960–2023) and the unemployment rate (1991–2023), we relied on data from the World Bank and the International Labour Organization (ILO), respectively. Each country was assigned to either a ‘high’ or ‘low’ group for each indicator according to whether its average value over the specified period was above or below the sample median value. The results in Figure 6 indicate little moderation from GDP. However, consistent with aggregate unemployment serving as a social norm (Clark, 2003, Clark and Lepinteur, 2019), the impact of lifetime unemployment on retirement well-being is larger in low-unemployment environments. Contrary to expectations, there is no buffering effect from either higher social expenditures or replacement rates against the negative well-being consequences of unemployment.

6. Conclusion

Using cross-European data from SHARE, we find that unemployment during the working life has a long-run negative effect on individual well-being even after retirement. Past unemployment is detrimental at all ages, but seems to be somewhat more so during the peak working ages of 30-50. In terms of individual characteristics, the scarring effect of past unemployment on post-retirement well-being is smaller for older individuals, women, and those who have been retired longer. There is on the contrary only little evidence of substantial cross-country heterogeneity. A mediation analysis concluded that only little of this effect of lifetime unemployment works via the income, health and family formation of the retired.

These results have a number of implications. First, as the shadow of unemployment continues to be felt even after labour-market exit, the total cost of unemployment should be calculated over the whole of life (including life during retirement). Second, although we find only few cross-country differences, it would seem likely that certain policies and institutions will help protect older individuals against persistent effects of past unemployment, and the identification of these via cross-country research with potentially larger samples would seem to be an important goal for continuing research in this area.

References

Arulampalam, W. (2001). “Is unemployment really scarring? Effects of unemployment experiences on wages”, *Economic Journal*, 111, 585-606.

Bell, D. N., and Blanchflower, D. G. (2011). “Young people and the Great Recession”, *Oxford Review of Economic Policy*, 27, 241-267.

Bond, T. N., and Lang, K. (2019). “The sad truth about happiness scales”, *Journal of Political Economy*, 127, 1629-1640.

Brugiavini, A., Orso, C. E., Genie, M. G., Naci, R., and Pasini, G. (2019). “Combining the retrospective interviews of wave 3 and wave 7: the third release of the SHARE Job Episodes Panel”, *SHARE Working Paper Series*, 36-2019.

Clark, A. E. (2003). “Unemployment as a social norm: Psychological evidence from panel data”, *Journal of Labor Economics*, 21, 323-351.

Clark, A., Flèche, S., Layard, R., Powdthavee, N., and Ward, G. (2018). *The Origins of Happiness*. Princeton University Press.

Clark, A., Georgellis, Y., and Sanfey, P. (2001). “Scarring: The psychological impact of past unemployment”, *Economica*, 68, 221-241.

Clark, A. E., and Lepinteur, A. (2019). “The causes and consequences of early-adult unemployment: Evidence from cohort data”, *Journal of Economic Behavior & Organization*, 166, 107-124.

Clark, A. E., and Oswald, A. J. (1994). “Unhappiness and unemployment”, *Economic Journal*, 104, 648-659.

Chen, L. Y., Oparina, E., Powdthavee, N., and Srisuma, S. (2022). “Robust ranking of happiness outcomes: A median regression perspective”, *Journal of Economic Behavior & Organization*, 200, 672-686.

Currie, J., and Schwandt, H. (2014). “Short-and long-term effects of unemployment on fertility”, *Proceedings of the National Academy of Sciences*, 111, 14734-14739.

De Fraja, G., Lemos, S., and Rockey, J. (2021). “The wounds that do not heal: the lifetime scar of youth unemployment”, *Economica*, 88, 896-941.

Di Nallo, A., and Lipps, O. (2023). “How much his or her job loss influences fertility: A couple approach”, *Journal of Marriage and Family*, 85, 873-897.

Dolan, P., Peasgood, T., and White, M. (2008). “Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being”, *Journal of Economic Psychology*, 29, 94-122.

Ellwood, D. (1982). “Teenage Unemployment: Temporary Scars or Permanent Blemishes?”, in *The Youth Labor Market Problem: Its Nature, Causes, and Consequences*, 349-390, eds. Freeman, R. B., and Wise, D. A., University of Chicago Press.

Filomena, M. (2024). “Unemployment scarring effects: An overview and meta-analysis of empirical studies”, *Italian Economic Journal*, 10, 459-518.

Hansen, H. T. (2005). “Unemployment and marital dissolution: A panel data study of Norway”, *European Sociological Review*, 21, 135-148.

Hetschko, C., Knabe, A., and Schöb, R. (2019). “Looking back in anger? Retirement and unemployment scarring”, *Demography*, 56, 1105-1129.

Hofmann, B., Kreyenfeld, M., and Uhlenborff, A. (2017). “Job displacement and first birth over the business cycle”, *Demography*, 54, 933-959.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). “Earnings losses of displaced workers”, *American Economic Review*, 83, 685-709.

Jalovaara, M. (2003). “The joint effects of marriage partners’ socioeconomic positions on the risk of divorce”, *Demography*, 40, 67-81.

Kaiser, C. and Lepinteur, A. (2024). “Reversing the reversal? A systematic replication and appraisal of the robustness of economic research on self-reported wellbeing”, University of Luxembourg and Warwick Business School, *Mimeo*.

Kaiser, C. and Vendrik, M. (2023). “How much can we learn from happiness data?”, Warwick Business School, *Mimeo*.

Knabe, A., and Rätzl, S. (2011). “Scarring or scaring? The psychological impact of past unemployment and future unemployment risk”, *Economica*, 78, 283-293.

Lester, D. (1996). “The impact of unemployment on marriage and divorce”, *Journal of Divorce and Remarriage*, 25, 151-154.

Narendranathan, W., and Elias, P. (1993). “Influences of past history on the incidence of youth unemployment: Empirical findings for the UK”, *Oxford Bulletin of Economics and Statistics*, 55, 161-185.

Nilsen, Ø. A., and Reiso, K. H. (2014). “Scarring effects of early-career unemployment”, *Nordic Economic Policy Review*, 1, 13-46.

Oliver, A., Sentandreu-Mañó, T., Tomás, J. M., Fernández, I., and Sancho, P. (2021). “Quality of life in European older adults of SHARE wave 7: Comparing the old and the oldest-old”, *Journal of Clinical Medicine*, 10, 2850.

Oreopoulos, P., Page, M., and Stevens, A. H. (2008). “The intergenerational effects of worker displacement”, *Journal of Labor Economics*, 26, 455-483.

Ruhm, C. J. (1991). “Are workers permanently scarred by job displacements?”, *American Economic Review*, 81, 319-324.

Sayer, L. C., England, P., Allison, P. D., and Kangas, N. (2011). “She left, he left: How employment and satisfaction affect women’s and men’s decisions to leave marriages”, *American Journal of Sociology*, 116, 1982-2018.

Schröder, C., and Yitzhaki, S. (2017). “Revisiting the evidence for cardinal treatment of ordinal variables”, *European Economic Review*, 92, 337-358.

Stauder, J. (2019). “Unemployment, unemployment duration, and health: selection or causation?”, *European Journal of Health Economics*, 20, 59-73.

Stevens, A. H. (1997). “Persistent effects of job displacement: The importance of multiple job losses”, *Journal of Labor Economics*, 15, 165-188.

Stutzer, A., and Frey, B. S. (2010). “Recent advances in the economics of individual subjective well-being”, *Social Research: An International Quarterly*, 77, 679-714.

Tumin, D., and Qian, Z. (2017). “Unemployment and the transition from separation to divorce”, *Journal of Family Issues*, 38, 1389-1413.

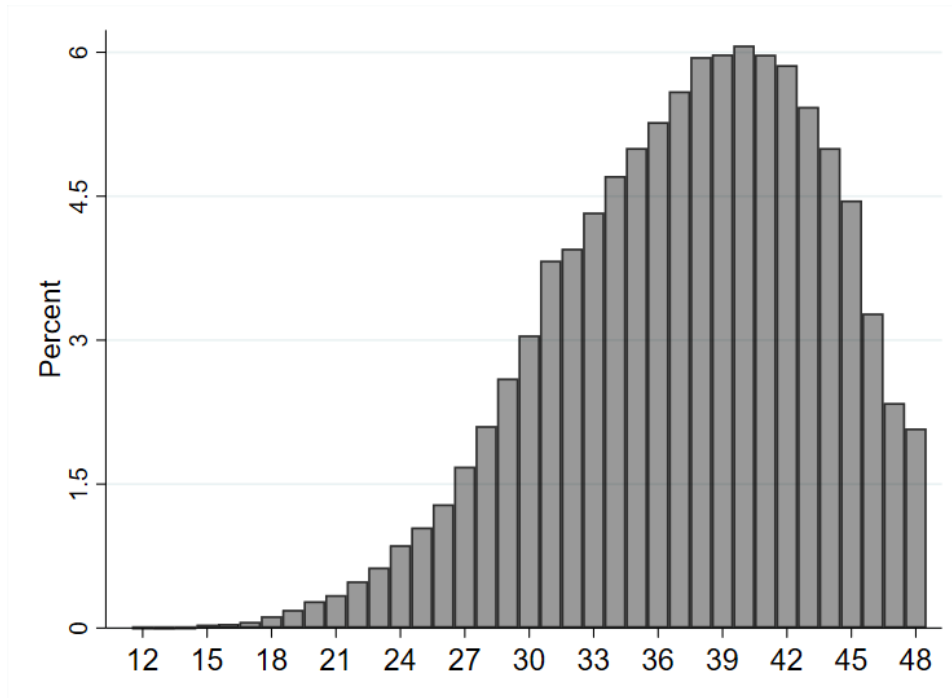
Von Wachter, T. (2020). “The persistent effects of initial labor market conditions for young adults and their sources”, *Journal of Economic Perspectives*, 34, 168-194.

Von Wachter, T., and Bender, S. (2006). “In the right place at the wrong time: The role of firms and luck in young workers’ careers”, *American Economic Review*, 96, 1679-1705.

Winkelmann, L., and Winkelmann, R. (1998). “Why are the unemployed so unhappy? Evidence from panel data”, *Economica*, 65, 1-15.

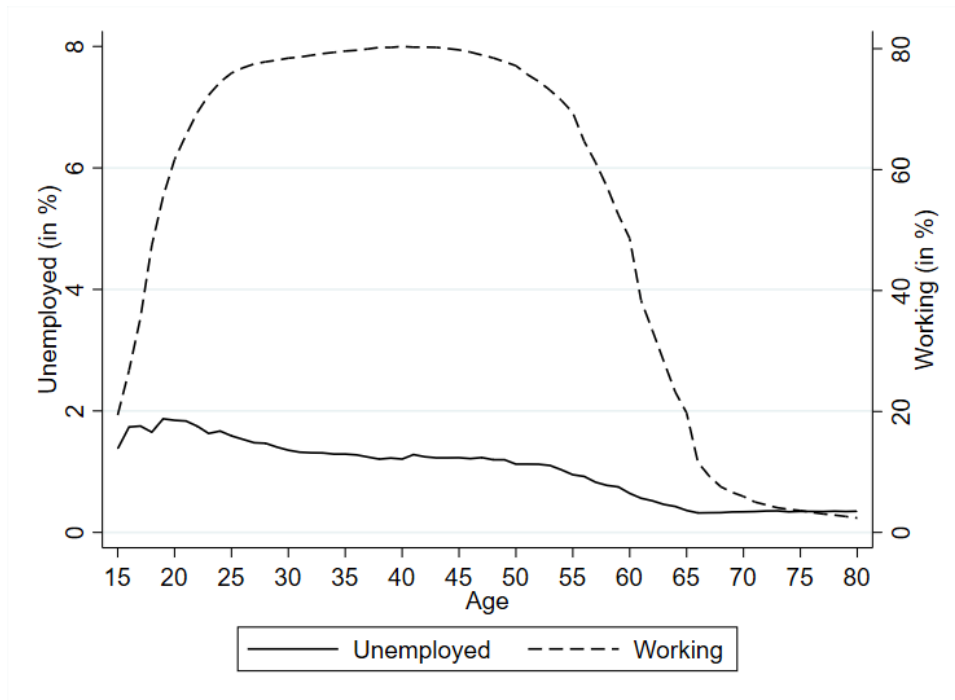
Figures and Tables

Figure 1: The Distribution of CASP



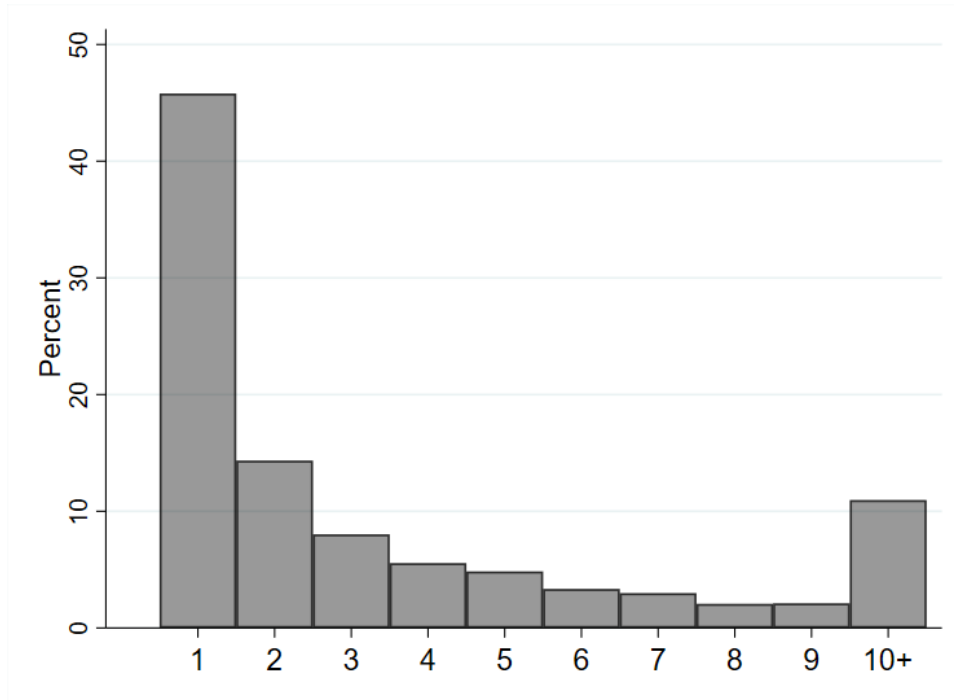
Notes: This figure refers to the estimation sample of 141,084 observations from SHARE. The CASP index ranges from 12 to 48.

Figure 2: The percentages of unemployed and working over the life cycle



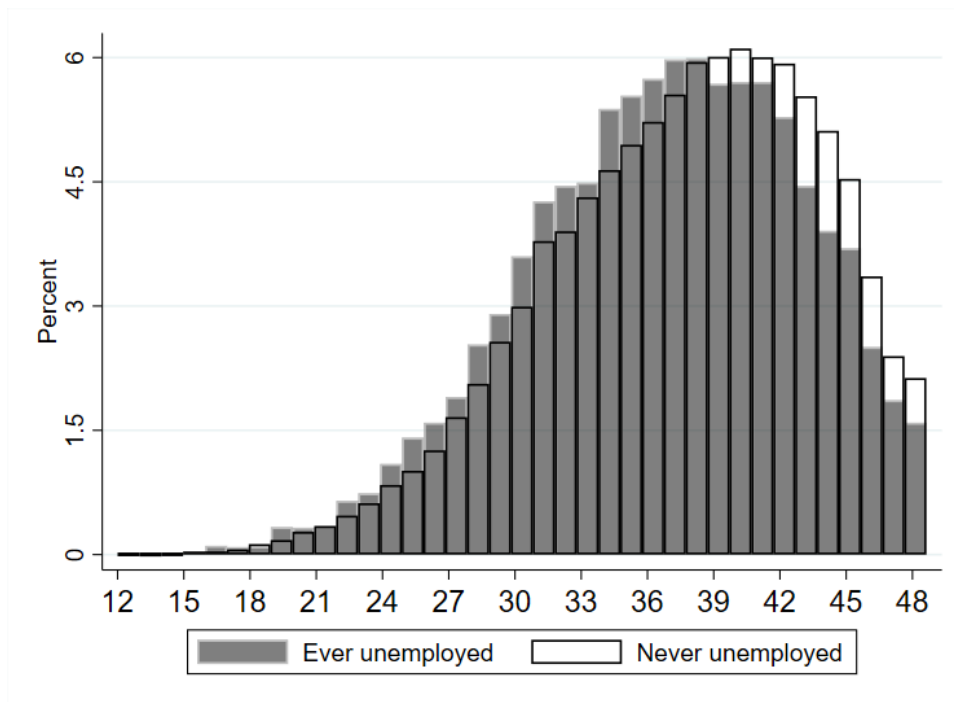
Note: This figure refers to the estimation sample of 141,084 observations from SHARE.

Figure 3: The distribution of the number of episodes of unemployment



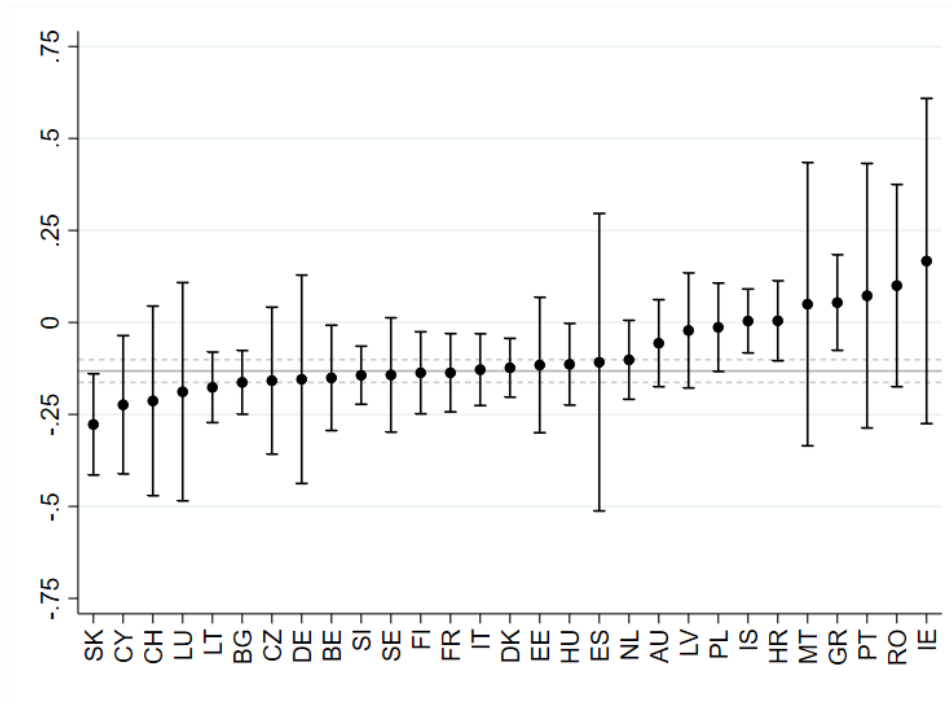
Note: This figure refers to the 3,002 observations who experienced at least one episode of unemployment in our estimation sample from SHARE.

Figure 4: The distribution of CASP by lifetime unemployment status



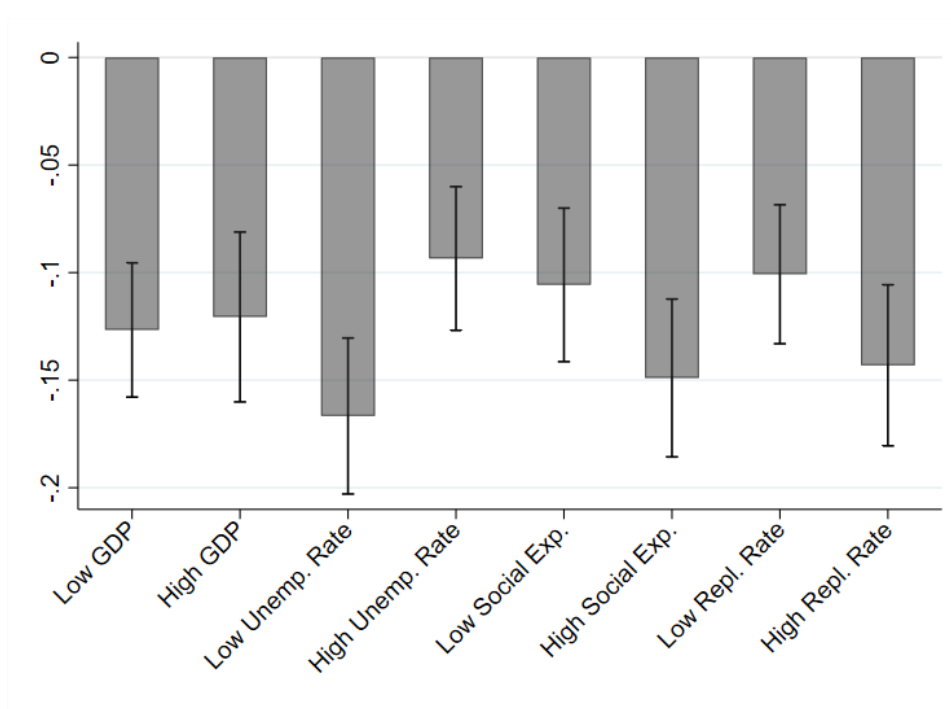
Notes: This figure refers to the estimation sample of 141,084 observations from SHARE. The CASP index ranges from 12 to 48.

Figure 5: The effect of being ever unemployed on CASP after retirement – Results by country



Notes: Each dot corresponds to an estimated coefficient on the ever-unemployed dummy in a linear regression in the given country, where the dependent variable is the standardised CASP index. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases and household annual net income in logs), cohort and interview-year dummies, and the length of the active life (in years). The vertical black bars are 95% confidence intervals. The solid and dashed grey horizontal lines are respectively the effect of unemployment experience and the 95% confidence intervals from the estimation using the whole sample.

Figure 6: The effect of being ever unemployed on CASP after retirement – Results by country groups



Notes: Each grey bar corresponds to an estimated coefficient on the ever-unemployed dummy in a linear regression in the given group, where the dependent variable is the standardised CASP index. The vertical black bars are 95% confidence intervals. Time series for social expenditures (1980 to 2022) and replacement rates (after one year – 2001 to 2023) were downloaded from the website of the OECD. Times series for GDP (1960 to 2023) and unemployment rates (1991 to 2023) were respectively downloaded from the websites of the World Bank and the ILO. Country assignment to a ‘high’ or ‘low’ group depends on the country average value of the macroeconomic indicator relative to the sample median in that country. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases and household annual net income in logs), cohort and interview-year dummies, and the length of the active life (in years).

Table 1: Descriptive statistics

	Mean	SD	Min	Max
CASP Index	37.27	6.21	12	48
Ever unemployed	0.09		0	1
Ever unemployed before age 30	0.05		0	1
Ever unemployed between age 30 and 50	0.04		0	1
Ever unemployed after age 50	0.02		0	1
Total no. episodes of unemployment: one	0.04		0	1
Total no. episodes of unemployment: two	0.01		0	1
Total no. episodes of unemployment: three or more	0.04		0	1
Age	74.32	6.50	65	104.5
Female	0.52		0	1
Years of education	10.87	4.15	0	35
Length of active life (in years)	37.84	10.48	1	86
Health in childhood: Excellent	0.25		0	1
Health in childhood: Very good	0.30		0	1
Health in childhood: Good	0.30		0	1
Health in childhood: Fair	0.10		0	1
Health in childhood: Poor	0.04		0	1
Health in childhood: Health varied a great deal	0.01		0	1
Relative level in Maths at age 10: Much better	0.09		0	1
Relative level in Maths at age 10: Better	0.23		0	1
Relative level in Maths at age 10: About the same	0.54		0	1
Relative level in Maths at age 10: Worse	0.12		0	1
Relative level in Maths at age 10: Much worse	0.02		0	1
Household size	1.89	0.82	1	12
Partner in household	0.67		0	1
No. chronic diseases	1.49	1.29	0	10
Household Annual Net Income (log)	9.95	0.80	0.07	15.73

Note: This table refers to the estimation sample of 141,084 observations from SHARE.

Table 2: Ever having been unemployed and CASP after retirement – Linear regressions

	CASP (std)		
	(1)	(2)	(3)
Ever unemployed (dummy)	-0.183*** (0.013)	-0.145*** (0.013)	-0.125*** (0.013)
Age		0.058*** (0.014)	0.082*** (0.014)
Age-squared (/100)		-0.066*** (0.006)	-0.079*** (0.006)
Female		-0.047*** (0.008)	-0.024*** (0.008)
Years of education		0.088*** (0.004)	0.065*** (0.004)
Health in childhood (Ref: Excellent)			
Very good		-0.058*** (0.010)	-0.053*** (0.009)
Good		-0.152*** (0.010)	-0.131*** (0.010)
Fair		-0.274*** (0.015)	-0.230*** (0.014)
Poor		-0.362*** (0.024)	-0.294*** (0.022)
Health varied a great deal		-0.220*** (0.054)	-0.179*** (0.052)
Relative level in Maths at age 10 (Ref: Much better)			
Better		-0.036** (0.015)	-0.039*** (0.014)
About the same		-0.081*** (0.014)	-0.079*** (0.013)
Worse		-0.199*** (0.017)	-0.182*** (0.016)
Much worse		-0.307*** (0.031)	-0.275*** (0.030)
High parental SES		0.034*** (0.009)	0.024*** (0.009)
Household size			-0.033*** (0.004)
Partner in household			0.124*** (0.010)
No. chronic diseases			-0.172*** (0.003)
Household annual net income (log)			0.069*** (0.003)
Observations	141084	141084	141084
Adjusted R ²	0.200	0.225	0.260

Notes: These are linear regressions. All continuous variables are standardised. All regressions control for country, cohort and interview-year dummies and the length of the active life (in years). Standard errors in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Past unemployment experience and CASP after retirement – Additional Specifications

	CASP (std)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ever unemployed	-0.125*** (0.013)	-0.148*** (0.014)	-0.134*** (0.010)	-0.119*** (0.012)				-0.188*** (0.035)	-0.214*** (0.044)	
Total no. episodes of unemployment: one					-0.077*** (0.018)					
Total no. episodes of unemployment: two					-0.101*** (0.031)					
Total no. episodes of unemployment: three or more					-0.193*** (0.019)					
Share of time spent unemployed						-0.028*** (0.004)				
Ever unemployed (before age 30)							-0.095*** (0.017)			
Ever unemployed (between ages 30 and 50)							-0.120*** (0.019)			
Ever unemployed (after age 50)							-0.077*** (0.025)			
Ever unemployed*Retired more than five years ago								0.081** (0.035)		
Ever unemployed (layoff or plant/office closure - dummy)										-0.133*** (0.031)
Observations	141084	141084	141084	137683	141084	141084	141084	141084	141084	141084
Adjusted R ²	0.260	-	-	0.254	0.261	0.260	0.260	0.261	0.260	0.260
F-statistic	-	-	-	-	-	-	-	-	1983.2	-

Notes: These are linear regressions, except in Columns (2) and (3) which refer to ordered probit and median regression respectively. Column (9) is a Two Stage Least Squares regression where individual unemployment experience is instrumented by the average unemployment experience of all of the other individuals who were born in the same country up to two years before or after the respondent, are of the same gender, and have the same level of education. Column (4) excludes respondents who gave the same answer to all of the CASP-12 questions. All continuous variables are standardised. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases, and household annual net income in logs), country, cohort and interview-year dummies, and the length of the active life (in years). Column (8) also includes the main effect of Retired more than five years ago. Standard errors in parentheses are clustered at the individual level, except in Column (2) where they are bootstrapped and Column (9) where they are clustered at the country*cohort*education*gender level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The effect of past unemployment experience on CASP after retirement – Heterogeneity analysis

	CASP (std)							
	Young (1)	Old (2)	Men (3)	Women (4)	Low education (5)	High education (6)	Low parental SES (7)	High parental SES (8)
Ever unemployed (dummy)	-0.137*** (0.014)	-0.104*** (0.019)	-0.136*** (0.018)	-0.110*** (0.017)	-0.102*** (0.016)	-0.151*** (0.020)	-0.121*** (0.016)	-0.133*** (0.020)
Observations	71068	70016	68163	72921	82100	58984	84841	56243
Adjusted R ²	0.237	0.259	0.258	0.261	0.265	0.230	0.279	0.235

Notes: These are linear regressions. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases and the household annual net income in logs), country, cohort and interview-year dummies, and the length of the active life (in years). Standard errors in parentheses are clustered at the individual level. “Young” and “Old” respectively refer to respondents below and above the median age per country. “Low education” and “High education” are calculated analogously using the median years of education per country, and “Low parental SES” and “High parental SES” the median parental SES (proxied by the ISCO88 of the household breadwinner at respondent age 10) per country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A

In Waves 3 and 7 of SHARE, each respondent was asked to list all of the jobs that they had held since leaving education. For those who had missing information at Wave 3, the Wave 7 responses are used to fill in the gaps; for those joining SHARE after Wave 3, Wave 7 is the first time they provided this information.

For each job episode (employment or self-employment), respondents answered a series of questions, as follows:

1. When did the job start?
2. When did it stop?
3. What did you do immediately afterward?

The dates that respondents report for the first and second of these questions are only in terms of the year, without specifying the month or day. For the third question, any gap of under six months before starting the next job is considered as an immediate transition to the next job. As such, any unemployment spell of under six months between two jobs is not recorded. If the gap is six months or more, the respondent indicates what they were doing during this period (with response categories of 'Employee or self-employed', 'Unemployed and searching for a job', 'Unemployed but not searching for a job', 'Short term job (less than 6 months)', 'Sick or disabled', 'Looking after home or family', 'Leisure, travelling or doing nothing', 'Retired from work', 'Training', 'Further full time education', 'Military services, war prisoner or equivalent', 'Managing your assets', 'Voluntary or community work', 'Forced labour or in jail', 'Exiled or banished', 'Labour camp', 'Concentration camp' and 'Other').

This sequence of questions, combined with the respondent's birth year, is used to construct the Job Episode Panel, which matches each discrete age value, a , for the respondent to a labour-force status. Age, a , is calculated by SHARE as the calendar year, t , minus the individual's birth year, b . Priority is given to employment in this construction, in that an individual who reports an employment spell that covers any part of the year t is considered to be in employment in that year, and therefore coded as being in employment at age $a (= t-b)$. Unemployment is thus only recorded in the Job Episode Panel for an individual at age a if they did not report any employment spell during the year t (in which they were age a).

Here is an example, drawn from Wave 3 of SHARE: Respondent AT-013179-02, born in 1919, reported working from 1937 to 1938 (in which they are assigned the ages of 18 and 19 respectively), then experienced an unemployment spell of six months or more while looking for a new job, and then started their next job in 1940. The Job Episode Panel assigns a labour-force status for each age for this individual as shown below:

- At ages 18 and 19 (*i.e.* in 1937 and 1938), AT-013179-02 had a job.
- At age 21 (1940), AT-013179-02 resumed work.
- As there was a gap of six months or more between the two job spells, and the respondent reported being unemployed during this gap, and there was no employment spell recorded in 1939, AT-013179-02 is classified as “unemployed” at age 20 (in 1939).

We have identified two situations where respondents reported experiencing unemployment, but these episodes do not appear in the labour-force status assigned to each individual at each age.

1. **Case 1:**

- Job Spell 1 ends in year t .

- There is a reported unemployment spell of six months or more, again during year t .
- Then job Spell 2 begins within the same year t .

2. **Case 2:**

- Job Spell 1 ends in year t (the respondent is age a)
- The subsequent reported unemployment spell spans years t and $t+1$
- Job Spell 2 begins in year $t+1$ (where the respondent is age $a+1$)

In both cases, the Job Episode Panel code classifies these respondents as employed at both ages a and $a+1$, not recording the periods of unemployment.

To address this issue, we have recoded our analysis to ensure that these previously-hidden unemployment spells now appear in the Job Episode Panel. This adjustment increases the reported incidence of any past unemployment from 6% to 9% of observations.

Appendix B

Table B1: CASP-12 questionnaire

Here is a list of statements that people have used to describe their lives or how they feel. We would like to know how often, if at all, you think this applies to you. (Please tick one box in each row)				
	Often	Sometimes	Rarely	Never
My age prevents me from doing the things I would like to [C]	1	2	3	4
I feel that what happens to me is out of my control [C]	1	2	3	4
I feel left out of things [C]	1	2	3	4
I can do the things that I want to do [A]	4	3	2	1
Family responsibilities prevent me from doing what I want to do [A]	1	2	3	4
Shortage of money stops me from doing the things I want to do [A]	1	2	3	4
I look forward to each day [P]	4	3	2	1
I feel that my life has meaning [P]	4	3	2	1
On balance, I look back on my life with a sense of happiness [P]	4	3	2	1
I feel full of energy these days [SR]	4	3	2	1
I feel that life is full of opportunities [SR]	4	3	2	1
I feel that the future looks good for me [SR]	4	3	2	1

Table B2: Descriptive Statistics at the Individual Level

	Mean	SD	Min	Max
CASP Index	37.01	5.74	12	48
Ever unemployed	0.10		0	1
Ever unemployed before age 30	0.04		0	1
Ever unemployed between age 30 and 50	0.03		0	1
Ever unemployed after age 50	0.02		0	1
Total no. episodes of unemployment: one	0.02		0	1
Total no. episodes of unemployment: two	0.01		0	1
Total no. episodes of unemployment: three or more	0.04		0	1
Age	73.26	6.05	65	102.53
Female	0.52		0	1
Years of education	10.84	4.10	0	35
Length of active life (in years)	37.50	10.81	1	86
Health in childhood: Excellent	0.26		0	1
Health in childhood: Very good	0.30		0	1
Health in childhood: Good	0.30		0	1
Health in childhood: Fair	0.10		0	1
Health in childhood: Poor	0.04		0	1
Health in childhood: Health varied a great deal	0.01		0	1
Relative level in Maths at age 10: Much better	0.09		0	1
Relative level in Maths at age 10: Better	0.22		0	1
Relative level in Maths at age 10: About the same	0.54		0	1
Relative level in Maths at age 10: Worse	0.13		0	1
Relative level in Maths at age 10: Much worse	0.02		0	1
Household size	1.93	0.81	1	10.67
Partner in household	0.68		0	1
No. chronic diseases	1.47	1.14	0	9
Household Annual Net Income (log)	9.96	0.66	1.68	14.63

Note: This table refers to the average characteristics of the 47,795 individuals in the SHARE estimation sample.

Table B3: The effect of past unemployment experience on different outcomes

	CASP (std)					EURO-D (std)	Self- assessed health (std)
	Total Score (1)	Control Score (2)	Autonomy Score (3)	Self-Realisation Score (4)	Pleasure Score (5)		
Ever unemployed (dummy)	-0.125*** (0.013)	-0.081*** (0.012)	-0.124*** (0.012)	-0.077*** (0.013)	-0.096*** (0.012)	-0.083*** (0.014)	-0.077*** (0.012)
Observations	141084	141084	141084	141084	141084	117016	141062
Adjusted R ²	0.260	0.168	0.188	0.229	0.134	0.152	0.283

Notes: These are linear regressions. The EURO-D scale for depression is reversed so that higher scores indicate a lower probability of suffering from depression. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases and the household annual net income in logs), country, cohort and interview-year dummies, and the length of the active life (in years). Standard errors in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Correlation matrix between different well-being and health measures

	CASP	EURO-D	Self-assessed health
CASP	1		
EURO-D	0.518	1	
Self-assessed health	0.479	0.421	1

Notes: These are pairwise correlations. They refer to our estimation sample of 141,084 observations. The EURO-D scale for depression is reversed so that higher scores indicate a lower probability of suffering from depression.

Table B5: Past unemployment experience and EURO-D after retirement – Additional Specifications

	EURO-D (std)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ever unemployed	-0.083*** (0.014)	-0.103*** (0.015)	-0.096*** (0.012)	-0.061*** (0.014)				-0.152*** (0.038)	-0.135*** (0.046)	
Total no. episodes of unemployment: one					-0.074*** (0.019)					
Total no. episodes of unemployment: two					-0.081** (0.032)					
Total no. episodes of unemployment: three or more					-0.096*** (0.022)					
Share of time spent unemployed						-0.017*** (0.004)				
Ever unemployed (before age 30)							-0.057*** (0.019)			
Ever unemployed (before age 30 and 50)							-0.079*** (0.021)			
Ever unemployed (after age 50)							-0.070*** (0.026)			
Ever unemployed*Retired more than five years ago								0.085** (0.040)		
Ever unemployed (layoff or plant/office closure - dummy)										-0.101*** (0.031)
Observations	117016	117016	117016	91488	117016	117016	117016	117016	117016	117016
Adjusted R ²	0.152	-	-	0.117	0.152	0.152	0.152	0.152	0.152	0.151
F-statistics	-	-	-	-	-	-	-	-	1971.0	-

Notes: These are linear regressions, except in Columns (2) and (3) which refer to ordered probit and median regression respectively. Column (9) is a Two Stage Least Squares regression where we instrument individual unemployment experience by the average unemployment experience of all of the other individuals who were born in the same country up to two years before or after the respondent, are of the same gender, and have the same level of education. Column (4) excludes respondents who reported the same score to all EURO-D items. All continuous variables are standardised. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases, and household annual net income in logs), country, cohort and interview-year dummies, and the length of the active life (in years). Column (8) also includes the main effect of Retired more than five years ago. Standard errors in parentheses are clustered at the individual level, except in Column (2) where they are bootstrapped and Column (9) where they are clustered at the country*cohort*education*gender level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Past unemployment experience and Self-assessed health after retirement – Additional Specifications

	Self-assessed health (std)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever unemployed	-0.077*** (0.012)	-0.098*** (0.015)	-0.077*** (0.009)				-0.125*** (0.033)	-0.133*** (0.042)	
Total no. episodes of unemployment: one				-0.058*** (0.017)					
Total no. episodes of unemployment: two				-0.043 (0.028)					
Total no. episodes of unemployment: three or more				-0.114*** (0.018)					
Share of time spent unemployed					-0.017*** (0.003)				
Ever unemployed (before age 30)						-0.054*** (0.016)			
Ever unemployed (before age 30 and 50)						-0.084*** (0.018)			
Ever unemployed (after age 50)						-0.037 (0.024)			
Ever unemployed*Retired more than five years ago							0.057* (0.034)		
Ever unemployed (layoff or plant/office closure - dummy)									-0.039 (0.031)
Observations	141062	141062	141062	141062	141062	141062	141062	141062	141062
Adjusted R ²	0.283	-	-	0.283	0.283	0.283	0.283	0.283	0.283
F-statistics	-	-	-	-	-	-	-	-	-

Notes: These are linear regressions, except in Columns (2) and (3) which refer to ordered probit and median regression respectively. Column (8) is a Two Stage Least Squares regression where individual unemployment experience is instrumented by the average unemployment experience of all of the other individuals who were born in the same country up to two years before or after the respondent, are of the same gender, and have the same level of education. All continuous variables are standardised. All regressions control for age, age-squared, gender, years of education, childhood characteristics (health during childhood, relative level in Maths at age 10, and a dummy for high parental SES), contemporaneous adult characteristics (household size, a dummy for having a partner in the household, number of chronic diseases, and household annual net income in logs), country, cohort and interview-year dummies, and the length of the active life (in years). Column (7) also includes the main effect of Retired more than five years ago. Standard errors in parentheses are clustered at the individual level, except in Column (2) where they are bootstrapped and Column (8) where they are clustered at the country*cohort*education*gender level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: Number of observations per country in the estimation sample

Country	Frequency	Percentage
Austria	7,714	5.47
Germany	9,749	6.91
Sweden	10,853	7.69
Netherlands	2,995	2.12
Spain	6,746	4.78
Italy	8,931	6.33
France	8,929	6.33
Denmark	7,977	5.65
Greece	4,531	3.21
Switzerland	6,700	4.75
Belgium	10,966	7.77
Israel	2,223	1.58
Czech Republic	12,346	8.75
Poland	5,555	3.94
Ireland	159	0.11
Luxembourg	1,685	1.19
Hungary	2,452	1.74
Portugal	1,614	1.14
Slovenia	7,658	5.43
Estonia	11,885	8.42
Croatia	2,997	2.12
Lithuania	1,104	0.78
Bulgaria	1,134	0.80
Cyprus	685	0.49
Finland	1,061	0.75
Latvia	895	0.63
Malta	259	0.18
Romania	457	0.32
Slovakia	824	0.58
Total	141,084	100.00

Note: This table refers to the estimation sample of 141,084 observations from SHARE.