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**Jacques Wels
Natasia Hamarat**

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Centre Metices
Université libre de Bruxelles
Avenue Jeanne 44 - CP 124
1050 Brussels, Belgium

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Are employment arrangements implemented during the first wave of COVID-19 associated with better health outcomes for women aged 55 and over?

Jacques Wels

Université libre de Bruxelles (Belgium), METICES centre & University of Cambridge (United Kingdom)

Avenue Jeanne 44 – CP124 - 1050 Brussels, Belgium

jcqwels@gmail.com

Natasia Hamarat

Université libre de Bruxelles (Belgium), METICES centre & Centre de Droit Public

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Abstract:

The first wave of COVID-19 has had a massive impact on work arrangements settings in many European countries with potential effects on health that are likely to vary across gender. Focusing on the workforce aged 55 and over in 27 European countries using data from SHARE (wave 8), the study applies a generalized logit mixed-effects model to assess the relationship between negative or positive change in self-reported health since the start of the epidemic and change in employment settings using an interaction effect between gender and employment arrangements to distinguish the specific impact of these arrangements by gender and the impact of gender as such after controlling for socio-economic covariates and multicollinearity. Results indicate that female respondents have higher probabilities to declare a positive health when working fully or partially from home compared with men and higher working time is associated with higher odds to declare a negative change in health. However, introducing the main effect of gender exacerbates discrepancies so that the benefits of home working fade away and the impact of higher working time worsens. Differences across countries do not significantly change the estimates. The benefits of work arrangements to improve women's health during the first wave of COVID-19 have not compensated the negative effect of gender discrepancies to the extent that work arrangements have no role, of just a negative impact, in modulating it.

Background

Yesterday promoted, negotiated or debated, work and employment arrangements became a new norm during the first wave of COVID-19 that has hit Europe in the early months of 2020, with a particular impact on working time and home working. Working time is known as being a key factor in explaining health variations among the workforce (1) but the voluntariness or involuntariness of change in working time (2) such as the policies that allow for working time regulations and the arrangements that compensate the income loss after reducing working time (3) play a role. This also applies to the ageing workforce with particular positive health effects on low-income workers (4). Another main issue for understanding working time-health relationship is gender inequity, especially the gender-based employment segregation and the gendered division of domestic labour. On the one hand, non-standard work arrangements – increasing since the mid-1970s and majorly occupied by women (5,6) – has constrained effects on self-rated health and mental health (7). On the other hand, a fair number of studies found a positive association between work-life balance and health outcomes among women. For example, Mensah & Adjei (8) recently reported particularly poor self-reported health among women across welfare states regimes in Europe. Examining the gendered impact of the COVID-19 pandemic, many studies address the controversy about scientific evidence for the consequences of flexible work arrangements and home working on domestic labour and childcare (9). Some contributions argue that, even if the pandemic has had an impact on female employment and female overrepresented sectors, the lockdown may represent an opportunity to reduce the gender gap, especially since companies must adopt flexible working arrangements (10,11) and men have increased the amount of time devoted to housework (12). By contrast, other studies demonstrate that gender discrepancies have been exacerbated by the pandemic and are at risk of escalating due to the post-pandemic recession. This is especially the case for the work of Collins et al. (13) who show that American mothers with children less than 13 have reduced their work hours five times more than fathers between February and April 2020, or of Cook & Grimshaw's contribution (14), whose highlight the role of the public policies to support the long-term consequences on women's employment. However, little attention has been paid so far to the effects on health, especially regarding the specific case of the older workforce (15).

Lying between optimism for the changes implemented in our societies by work and employment arrangements and concerns about the impact of these changes on gender discrepancies, research on the relationship between women's health and work arrangements in the current context has just started. The purpose of this study is to bring some new flesh to this question. Using data from the recently released wave eight of the Survey of Health, Ageing and Retirement (SHARE), this study investigates the relationship between work arrangements and self-reported change in health following the first wave of COVID-19 in Europe for workers aged 55 and over, distinguishing the effects on self-reported health these arrangements had, on the one hand, and how these effects have

been compensated by gender, on the other hand. Put in another way, the study questions the respective role of work arrangements and gender in explaining health and how their interaction results in different health outcomes.

Data and variables

SHARE wave 8 & ShareLife

The study uses micro-data from the Survey of Health, Ageing and Employment in Europe (SHARE) (16,17), 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 (18). 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 (19). 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 from whom retrospective data were available either in wave 3 or 7 (N= 9,593 over 27 country-units). Countries are not represented in 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 (20). 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 has 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 health statuses (21–23). 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) (24) 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 (25). 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.

Variables of interest

The model pays particular attention to gender (that is coded binarily with ‘male’ as the reference category) and Work and employment arrangements. 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) from 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.

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 part-time and multiple changes between full-time and part-time (26,27). 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 (28,29) with 9,520 sequences containing 3,963 distinct sequences. Four clusters flow from the sequence analysis: early education exit with a full-time career (cluster 1); late education exit with a full-time career (cluster 2); part-time career (cluster 3); multiple employment transitions (cluster 4).

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 (2). The model is replicated twice. 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. The formula can be written as follows:

$$(model\ 1)\ Y_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_c C_{ij} + U_j + \varepsilon_{ij}$$

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 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 formula for model 2 is:

$$\begin{aligned} (model\ 2)\ Y_{ij} &= \beta_0 + (\beta_1 + U_{1is})X_{1ij} + \beta_c C_{ij} + U_{0j} + \varepsilon_{0ij} \\ &= \beta_0 + \beta_1 X_{1ij} + \beta_c C_{ij} + U_{0j} + U_{1j} X_{1ij} + \varepsilon_{0ij} \end{aligned}$$

Where a random slope 'U_{is}' is introduced to allow differences in slope across counties for the variable of interest 'X' Types of employment and work arrangements during the pandemic combine information about unemployment, home working and working time.

The models are replicated twice 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 (30,31). The matching was calculated based on 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 nearest neighbor matching selection (32). 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. The model includes 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.

Finally, to assess the relationship between gender and work and employment arrangements and self-perceived health, results were replicated using an interaction effect between both variables. As the model is in logit, predicted probabilities were calculated to better interpret the impact of the interaction. Two types of probabilities were calculated (P1 and P2). P1 looks up at the difference in probability (to declare a worse SPH) between man and women taking into account the interaction effect of work and employment arrangements by gender but excluding the main effect of gender so that:

$$P_1 = \left[\frac{\exp(\beta_b b + \beta_c ab)}{1 + \exp(\beta_b b + \beta_c ab)} - \frac{\exp(\beta_b b)}{1 + \exp(\beta_b b)} \right]$$

Where β_b is the coefficient for employment arrangements (b) and β_c is the coefficient for the interaction term. P2 replicates the difference in probability but including the main effect for gender so that:

$$P_2 = \left[\frac{\exp(\beta_a a + \beta_b b + \beta_c ab)}{1 + \exp(\beta_a a + \beta_b b + \beta_c ab)} - \frac{\exp(\beta_b b)}{1 + \exp(\beta_b b)} \right]$$

Where β_a is the coefficient for gender (a), β_b is the coefficient for employment arrangements (b) and β_c is the coefficient for the interaction term. By doing so, one can distinguish the specific impact of work and employment arrangements by gender excluding the impact of gender that is not related to work and employment arrangements

(P1) and the impact of work and employment arrangements combined with the impact of gender independently from work and employment settings.

Results

Table 1 exhibits descriptive statistics for work and employment arrangements by gender, the percentage of female within each arrangement and the total percentage of arrangements among the workforce in the original and the matched datasets. What can be observed first that those working within the workplace and keeping the same working time account for 37 and 50 percent of the sample of the original and matched datasets, respectively. Male and female were distributed equally with 50 and 51 percent of female in both datasets. The second type of arrangements is partial home working (i.e., the combination of workplace and home working) with no change in working time (same) as they account for 15 and 12 percent of the sample again equally distributed across gender (56 and 50 percent of female). Discrepancies occur when looking at unemployment and home working with higher working time as female were more likely to be in these configurations than men.

Table 1. Employment arrangements by gender, descriptive statistics

	Dataset				Matched dataset			
	Male	Female	Percentage of female	Total percentage	Male	Female	Percentage of female	Total percentage
Unemployment	375	575	0.61	0.10	161	181	0.53	0.08
Partial unemployment	351	439	0.56	0.08	156	134	0.46	0.07
Partial home working / higher	79	103	0.57	0.02	22	26	0.54	0.01
Partial home working / lower	99	130	0.57	0.02	37	39	0.51	0.02
Partial home working / same	626	794	0.56	0.15	235	236	0.50	0.12
Home working / higher	79	195	0.71	0.03	28	52	0.65	0.02
Home working / lower	114	178	0.61	0.03	37	49	0.57	0.02
Home working / same	314	497	0.61	0.09	107	129	0.55	0.06
Workplace / higher	166	232	0.58	0.04	80	67	0.46	0.04
Workplace / lower	245	303	0.55	0.06	120	113	0.48	0.06
Workplace / same	1,770	1,779	0.50	0.37	999	1,041	0.51	0.50
Other	42	46	0.52	0.01	19	12	0.39	0.01
Total	4,260	5,271		1	2,001	2,079		1.
Average			0.58				0.51	

Results flowing for the four models (without interaction effect) are in table 2 (variables of interest) and 3 (covariates). What table 2 shows is that unemployment and partial unemployment had a negative and significant impact on SPH (OR are above 1) but that the significance of these arrangements fades always in models 2 and 4, which indicates differences across countries. Similarly, home same working with higher working time and work in the usual workplace with higher working time have detrimental effects in models 1 and 2 but positive effects when including country variations. What is constant is that those who benefited from home working had a much positive health, independently from their working time compared with those who worked from the usual workplace, independently from the type of model used. Finally, gender is a key factor in explaining negative change in SPH with negative and significant effects in all models.

Table 2. Variable of interest

	Model 1		Model 2		Model 3		Model 4	
	OR	CI95%	OR	CI95%	OR	CI95%	OR	CI95%
Unemployment	2.12 ***	[1.81;2.48]	1.27	[0.60;2.73]	2.25 ***	[1.88;2.70]	1.77	[0.92;3.41]
Partial Unemployment	1.59 ***	[1.34;1.89]	0.89	[0.31;2.54]	2.32 ***	[1.92;2.81]	0.31	[0.07;1.44]
Part home working / Higher	1.41 *	[1.06;1.89]	0.03 ***	[0.01;0.13]	1.33	[0.92;1.93]	0.02 **	[0.00;0.30]
Part home working / Lower	0.20 ***	[0.11;0.39]	0.00 ***	[0.00;0.04]	0.00	[0.00;inf.]	0.00	[0.00;Inf]
Part home working / Same	2.22 ***	[1.93;2.54]	1.14	[0.61;2.16]	2.51 ***	[2.13;2.97]	1.08	[0.45;2.57]
Home working / Higher	0.37 ***	[0.23;0.59]	0.17 *	[0.04;0.68]	0.23 ***	[0.10;0.53]	0.01 *	[0.00;0.61]
Home working / Lower	0.80	[0.59;1.10]	0.48	[0.16;1.49]	0.54 *	[0.32;0.90]	0.51	[0.16;1.64]
Home / Same	0.51 ***	[0.39;0.66]	0.31 **	[0.14;0.69]	0.12 ***	[0.07;0.20]	0.13 **	[0.03;0.49]
Workplace / Lower	0.82	[0.65;1.04]	0.25 *	[0.09;0.73]	1.08	[0.83;1.40]	0.53	[0.25;1.14]
Workplace / Higher	1.50 ***	[1.19;1.90]	0.29 *	[0.11;0.77]	1.51 **	[1.11;2.06]	0.08 **	[0.02;0.41]
Other	0.21 ***	[0.09;0.51]	0.00 ***	[0.00;0.06]	0.00	[0.00;inf.]	0.00	[0.00;2.25]
Gender: Female	1.92 ***	[1.72;2.13]	2.01 ***	[1.79;2.25]	2.08 ***	[1.83;2.36]	2.27 ***	[1.98;2.60]

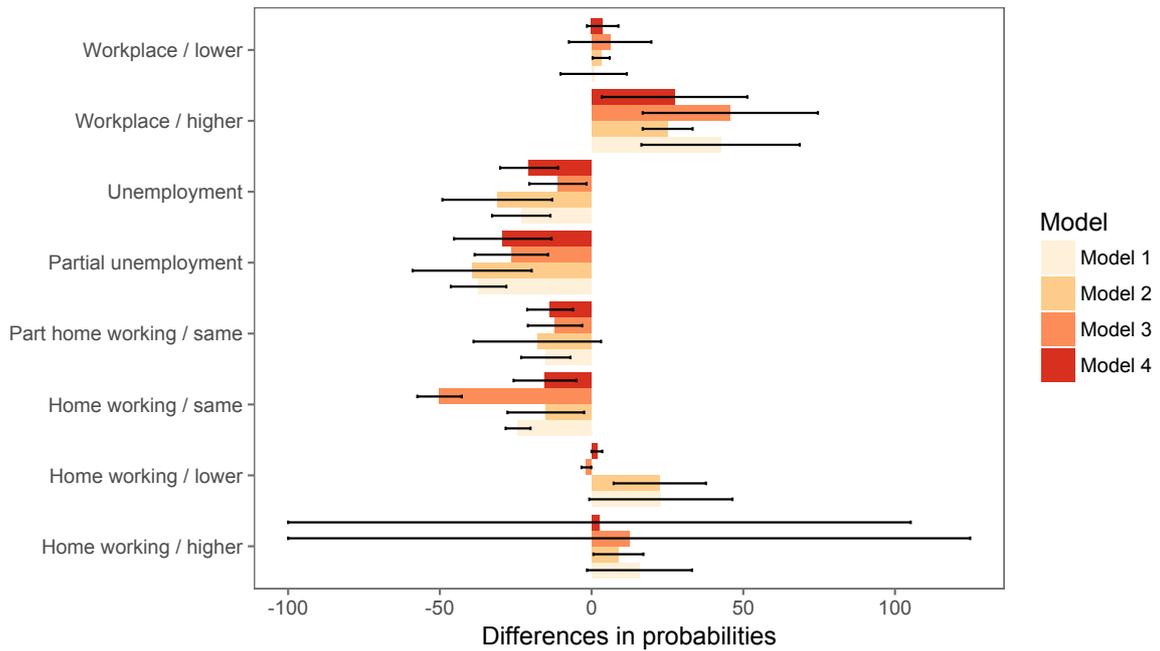
Notes: SHARE waves 7 and 8, author's calculation. Those who kept working the same working time and did not benefit from home working are the reference category. The reference for gender is 'male'.

Table 3. Covariates

	Model1		Model 2		Model 3		Model 4	
	OR	CI95	OR	CI95	OR	CI95	OR	CI95
(1) SPH_prior: Excellent	0.51 ***	[0.42;0.61]	0.58 ***	[0.48;0.71]	0.66 ***	[0.53;0.81]	0.65 ***	[0.52;0.82]
SPH_prior: Very Good	0.54 ***	[0.47;0.61]	0.52 ***	[0.45;0.60]	0.54 ***	[0.45;0.63]	0.53 ***	[0.44;0.63]
SPH_prior: Fair	2.38 ***	[2.10;2.70]	2.23 ***	[1.95;2.55]	2.45 ***	[2.11;2.83]	2.44 ***	[2.08;2.86]
SPH_prior: Poor	2.05 ***	[1.57;2.68]	2.00 ***	[1.51;2.64]	2.01 ***	[1.40;2.89]	2.80 ***	[1.91;4.10]
(2) Covid symthoms	6.93 ***	[5.98;8.03]	6.81 ***	[5.81;7.98]	7.68 ***	[6.36;9.27]	8.71 ***	[7.08;10.71]
(3) Age	1.45 ***	[1.31;1.60]	1.39 ***	[1.17;1.65]	1.53 ***	[1.25;1.86]	1.65 ***	[1.34;2.03]
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]
(4) 1 Child	0.63 ***	[0.54;0.75]	0.60 ***	[0.50;0.71]	0.78 *	[0.63;0.96]	0.62 **	[0.49;0.78]
2 Children	0.80 **	[0.69;0.92]	0.90	[0.78;1.05]	1.03	[0.86;1.24]	0.98	[0.81;1.18]
3 Children or more	1.12	[0.96;1.30]	1.18 *	[1.01;1.39]	1.74 ***	[1.44;2.11]	1.69 ***	[1.38;2.07]
(5) Other education	1.04	[0.92;1.17]	1.04	[0.92;1.18]	1.04	[0.88;1.23]	0.97	[0.82;1.16]
None to ISCED 2	1.06	[0.91;1.23]	0.91	[0.77;1.07]	1.36 ***	[1.15;1.61]	1.30 **	[1.09;1.56]
ISCED 4 and above	1.52 ***	[1.27;1.81]	1.59 ***	[1.32;1.91]	1.98 ***	[1.65;2.39]	2.24 ***	[1.85;2.73]
(6) Cluster 2	0.99	[0.88;1.13]	1.03	[0.90;1.17]	0.87	[0.74;1.02]	0.96	[0.81;1.13]
Cluster 3	1.55 ***	[1.32;1.81]	1.38 ***	[1.17;1.63]	1.50 ***	[1.24;1.82]	1.47 ***	[1.20;1.80]
Cluster 4	0.58 ***	[0.48;0.70]	0.52 ***	[0.43;0.64]	0.42 ***	[0.32;0.54]	0.39 ***	[0.29;0.51]
(7) Net incomes prior	1.12 **	[1.03;1.22]	1.07	[0.97;1.17]	1.00	[1.00;1.00]	1.00	[1.00;1.00]
Ratio prior / post	0.83 ***	[0.75;0.92]	0.75 ***	[0.66;0.84]	0.66 ***	[0.57;0.77]	0.64 ***	[0.54;0.75]

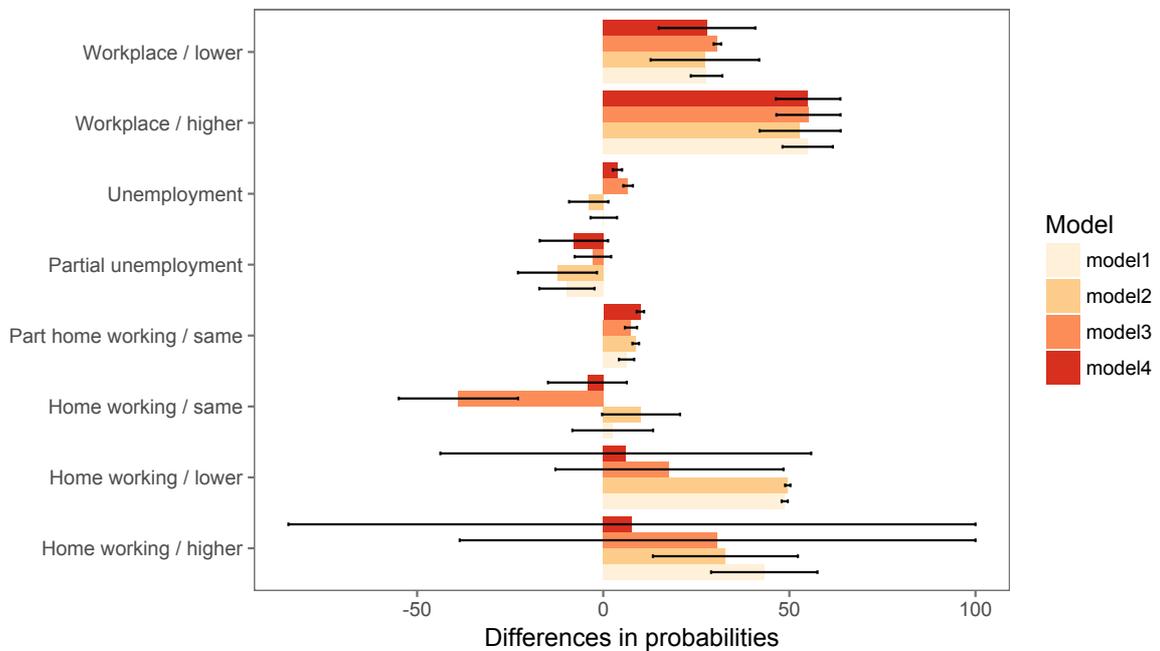
Source: SHARE waves 7 and 8, author's calculation. Notes: (1) self-perceived health (SPH) prior the start of the pandemic (retrospective). The reference is 'good'; (2) respondents who declared having COVID-19 symptoms (independently of whether they were tested or not). The reference category is 'no symptoms'; (3) quadratic function of age; (4) number of children at 50 – the reference is 'no children'; (5) level of education based on the ISCED (International Standard Classification of Education) nomenclature – the reference is 'ISCED 3'; (6) clusters flowing from the Sequence Analysis, 'cluster 1' is the reference category; (7) 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.

Figure 1. Differences in probability for work arrangements by gender, excluding gender main effect



Note: The figure summarizes the difference in probability between men and women by work arrangement ignoring the coefficient for female main effect.

Figure 2. Differences in probability for work arrangements by gender, including gender main effect



Note: The figure summarizes the difference in probability between men and women by work arrangement including the coefficient for female main effect.

Therefore, with work and employment arrangements having different effects and gender which is a strong cofounder of negative change in SPH, the question is to know how these variables interact. Figure 1 answers this question by calculating the predicated probabilities of the interaction between these two terms, including the interaction term only and excluding the main effect of gender. What pops out of the figure is that working within the usual workplace with a higher working time is the only variable that is associated with higher probabilities than men to get a worse SPH (between 30 and 45 per cent more, dependent on the model). In comparison with male, female respondents have lower probabilities to declare a negative change in SPH when unemployed (fully or partially) working partially from home or working fully from home with same working time.

However, one must assume that work is not the only explanation in understanding health discrepancies between male and female. That is the reason why the second figure includes the main effect of being a female (i.e., what being a female adds up to the probabilities of declaring a negative change in SPH independently from the type of work and employment setting). By doing so, it can be observed that change in working time for those working at the usual workplace (versus those who kept the same working time) has negative effects on women's health compared with male respondents. The association with higher working time increases sharply the probabilities to declare a worse SPH for women but what is interesting is that lower working time also has – with a lower intensity – a negative effect on women's health. Unemployment had a positive effect on health (women had lower probabilities to declare a negative change in SPH) but including the main effect reduces these probabilities, which means that, even though women have benefited from unemployment in a way, other factors have neutralised such a positive impact. Finally, women working partially from home and keeping the same working time had lower probabilities than men to declare a negative change in SPH but being a woman, independently from the type of arrangements that is used, reverses the probabilities so that, in the end, the positive effect of home working is negative, with higher probabilities to declare a negative change in SPH.

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.

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. Second, the survey does not distinguish partial from permanent unemployment. 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 whilst the current situation could contribute to pushing older workers to retire earlier than expected (33). 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 amount 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. Fourth, no question was asked about care activities, particularly for parents, children and grandchildren whilst grandparenthood and care for a relative have detrimental effects on health, particularly for women (34,35). 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.

Discussion

Work and employment arrangements implemented during the first wave of COVID-19 partially explains gender discrepancies when looking at older workers' change in self-perceived health as the specific impact of each arrangement varies between men and women. However, they do not, at such, explain these differences as other aspects related to gender, independently from work and employment arrangements, are associated with negative change self-perceived health. Three results of interest flow from the study. First, it shows that unemployment and temporary unemployment were positively associated with women's health, but this association has been balanced by other factors related to gender so that, in the end, they have not been beneficial to women. Similarly, partial home working has reduced the probabilities to declare a negative change in self-perceived health but being a female compensates this reduction so that women's health did not benefit from such arrangements. Finally, change in working time (either higher or lower), has had a negative effect on women's health and this effect has been amplified by other factors related to gender. Based on these results, it can be assumed that work and employment settings certainly were associated with self-perceived health discrepancies across gender but that gender, as an independent factor, has worsened these effects. The workplace plays a key role but, even when positive, these effects were cancelled out by factors that come from outside work and employment configurations.

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