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Work and Employment Arrangements during the First Wave of COVID-19 in Europe and their Relationship with the Self-Reported Change in Health of Workers aged 55 and over. Results from SHARE.

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Work and Employment Arrangements during the First Wave of COVID-19 in Europe and their Relationship with the Self-Reported Change in Health of Workers aged 55 and over. Results from SHARE.

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Abstract:

The first wave of COVID-19 has had a massive impact on the use of work and employment arrangements, but little is known about their specific impact on older workers' health. Using data from SHARE (waves 8) collected during summer 2020 (N=9,593), the study looks at the association between self-perceived change in health since the start of the pandemic and work and employment arrangements after controlling for covariates in 27 countries using mixed-effect models. Results indicate a positive effect of home working. In contrast, partial home working is associated with a negative impact on self-perceived health except when working time is reduced. Unemployment and partial unemployment have adverse effects on health but stop being significant after controlling for co-linearity. The study emphasises the need to promote home working together with working time reductions but also stresses the necessity to account for gender discrepancies outside of work and employment settings.

Background

Aside from increasing mortality in the countries affected by the COVID-19 pandemic, changes introduced in our society to contain it have had important effects. One of the obvious consequences of the policy response to the spread of COVID-19 in Europe is that it has generated a massive transformation in the way work and employment are organized. Unemployment, higher or lower working times and changes in workplace settings have transformed, for an appreciable length of time, the way working lives are organized with potential effects on health that are still to be assessed. The older workforce is particularly affected by the current crisis. On the one hand, the COVID-19 is evidenced has having severe effects on those who already suffer from pathologies, and the likelihood of being in this case increases with age. It is not surprising therefore that anxiety about developing COVID-19 is associated with more COVID-19 stress for older adults relative to younger adults (Pearman et al. 2020). On the other hand, changes in the way work and employment are organized were more likely to affect the older workforce as many arrangements were already implemented for this age category, with important variations across countries. Indeed, the phenomenon is not new. Employment arrangements implemented to smooth the transition from work to retirement have flourished over the past decades (Wels 2018) and have deeply diversified the types of work and employment arrangements in late career. Similarly, many efforts have been made to allow flexible working time and home working. But it is the first time in recent history these arrangements have been used by a such a large share of the workforce (Bick et al. 2020) so that what was considered in 2019 as some forms of non-standard employment became the norm in 2020 and will still probably be in the coming months and years. Though, the relationship between these aspects and workers' health is still to investigate in-depth (Blustein et al. 2020; Farré et al. 2020) and no study has focused on such a relationship at the European level since the start of the pandemic. The current study pays particular attention to three aspects of these changes – unemployment, home working and working time variations – that have played a prominent role in containing the epidemic.

It has long been evidenced that unemployment has detrimental effects on health (Wilson and Walker 1993) and mortality (Gerdtham and Johannesson 2003), including all causes mortality, death from cardiovascular disease and suicide, and higher rates of mental distress, substance abuse, depression, and anxiety. What the COVID-19 situation brings is that the population that has been unemployed is not similar to the one could have observed during the previous economic crises (Farré et al. 2020) as this very particular crisis did not particularly hit the industrial sector at first. The pandemic has created a situation with partial unemployment statuses – more or less protected by the state – that aim to protect people over a relatively short period of time together with an economic slump that has caused business closures and long-term unemployment. Hence, it is necessary to distinguish partial unemployment on the one hand from long terms forms of unemployment that will have more severe effects in the future, on the other hand. Over

the first wave of the pandemic, a change in working time was also observed for those who kept working or moved back to work after being unemployed. Working time is a key factor in explaining health variations among the workforce (Kamerāde et al. 2019) but the voluntariness or involuntariness of change in working time (De Moortel et al. 2017) such as the policies that allow for working time regulations and the arrangements that compensate the incomes loss after reducing working time (Wels 2020) play a role. This applies also to the ageing workforce with particular positive health effects on low incomes workers (Wels 2019). Finally, home working has developed has it has never developed before. Evidences in terms of health effects of flexible work arrangements – including home working – are sparse and the debate about home working is open in Europe. Even though flexible work arrangements tend to be associated with better employees' satisfaction (Wheatley 2017), trade unions were – before the pandemic – reluctant to implement home working whilst they were keen to support other types of flexible arrangements (Wels 2021). One thing for sure is that the pandemic has increased home working in an important way with important differences across Europe (Fana et al. 2020). What unemployment, working time variations and home working have in common since the policy response to the outbreak of the virus is that they have been implemented in a quasi-non-voluntary basis and, as voluntariness remains a key for understanding the negative health effects of changes in employment arrangements (Henkens et al. 2008; Bender 2012), it is necessary to provide estimates about their impact to better decide what are the adaptations to implement and those one should avoid. Against this backdrop, this study aims to assess the relationship between these transformations and the self-reported change in health of workers aged 55 and over in 27 countries included in the recently released wave 8 of the Survey of Health, Ageing and Retirement in Europe (SHARE).

Data and methods

SHARE wave 8 & ShareLife

The study uses micro-data from the Survey of Health, Ageing and Employment in Europe (SHARE) (Borsch-Supan et al. 2013; Borsch-Supan 2017), waves 7 and 8. Data collection for wave 8 was planned to start in late 2019 but the spread of COVID-19 in February 2020 has changed the original plan (Scherpenzeel et al. 2020). Instead, it was decided to carry one with follow-up phone interviews with a questionnaire specifically dedicated to the pandemic situation that includes questions about different aspects including health, safety and work and employment conditions. The current dataset is an early beta release containing data collected via computer-assisted telephone interviews between June and August 2020. The current study focuses on work and employment arrangements during the pandemic and uses data for all the countries (=27) included in the survey. These data were completed using retrospective data about employment trajectories and number of children from waves 3 and 7. Wave 7 shares some similarities with wave 3 (*ShareLife*) as it includes retrospective questions about several aspects including family, education and

employment trajectories (Bergmann et al. 2019). The selected sample contains those aged 55 and over who declared being employed or self-employed prior the start of the pandemic, independently from their status following its first outbreak and form whom retrospective data were available either in wave 3 or 7 (N= 9,593 over 27 country-units). Countries are not represented the same way in the dataset, ranging from 12.2 per cent of the sample in Estonia to 1.5 per cent in Spain. That is one of the reasons why analyses are made using a multilevel framework and data are weighted.

Self-reported change in health

Wave 8 contains two main information about self-perceived health (SPH). Respondents were asked what was their SPH prior the start of the pandemic (in five modalities, from excellent to poor) and how their SPH has changed since the outbreak of COVID-19 (in three modalities, i.e., worse, better or same). The dependent variable is the self-reported change in health since the outbreak of the virus. The model looks at whether SPH has worsened since the start of the pandemic distinguishing, on a binary basis, those who reported a worsened health from those who reported the same or a better SPH (reference category). The model accounts for SPH prior the start of the pandemic as an independent (categorical variable). SPH-types variables are largely discussed in the literature on, at least, two aspects. First, the variable requires an in-depth understanding of its distribution features because, as calculated on a Likert scale, it could take the form of a Poisson distribution instead of a Gaussian Distribution that would be required when performing OLS. To tackle such an issue, it is common to perform OLS, ordered logit, ordered probit regression or interval regression when dealing with SPH-types of dependent variables and to compare results (Van Doorslaer and Jones 2003). As the variable contains only three modalities, the choice was made to use it as a binary variable by distinguishing those who experienced a negative change in SPH from those who did not. Second, the association between SPH and other health indicators such as the reliability of SPH when working with panel data have been discussed. On the one hand, an important corpus of studies has demonstrated that SPH could be a predictor of mortality that is independent of objective heath statuses (Singer et al. 1976; Mossey and Shapiro 1982; Idler and Benyamini 1997). But, on the other hand, the reliability of the self-assessed health status can also be questioned, particularly in a context of repeated measurements (panel data) (Crossley and Kennedy 2002) as the change in response over time largely depends on the socio-economic group and age but could also be affected by cross-national differences when working on comparative data (Jürges 2007). The study compares the self-perceived health prior and after the pandemic with the SPH prior the pandemic included as a control variable in the model. By doing so, the model accounts for the processual change in SPH without properly using a longitudinal perspective.

Variables of interest

Work and employment arrangements is the variable of interest. As data were collected following the first wave of COVID-19 in Europe and as various employment policies were implemented across Europe, no information was collected about the type of unemployment (i.e., short-term or permanent) respondents were moving to. Data provide information about whether respondents were unemployed and about unemployment duration but information about work arrangements were still collected for those who were partially unemployed during the first wave but also had work activities. For those who were working during part or the entirety of the first wave of the epidemic, data were collected about change in working time (higher, lower or same) and work arrangements (workplace, home or both). To deal with this methodological issue, several categories were created. First, one distinguishes those who were totally unemployed (9.91 per cent) form those who were partially unemployed (8.27 per cent). They both account for 18.18 per cent of the sample. Second, the remaining 81.82 per cent was divided based on whether home working was used or not or both and working time increased, remained the same or changed (see table 1).

Table 1. Employment status and work arrangement distribution within the sample

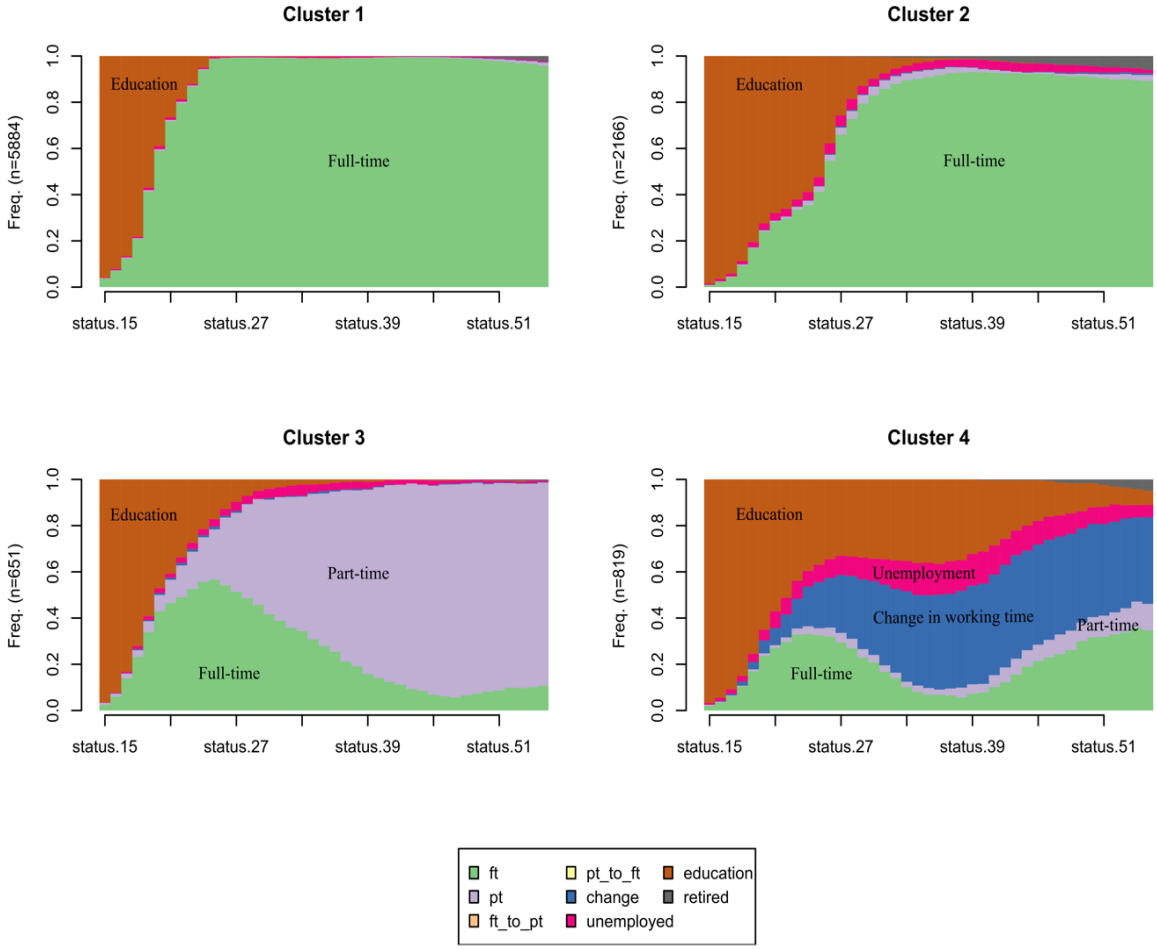
Unemployment Status	Home working	Working time	Category	%	Cum. %
Full unemployed	NA	NA	Full_Unemployment	9,9	9,9
Partial unemployment	home	higher	Partial Unemployment	0,2	10,1
	home	lower	–	1,2	11,3
	home	same	–	0,5	11,9
	workplace	higher	–	0,4	12,2
	workplace	lower	–	3,0	15,2
	workplace	same	–	1,7	16,9
	both	higher	–	0,1	17,1
	both	lower	–	0,8	17,8
	both	same	–	0,4	18,2
Employment	home	higher	Home Higher	2,9	21,1
	home	lower	Home Lower	3,1	24,2
	home	same	Home Same	8,5	32,7
	workplace	higher	Workplace Higher	4,2	36,9
	workplace	lower	Workplace Lower	5,7	42,6
	workplace	same	Workplace Same	37,1	79,7
	both	higher	Both Higher	1,9	81,6
	both	lower	Both lower	2,4	84,0
	both	same	Both Same	8,4	92,4
	other	same	Other	6,7	99,1
	other	lower	–	0,0	99,1
	other	higher	–	0,0	99,1
	both	vary	–	0,2	99,3
	workplace	vary	–	0,5	99,8
	home	vary	–	0,2	100,0
Total (N=9,518)				100,0	

Covariates

Aside from paying particular attention to work and employment arrangements, the model includes several covariates. 'Gender' picks up 'male' as the reference category; a quadratic function of age; SPH prior the start of the pandemic, as a factor variable; the number of children distinguishing no child, 1 child, 2 children and 3 or more children (no children being the reference category); the self-reported net household incomes prior the pandemic; and the ratio (in percentage) between self-reported net household incomes prior and after the pandemic. The model also controls for the direct impact of COVID-19. SHARE contains two information about this: whether respondents were tested positive and whether they reported COVID-19 related symptoms, independently from whether they were contaminated or tested. As the study looks at self-perceived health and as asymptomatic cases are frequent, one variable is included that distinguishes those who reported symptoms from those who did not (reference).

The model also controls for employment trajectories prior the pandemic. Sequence analysis was performed using seven possible statuses along the career: unemployment, retirement, education, full-time, part-time, part-time to full-time, full-time to par-time and multiple changes between full-time and part-time (Widmer and Ritschard 2009; van der Horst et al. 2017). By doing so, employment trajectories are distinguished depending on whether they were characterized by a stable or changing working time. The distance between the sequence clusters was calculated using optimal matching methods (Abbott and Forrest 1986; Abbott and Tsay 2000) with 9,520 sequences containing 3,963 distinct sequences. Four clusters flow from the sequence analysis: early education exit with full-time career (cluster 1) ; late education exit with full-time career (cluster 2) ; part-time career (cluster 3) ; multiple employment transitions (cluster 4). The first and second patterns are characterized by full-time employment trajectories but those in the first pattern left education around 20 whilst those in the second pattern left, on average, around 25. The third pattern is characterized by part-time employment trajectories, mainly after working full-time until 25-30 years of age, and throughout the career. Finally, the fourth pattern groups those for whom employment trajectories are characterized by frequent changes in employment status and frequent changes in working time. The first and second pattern patterns respectively account for 61.8 and 22.7 per cent of the total sample. Third and fourth patterns could be considered as non-standard forms of employment as they account respectively for 6.8 and 8.7 per cent of the sample. By doing so, the model also controls for the length of education and distinguishes those who left education early from those who did not. Figure 1 shows the states frequencies for each time point for the four clusters.

Figure 1. Sate distribution frequencies



Models

The model used in this study is a generalized logit mixed-effects model for binary outcomes that is a multilevel modeling allowing random intercept and slopes (De Moortel et al. 2017). The model is replicated two times. In model 1, a random intercept is set up based on the country-units and the fixed effects of each independent variable is observed. The random intercept allows the outcome to be higher or lower for each country with fixed effects for each explanatory variable. Model 2 sets up a random intercept based on country-units and a random slope for the work and employment arrangements variable, keeping the fixed effects of the other explanatory variables. In this case, the random slopes for a categorical independent variable is the random difference at the intercept and allows fixed effects of work and employment arrangements to vary by country. The model is run using normalized weights so that the sum of weights does not exceed the sample size and outliers are controlled. As the outcome variable is binary, the models require a logit transformation. Results are shown as the exponentials of the logits (the odds ratios) with a 95 per cent confidence interval. The models are replicated two times based on the original dataset, on the one hand, and on a matched dataset, on the other hand. As the models assess the relationship between a set of independent variables including gender, work and employment arrangements and incomes and the change in health since the outbreak of COVID-19, co-linearity between the independent variables is a possibility. Put in another way, gender, incomes and health prior the pandemic could explain the work and employment arrangements that are used following the virus outbreak. To control for this, a matched dataset was created using propensity score matching methods (Huber et al. 2013; Randolph et al. 2014). The matching was calculated based the propensities of moving to non-standard form of work and employment arrangements versus working within the workplace and keeping the same working time using a nearest neighbor matching selection (Geldof et al. 2020). The set of independent variables was composed of gender, age, SPH prior the pandemic, number of children, type of employment trajectory and household net incomes prior the pandemic.

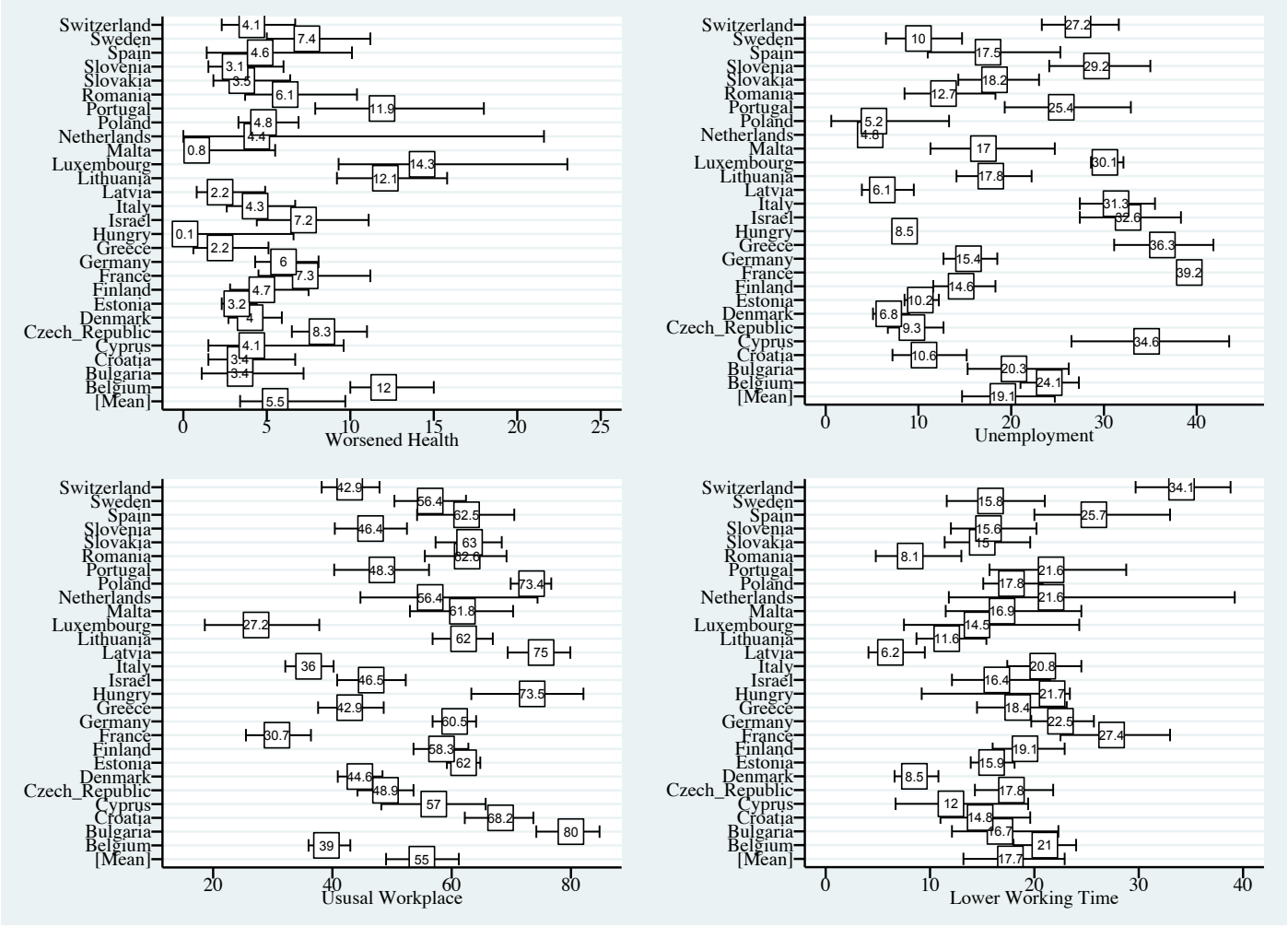
Results

Descriptive statistics

Figure 2 exhibits descriptive statistics – as percentages, with a 95 per cent confidence interval – for the outcome variable and work and employment arrangements, by country. The percentages for the negative self-perceived change in health indicate wide variations across Europe, with a high percentage of negative change in continental and southern Europe (e.g., Belgium, Luxembourg, Portugal) and a relatively low percentage in Eastern

European countries (e.g., Hungry, Latvia). Countries were not affected the same way by the pandemic and that is the reason why further analyses control for respondents' COVID-19 symptoms. There is a heterogeneity in the employment response to the pandemic. The percentages of workers declaring having been permanently or temporary unemployed range from 10 per cent in Sweden to 36.3 percent in Greece with a variety across countries. At descriptive level, the Pearson's correlation coefficient between unemployment rates and negative change in health is positive (0.24) but not significant (p-value = 0.22). Similarly, the percentage of workers who declared keeping working in their usual workplace tops 80 per cent in Bulgaria against 30 percent in France. The correlation, at country-level, indicates a significant (p-value = 0.008) negative association of -0.50 between working in the workplace and negative change in health. Finally, the percentages of respondent declaring a lower working time since the outbreak of the pandemic are between 6.2 in Latvia and 34.1 in Switzerland, with a non-significant (0.94) Pearson's coefficient of 0.02. What the descriptive picture shows is the huge heterogeneity of the employment response to the pandemic with a total relationship between health of work and employment arrangement and negative change in SPH that is only significant for home working.

Figure 2. Percentage of respondents declaring a worsened health, working at the usual workplace and reducing working time since the start of the pandemic by country, with 95% confidence interval. Data weighted using a normalized weight.



Random intercept

Estimates in table 2 are in odds ratios (OR). A OR higher than 1 indicates higher odds to experience a negative change in SPH whilst lower OR lower than 1 indicates the opposite relationship. Estimates are presented together with the 95% Confidence Interval (CI). In model 1, we are interested to know what the effects of the explanatory variables are on the response and the country-level in our data is just considered a nuisance which prevents us from fitting a single-level regression model. Fixed parameters are the coefficients shown in table 2.

Table 2. Generalized binary mixed-effects

		Original dataset				Matched dataset			
		Model 1 (OR [95%CI])		Model 2 (OR [95%CI])		Model 1 (OR [95%CI])		Model 2 (OR [95%CI])	
(1)	Part home working / higher WT	1.42*	[1.06 ; 1.90]	0.04***	[0.01 ; 0.18]	2.43***	[1.77 ; 3.34]	0.02***	[0.00 ; 0.22]
	Part home working / lower WT	0.21***	[0.11 ; 0.40]	0.00***	[0.00 ; 0.04]	0.11***	[0.04 ; 0.31]	0.00***	[0.00 ; 0.00]
	Part home working / same WT	2.18***	[1.90 ; 2.50]	1.26	[0.69 ; 2.32]	2.47***	[2.11 ; 2.89]	0.56	[0.20 ; 1.56]
	Home working / higher WT	0.37***	[0.24 ; 0.59]	0.22*	[0.06 ; 0.73]	0.24***	[0.13 ; 0.45]	0.16*	[0.03 ; 0.89]
	Home working / lower WT	0.80	[0.59 ; 1.09]	0.46	[0.15 ; 1.41]	1.32*	[0.95 ; 1.84]	0.31	[0.05 ; 1.91]
	Home working / same WT	0.63***	[0.49 ; 0.80]	0.29*	[0.10 ; 0.85]	0.66**	[0.50 ; 0.88]	0.08**	[0.02 ; 0.38]
	Workplace / Higher	1.51***	[1.19 ; 1.91]	0.31*	[0.13 ; 0.77]	1.51**	[1.11 ; 2.06]	0.28*	[0.07 ; 1.10]
	Workplace / Lower	0.85	[0.67 ; 1.08]	0.29*	[0.10 ; 0.85]	0.41***	[0.28 ; 0.61]	0.05**	[0.01 ; 0.31]
	Fully unemployed	2.09***	[1.79 ; 2.44]	1.23	[0.58 ; 2.62]	1.97***	[1.64 ; 2.37]	1.73	[0.82 ; 3.68]
	Partial unemployment	1.57***	[1.32 ; 1.86]	0.96	[0.32 ; 2.82]	1.23*	[0.98 ; 1.54]	0.87	[0.26 ; 2.86]
	Other	0.20***	[0.08 ; 0.49]	0.00***	[0.00 ; 0.08]	0.17***	[0.06 ; 0.48]	0.00***	[0.00 ; 0.00]
(2)	SPH_prior: Excellent	0.51***	[0.42 ; 0.61]	0.61***	[0.50 ; 0.74]	0.65***	[0.53 ; 0.80]	0.70**	[0.56 ; 0.88]
	SPH_prior: Very Good	0.53***	[0.46 ; 0.60]	0.53***	[0.46 ; 0.61]	0.63***	[0.54 ; 0.73]	0.62***	[0.53 ; 0.73]
	SPH_prior: Fair	2.27***	[2.01 ; 2.58]	2.15***	[1.88 ; 2.46]	1.45***	[1.24 ; 1.69]	1.41***	[1.19 ; 1.67]
	SPH_prior: Poor	2.06***	[1.59 ; 2.68]	2.00***	[1.52 ; 2.63]	1.17	[0.81 ; 1.69]	1.32	[0.91 ; 1.91]
(3)	Covid symthoms	7.21***	[6.23 ; 8.35]	7.24***	[6.19 ; 8.48]	6.45***	[5.35 ; 7.78]	5.90***	[4.82 ; 7.22]
(4)	Age	1.44***	[1.30 ; 1.59]	1.38***	[1.17 ; 1.64]	1.56***	[1.42 ; 1.71]	1.53***	[1.26 ; 1.85]
	Age square	1.00****	[1.00 ; 1.00]	1.00**	[1.00 ; 1.00]	1.00***	[1.00 ; 1.00]	1.00**	[1.00 ; 1.00]
(5)	Female	1.92***	[1.73 ; 2.14]	2.04***	[1.83 ; 2.29]	2.84***	[2.49 ; 3.23]	2.94***	[2.55 ; 3.37}
(6)	1 Child	0.66***	[0.56 ; 0.78]	0.61***	[0.51 ; 0.72]	0.78*	[0.63 ; 0.96]	0.73**	[0.58 ; 0.91]
	2 Children	0.81**	[0.70 ; 0.93]	0.90	[0.78 ; 1.05]	0.92	[0.77 ; 1.11]	0.96	[0.79 ; 1.16]
	3 Children or more	1.14*	[0.98 ; 1.32]	1.19*	[1.02 ; 1.40]	1.19*	[0.98 ; 1.45]	1.17	[0.95 ; 1.44]
(7)	Cluster 2	1.00	[0.89 ; 1.13]	1.03	[0.90 ; 1.17]	1.05	[0.90 ; 1.23]	1.14	[0.97 ; 1.35]
	Cluster 3	1.58***	[1.35 ; 1.85]	1.37***	[1.17 ; 1.62]	1.81***	[1.53 ; 2.15)	1.70***	[1.42 ; 2.03]
	Cluster 4	0.58***	[0.48 ; 0.70]	0.50***	[0.41 ; 0.61]	0.69**	[0.55 ; 0.87)	0.62***	[0.49 ; 0.78]
(8)	Incomes (basleine)	1.00	[1.00 ; 1.00]	1.00	[1.00 ;1.00]	1.00***	[1.00 ; 1.00]	1.00	[1.00 ; 1.00]
	Ratio (change in incomes)	0.80***	[0.72 ; 0.89]	0.72***	[0.64 ; 0.81]	0.99	[0.90 ; 1.10]	0.89*	[0.80 ; 1.00]

Source: SHARE waves 7 and 8, author's calculation. Model 1 is calculated as follow: $Y_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_c C_{ij} + \cup_j + \varepsilon_{ij}$; where the dependent variable is explained by fixed effects for the variable of interest 'X' and the covariates 'C' and a random intercept. Model 2 is calculated as follow: $Y_{ij} = \beta_0 + (\beta_1 + \cup_{1is}) X_{1ij} + \beta_c C_{ij} + \cup_{0j} + \varepsilon_{0ij} = \beta_0 + \beta_1 X_{1ij} + \beta_c C_{ij} + \cup_{0j} + \cup_{1j} X_{1ij} + \varepsilon_{0ij}$; where a random slope 'U_{is}' is introduced to allow differences in slope across counties for the variable of interest 'X'. Notes: (1) Types of employment and work arrangements during the pandemic combine information about unemployment, home working and working time. Those who kept working the same working time and did not benefit from home working are the reference category; (2) Self-perceived health (SPH) prior the start of the pandemic (retrospective). The reference is 'good'; (3) Respondents who declared having COVID-19 symptoms (independently from whether they were tested or not). The reference category is 'no symptoms'; (4) Quadratic function of age; (5) Reference: male; (6) Number of children at 50 – the reference is 'no children'; (7) clusters flowing from the Sequence Analysis, 'cluster 1' is the reference category; (8) declared total household incomes after tax and social contributions prior the start of the pandemic and declared change in incomes as a ratio between prior and post-pandemic household net incomes.

What can be clearly observed, when looking at the variable of interest, is that partial home working (those who combine working from home and within workplace) is significantly negatively associated with change SPH (the OR are above 1) when working time is the same or increases compared with those who keep working at their usual workplace with the same working time. In comparison, there is a positive relationship for those working partially from home when they reduce working time. These associations are significant and consistent in the original and in the matched dataset. Home working compared with working at the usual workplace is negatively associated with negative change in SPH independently from the dataset we are looking at, but the OR are not significant for those who reduced working time (3.1 per cent of the sample). In other words, homeworking has a clear positive impact on self-perceived health. The relationship between change in SPH and unemployment and partial unemployment is more complex. There is a significant association when looking at the original dataset so that unemployment is associated with negative change in SPH, but the relationship is not significant when using the matched dataset, which indicates co-linearity issues when looking at unemployment.

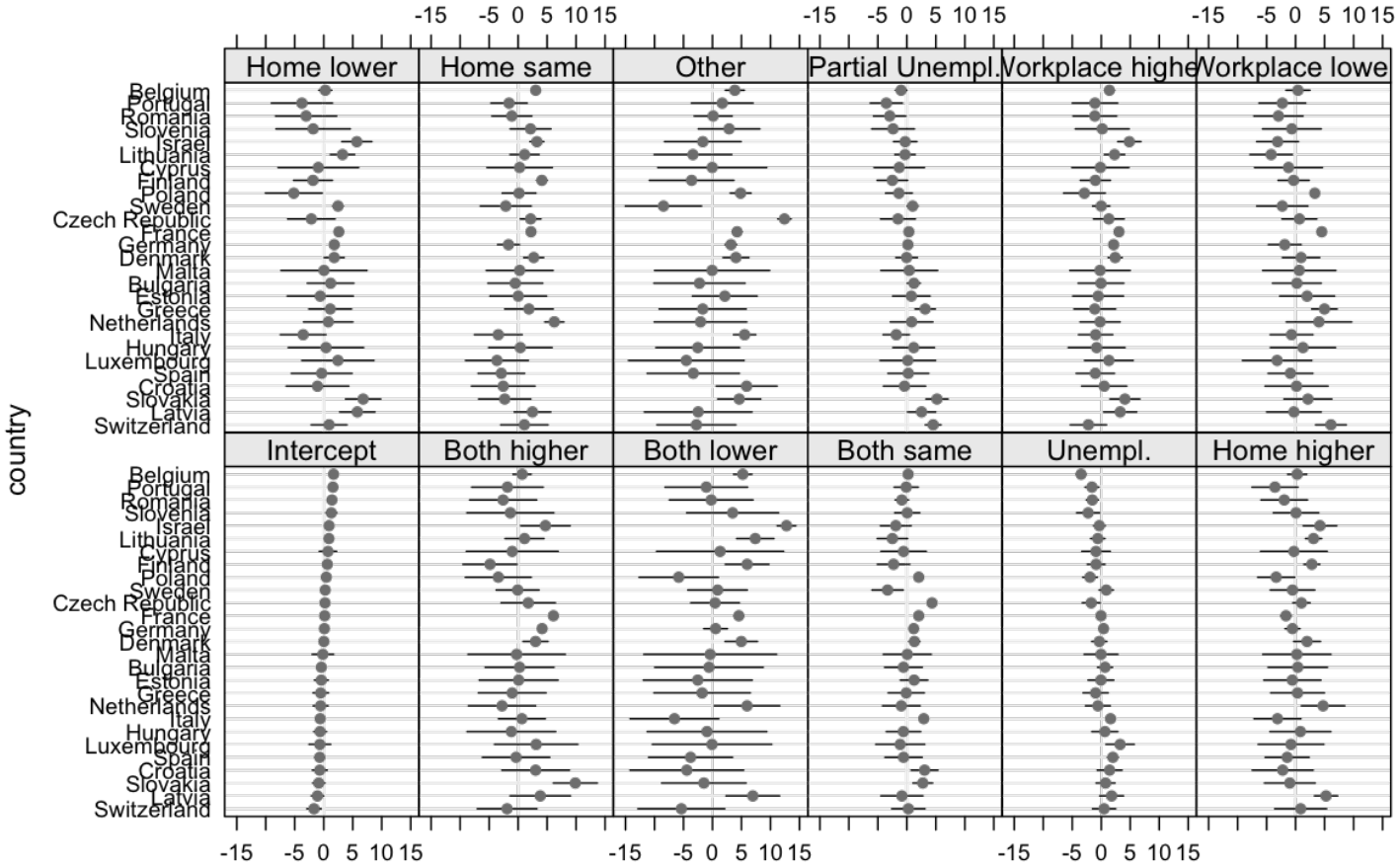
Results for the covariates are also of interest. The study shows that being a female is associated with a considerable negative change in SPH, independently from work and employment arrangements, type of employment trajectory, number of children or age. The number of children play also a role as having one (or two) child is positively associated with change in SPH. SPH prior the pandemic explains well the change in SPH following the virus outbreak as those who had a poor health had higher odds of declaring a worsening SPH and those who had an excellent health had lower odds to do so. Finally, the employment trajectory is an interesting factor to account for. It can be observed that those who had fragmented work trajectories (cluster 4) have lower odds than the reference category (cluster 1) to declare a negative change in SPH. In other words, those who left education early and got a full-time career had higher odds to declare a negative change in SPH. Those who had a part-time career (cluster 3) are in the opposite situation: their odds of having a worsening health are much higher than for those in cluster 1.

Random differences at the intercept

Model 1 includes a random intercept that is considered as a nuisance to assess the relationship between the explanatory variables and the dependent variables independently from the country-level. What model 2 does is to add a random slope for work and employment arrangements so that the slope (i.e., the difference at the intercept for a factor variable) is allowed to vary across countries. Here, the fixed effects can be interpreted as the average change in the dependent variable across countries and the variances give an information about the country dispersion around the mean for each employment arrangement. Fixed effects in the random slope model are not much different from those observed in the random intercept model. Looking at the random slopes, figure 3 gives the conditional modes, i.e., the difference between the population-level average

predicted response for a given set of fixed-effect values and the response predicted for a particular country. Overall, it can be assumed that country-specific effects do not radically change the estimates of the fixed effects model. Partial unemployment has a variance of 5.2 (SD=2.42) in the original dataset and 6.9 (SD=2.6) in the matched dataset. Differences at the intercept by country for the random term do not show significant negative logits, which indicates that the impact of partial unemployment on the odds of declaring a worsened SPH is positive in all cases – or, at least, cannot be assumed to be negative with a 5 per cent degree of risk. Similarly, OR higher than 1 were observed for those working both from home and in the workplace. The logits for the random coefficients by country indicate positive effects and no significant negative effects which, again, indicates that, despite national differences, the effect on SPH is negative in all countries. By contrast, volatility is observed for the category 'other' that had an OR near zero in the second model using the matched dataset which indicates that country-specific arrangements or cases have a high degree on variability when explaining change in SPH with a variance of 29 and a standard deviation of 5.4.

Figure 3. Conditional modes for the random intercept of model 2 (matched dataset) – in logits



Limitations

The study contains several limitations that will be partially addressed when further waves will be released. First, the study does not use proper longitudinal data as it is based on the use of retrospective data both about health prior and after the pandemic outbreak. This could be misleading as both variables were declared at the same time. Further waves will facilitate the use of a proper longitudinal perspective to assess the change in SPH at different time-points. Second, as data were collected internationally during the first wave of the pandemic, the survey does not distinguish directly partial from permanent unemployment and the reasons why workers were unemployed (workplace closure, bankruptcy, lockdown, etc.). Even though the way questions were asked allows to distinguish those who were unemployed since the outbreak of the virus to the interview time from those who had work activities, there is a lack of information about the type of employment that was used. Similarly, no question was asked about potential retirement plans or willingness to move to retirement within the current context whilst the current situation could contribute to push older workers to retire earlier than expected (Moen et al. 2020). Third, the country response to COVID-19 such as the percentage of infection were diversified across Europe. One faces different epidemiologic settings with different types of work and employment arrangements that cross-national comparison, based on a limited number of information (at this stage), cannot control. Fourth, the dataset does not contain clear information about the nature of the work that is actually done, nor does it include information about sectors of activity. SHARE will include additional information in follow-up interviews to be made in spring 2021 that will, partially, address these issues. Fourth, education was not directly controlled within the study but the clusters flowing from the sequence analysis do so. We have tried to run the model including ISCED levels collected in previous waves but with no significant effect of education on the outcome variable and no real impact on the set of covariates whilst, at the same time, this introduces co-linearity between education levels and employment trajectories. These are the reasons why education is not directly included in the results shown in this study. Fifth, no question was asked about care activities, particularly for parents, children and grandchildren whist grandparenthood and care for a relative have detrimental effects on health, particularly for women (Kalmijn 2012; Benson et al. 2017), which translates into particularly high positive odds ratios for them. Finally, various financial supports were implemented in Europe that are not included in this study as the detail about the nature of these arrangements is not available in SHARE. The model controls for the household incomes prior the pandemic and the incomes following the pandemic, including all supports, which controls, without providing enough details, for this.

Discussion

Results from this study indicates two profile-types of those aged 55 and over. On the one hand, those who suffered the most from the first during the first wave of COVID-19 are women who got unemployed after working part of their career part-time and have lost a large part of their household incomes. On the other hand, those who have been less negatively impacted and reported either no change or a positive change in health are men who kept working fully from home, preferably with the same or a higher working time, have a fragmented career and did not get household incomes reduction. The random slope by country for work and employment arrangements does not show any significant difference across countries which tends to indicate that the health impact of work and employment arrangements are not country-dependent even though their use greatly vary from one country to another.

The study draws up four policy implications. First, the combination of home and workplace working has detrimental effects on self-perceived health if not implemented together with working time reduction. Second, home working has, compared with working at the usual workplace, positive effects on change in SPH but the effect is not significant for those reducing working time but only for those increasing or keeping the same working time. Further research should focus on the interaction between home working and change in working time. This is a main issue as the way working time is calculated at home tends to be more volatile than within the workplace. Third, unemployment, even temporary, should be avoided as it has detrimental effects on the total population. However, the study shows that, after using propensity score matching, the negative effect of temporary unemployment and employment fades away, which indicates that workers have not been affected the same way by unemployment and that gender, employment histories or health are co-founders in explaining who is going to be unemployed and, therefore, who is going to suffer from it. Fourth – and this is consistent with was has been recently evidenced in the scientific literature (Bahn et al. 2020; Collins et al. 2020) –, women are still those suffering the most from the pandemic, independently from incomes, employment and education trajectories, whether they have child(ren) and health prior the pandemic.

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