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outcomes during the  
Coronavirus Pandemic

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### Abstract

Using data from the recent SHARE COVID-19 survey and additional information collected in the previous waves of SHARE, we explore the effects of occupation's characteristics on two outcomes: (i) the probability of work interruptions during the pandemic, coupled with the length of such interruptions and (ii) the probability of switching to homeworking during the lockdown. In order to assess how job features affected the likelihood of having experienced work interruptions or shifted to teleworking, we define six occupation categories by classifying the ISCO job titles according to two criteria: the safety level of the occupation and the essential (unessential) nature of the good or service provided. We find that characteristics of the occupation are major determinants of the probability of experiencing work interruptions and determine the length of such interruptions. Working from home also largely depends on the features of the job, even controlling for many other covariates at the individual level. In addition, we show that labour market outcomes of women, self-employed and less educated workers are negatively affected by the pandemic to a much larger extent than men.

### Keywords

Pandemic, work-interruption, homeworking, safe/unsafe occupation, essential/unessential job

### JEL Codes

J01, J21, J24

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# Occupation and working outcomes during the Coronavirus Pandemic

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**Abstract:** Using data from the recent SHARE COVID-19 survey and additional information collected in the previous waves of SHARE, we explore the effects of occupation's characteristics on two outcomes: (i) the probability of work interruptions during the pandemic, coupled with the length of such interruptions and (ii) the probability of switching to homeworking during the lockdown. In order to assess how job features affected the likelihood of having experienced work interruptions or shifted to teleworking, we define six occupation categories by classifying the ISCO job titles according to two criteria: the safety level of the occupation and the essential (unessential) nature of the good or service provided. We find that characteristics of the occupation are major determinants of the probability of experiencing work interruptions and determine the length of such interruptions. Working from home also largely depends on the features of the job, even controlling for many other covariates at the individual level. In addition, we show that labour market outcomes of women, self-employed and less educated workers are negatively affected by the pandemic to a much larger extent than men.

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*Acknowledgments:* This publication is based on preliminary SHARE wave 8 release 0 data (Börsch-Supan 2020). Therefore, the analyses, conclusions and results are preliminary. Please see Scherpenzeel et al. (2020) for methodological details. In addition, this paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6 and 7 (DOI: 10.6103/SHARE.w1.710, 10.6103/SHARE.w2.710, 10.6103/SHARE.w3.710, 10.6103/SHARE.w4.710, 10.6103/SHARE.w5.710, 10.6103/SHARE.w6.710, 10.6103/SHARE.w7.710), see Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628SERISS: GA N°654221, SSHOC: GA N°823782) and by DG Employment, Social Affairs & Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01\_AG09740-13S2, P01\_AG005842, P01\_AG08291, P30\_AG12815, R21\_AG025169, Y1-AG-4553-01, IAG\_BSR06-11, OGHA\_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged, (see [www.share-project.org](http://www.share-project.org)).

## 1. Introduction

The outbreak of the COVID-19 Pandemic at the beginning of 2020 led to radical changes in many aspects of individuals' lives. Mitigation policies, based on limiting social contacts and physical distancing, implied suspension, reduction and/or converting several activities to remote mode, including work. As shown by a series of indicators (OECD, Eurostat, 2020), the lockdown measures had enormous negative economic effects as well as changing several aspects of life, from the labour market activities to individuals' health and social behaviour.

The available macroeconomic evidence documents a dramatic increase in unemployment (OECD, 2020) in spite of the joint efforts of governments and firms to prevent work interruptions by fostering homeworking/teleworking. The OECD and ILO publications on employment trends indicate that low-qualified workers, individuals engaged in the informal economy, immigrants and women are the most vulnerable groups.

In the effort to identify the job-related drivers of the negative effects of social distancing measures and mobility restrictions, the recent literature has focused on *jobs that can be performed at home* (WFH). Dingel and Neiman (2020) analyse occupation's traits in the US starting from the O\*NET dictionary of occupations, while Yasonev (2020) investigates workers' characteristics, showing that young, low educated and low-wage workers, as well as ethnic minorities and immigrants, are less likely to have jobs suitable for homeworking. Cetrulo et al. (2020) make use of the Italian INAPP-ICP data and find that marked occupational inequalities may result from the lockdown restrictions, with a high concentration of WHF jobs among managerial and executive categories, academics, technical professionals and clerical support workers as opposed to sales and service workers, manual operators, artisans and elementary occupations. In a cross-country study, Boeri et al. (2020) report that the percentage of jobs that can be performed remotely differs among European countries, from 23.95% in Italy to 31.38% in UK.

This evidence suggests that there exists high heterogeneity in measuring the potential effects of the Coronavirus Pandemic on labour market experiences, partly due to general labour market conditions in a given country, partly to socioeconomic conditions and largely due to intrinsic characteristics of the job performed. Therefore, individual-level data are a crucial requirement to disentangle the role of these determinants. Indeed, the information requirements are significant: one needs to know about the restriction policies implemented in the different countries, but also the degree of IT infrastructure and digitalisation of the country and workplace and finally the characteristics of each specific job. On top of this, individual characteristics such as education or family structure may partly determine the working status of sample respondents.

This paper investigates to what extent the type of occupation determined the respondents' labour market condition during the Coronavirus Pandemic. Recent data collected by the SHARE COVID-19 Survey allows for a detailed study of the changes experienced by individuals aged 50 and over in their working condition during the pandemic, as it contains information about individuals both before the COVID-19 situation as well as during.

We develop a novel approach to explain the working conditions of Europeans during the first outbreak of the pandemic. We create a detailed dataset based on the pre-COVID19 information available in panel format at the individual level in the ongoing SHARE survey, plus the information collected during the first wave of SHARE COVID-19 survey, and a classification of the occupations based on ISCO-4 digits codes. Hence, we can control for several individual specific characteristics – such as education, gender and IT knowledge and also job characteristics based on ISCO08 codes.

Our approach is also innovative in the way it deals with the features of the job performed: we rank jobs according to two dimensions defined as “relevance” and “safeness”, as these are particularly salient features for workers in the age group 50 and over. In this we follow Fasani and Mazza (2020) and Basso, Boeri, Caiumi, Paccagnella (2020) who provide a classification of occupations based on three-digits ISCO08 categories distinguishing *essential or not essential* (in terms of providing essential goods and services) and *safeness* (in terms of exposure to the risk of contagion) of the job. This classification generates six categories, which capture in a parsimonious way the crucial characteristics of jobs. For example, medical doctors, personal care workers in health service and food processing activities are classified as essential and unsafe jobs, while sport and fitness workers are unessential and unsafe. It is important to observe that in our classification, jobs that can be performed remotely are a part of the “safe” group as they do not exhibit exposure risks, but not all safe jobs can be performed remotely, and this is a crucial distinction for our analysis as will become clear in the next sections.

We model work continuity through a two-step analysis. First, we estimate the effect of occupation on the probability of having experienced a temporary or permanent work-interruption, then we assess the correlation between the type of job and the length of such spells. Finally, we analyse the effect of a specific occupation on the probability of switching to home working during the pandemic. Our findings reveal important differences in the impact of the various job categories both on the estimated probability of work interruptions and the likelihood of shifting to teleworking.

The paper is organized as follows: in Section 2 we present the data and relevant questions of the SHARE COVID-19 questionnaire used in the analysis. Section 3 describes the empirical specifications while Section 4 presents the results. Section 5 concludes.

## 2. Data

We use information from the first wave of the SHARE COVID-19 survey to assess how working conditions of Europeans aged 50 and over evolved during the first wave of the Coronavirus Pandemic. The data-collection was carried out three to six months after the pandemic outbreak, therefore it overlaps with lockdown periods in some countries and possibly, with periods when the lockdown measures were already lifted in some others. Our analysis focuses on individuals who report to have been working (as employee or self-employed) at the time of the Covid-19 outbreak<sup>1</sup>. Our final sample includes 7,719 people of which 44.33% are men and 55.67% are women. Figure 1 (provided in the supplementary information) describes the sample composition by country and age groups.

### 2.1 Working status during the Pandemic

A first outcome of interest to develop our research question is the event “work interruption” experienced by the respondents during the first wave of the pandemic. This outcome is elicited through the question: “*Due to the Corona crisis have you become unemployed, were laid off or had to close your business?*”. Note that in this question respondents are instructed to answer “yes” also

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<sup>1</sup> We drop individuals from Hungary and the Netherlands because some relevant information is missing.

when they have only temporarily suspended their working activity. In order to estimate the parameters of interest, we define a categorical variable, which takes value one if the respondent reports work interruptions or value zero otherwise. Figure 1 shows the fraction of work interruptions by gender and country: a significant heterogeneity emerges between countries and unconditional frequencies do not show any clear gender patterns. The fraction of women who stopped their activity temporarily or permanently is particularly high in Israel and Greece but lower than for men in Luxembourg, Latvia and Lithuania. As we argued, in order to explain these patterns, one needs detailed information on the characteristics of the labour market and individual characteristics, including demographics and type of activities performed at work.

FIGURE 1 HERE

A second outcome is the intensive margin: i.e. the length of a work interruption, based on the question: "*How long were you unemployed, laid off or had to close your business?*" – measuring the number of weeks of interruption. This variable lends itself to different possible specifications, as we shall later explain. As a first approximation, we define a categorical variable taking three possible values: value zero if respondents continued working, value one if they experienced a "short" interruption (between 1 and 8 weeks<sup>2</sup>) or value two if they stopped working for more than 8 weeks.

Finally, in order to model the transition from working at the workplace to home working, we use the question: "*Since the outbreak of Corona, some people worked at home, some at their usual workplace outside their home, some both. How would you describe your situation?. 1. Worked at home only. 2. Worked at the usual workplace. 3. Worked from home and at the usual workplace. 4. None of these.*". We construct a categorical variable taking value one if respondents report having worked from home totally or partially (response items 1 and 3) and zero otherwise. It should be noted that in this analysis we only consider individuals who experienced work interruptions of at most 12 weeks<sup>3</sup>. Figure 2 shows the composition of the sample in percentage terms: around 20% of the respondents of all countries have switched to homeworking (or working from home and the usual workplace), hence suggesting that there has been an important shift in the way workers performed their job.

FIGURE 2 HERE

## 2.2 The role of the job characteristics

We aim at studying whether the type of job performed is a major determinant of work interruptions (and in case, the length of the interruption). Secondly, we investigate the role of occupation characteristics on different working arrangements, such as home working/teleworking.

The descriptive evidence provided in Figure 1 and Figure 2 suggests that the pandemic played a major role in changing working patterns. Explanations of the different labour market experiences

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<sup>2</sup> We set the threshold at 8 weeks as the median value of the variable CAW003\_

<sup>3</sup> For the analysis of homeworking we wanted to exclude individuals that did not work at all during pandemics. Questions CAW002\_ and CAW010\_ do not allow to distinguish between those who experienced a temporary work interruption and those who got permanently unemployed. In order not to erroneously increase the number of "no teleworking" we considered those with 13 or more weeks of unemployment were likely to have not worked at all and preferred to drop them. Among the 7,719 individuals, only 136 of them experienced a work interruption longer than 12 weeks.

could be partly related to the labour market conditions and lockdown measures in a given country, partly to the socioeconomic conditions and largely due to the intrinsic characteristics of the job performed. Hence, we set up a model that can capture in a simple way these different determinants: we combine information on the characteristics of each specific job for each respondent, plus individual characteristics such as education or family structure, which are clearly related to the outcomes of interest.

The restriction policies implemented in different countries affect the labour market arrangements and in turn characterize the observed changes between the pre-COVID-19 and during COVID-19 conditions. Hence, we build a unique dataset based on the information provided by the ongoing SHARE Survey (pre-COVID19) and the SHARE COVID-19 Survey. A specific innovation of our paper is that we make use of the ISCO 4-digit codes associated with the job performed, collected for working respondents in waves 6 through to wave 8. For respondents not providing this type of information in wave 8 – either because they were not administered the regular questionnaire or because they had no change in their occupation since the previous interview – we recover their ISCO 08 4-digit code from the previous (most recent) wave in which they participated<sup>4</sup>. This provides us with a very large set of possible occupational titles, i.e. a detailed description of job characteristics, uniquely associated to each job performed by the respondent. The potential drawbacks of such a wealth of information are that if we assign an indicator variable to each occupational title, we run into sample size limitations (the number of observations in some specific occupation cells may become very small). We also face the “curse of dimensionality”, i.e. reduce the degrees of freedom of the statistical estimation procedure as these codes translate into a very large number of explanatory variables when performing regression analysis or other estimation techniques. At the same time, it is hard to draw conclusions on the role played by the characteristics of the job, when the information is very “granular” and comparisons between jobs become meaningless.

It is worth recalling that we are looking at a sample of Europeans aged 50 and over, so that the job characteristics which may be relevant for younger workers, may not apply in our study. Also, some characteristics are more “supply driven”, i.e. they have to do with the nature of the job that may affect the labour supply response by workers, while some are more “demand driven” i.e. they are related to the specific demand of goods and services and the sector or industry of the job, or even the arrangement in the workplace.

On the basis of these considerations, we build a classification of jobs based on two dimensions which are deemed relevant during the pandemic: *safeness of the job*, in terms of exposure to the risk of contagion, and *relevance of the job*, in terms of producing or providing essential goods or services.

This classification requires a number of steps. First, each 3-digit ISCO08 code receives a “safeness index” on the basis of a scoring system derived from the classification proposed by Basso et al. (2020). Jobs are then classified as *safe*, *partially safe* or *unsafe*.<sup>5</sup> The first group identifies jobs that have a very low exposure risk, i.e. jobs that can be performed remotely; the second one includes jobs that entail ‘low physical proximity and limited exposure to customers and to the public’ and ‘substantial exposure to external people, while still maintaining low physical proximity’. The third category includes jobs that are totally unsafe (Basso, et al., 2002). The other dimension of interest is whether the occupation is *relevant*, i.e. if workers perform crucial tasks, spanning from high skilled

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<sup>4</sup> SHARELIFE-wave 7 is a retrospective survey, allowing us to recover job codes for those who entered the survey in wave 4 (2011) and wave 5 (2013).

<sup>5</sup> Details on how we allocate occupations to these categories can be available upon request.

professionals such as doctors, to low skilled workers, like food processing: in this case we will refer to *essential* (or *unessential*) *jobs* as in Fasani and Mazza, 2020.

The interaction of these two dimensions generates a classification, which allocates jobs to six clusters, or even “ranks” jobs: some jobs may be safe and essential, to the extent that they involve public services such as education or the provision of key goods to the population. At the same time, they do not entail major risk exposure, so that job interruptions are clearly less likely to occur. Once again, some examples clarify the taxonomy: life science professionals are essential and safe jobs, while medical doctors and personal care workers in health service are essential but unsafe occupations. Table 1 shows the number of people in our sample for each country and the distribution by job category.

TABLE 1 HERE

Figures 3 and 4 describe our outcome variables in relation to the job characteristics. As expected, work interruptions seem to increase as the type of jobs becomes more unsafe, irrespective of their essential/unessential nature. Interestingly, the gap between men and women who have experienced an interruption is more marked for the unsafe and unessential jobs. Coherently with country-specific lockdown measures, all subgroups show some interruption: the distribution is mainly concentrated between 6 and 12 weeks of interruption. Figure 4 groups together individuals reporting home working (a case of safe job) and those who have worked partially at home or at the usual workplace. As expected, safe jobs – both essential and unessential – show the highest shares of people working at least partially at home: this is a particularly relevant feature of the preliminary evidence considering that we are looking at people aged 50 and over, who may value particularly the safeness of the job over other characteristics.

FIGURE 3 HERE

FIGURE 4 HERE

### 3. Empirical Strategy

Our paper explores two aspects of the individuals’ working experience during the pandemic: having undergone work interruptions and switching to homeworking. In modelling work interruption, we perform a two-step analysis: first, we estimate the effect of the type of occupation on the probability of having experienced a (temporary or permanent) work-interruption; in the second step, we analyse the correlation between the type of job and the length of such spells.

A simple specification for the probability of stopping the work activity, or switch to homeworking/teleworking, is:

$$y_i = \alpha + \beta_1 O_i + \beta_2 X_i + \rho_c + u_i \quad (1)$$

which we estimate using a Probit model for both outcomes. The dependent variable,  $y_i$ , is a binary variable taking the value of 1 if the respondent has experienced work interruptions (or switched to homeworking as second outcome) and 0 otherwise. The key explanatory variable is  $O_i$ , which represents characteristics of the job described by a categorical variable indicating six possible cases:



safe-essential, partially safe-essential, unsafe-essential, safe-unessential, partially safe-unessential, unsafe-unessential.

In order to assess the relevance of the job characteristics on the outcomes of interest we control for other determinants concerning workers and work environment. A particularly relevant variable is the self-evaluated IT skills of the individual - which is recovered from the previous waves of SHARE. We also control for a set of socio-economic and demographic variables, such as gender, age, education, health status (whether the individual experienced major illnesses immediately before the pandemics), whether the individual used to work as a private employee, public-sector employee or was self-employed. Moreover, in order to account for heterogeneity between countries while preserving a parsimonious representation, we group countries in four country clusters based on a geographical criterion: Northern-Europe countries, Centre-Europe countries, Eastern countries and Southern countries plus Israel.

In the second step, we estimated the impact of occupation on the length of job interruption by means of an ordered Probit specification:

$$L_i = \alpha + \beta_1 O_i + \beta_2 X_i + \rho_c + u_i \quad (2)$$

The dependent variable is a categorical ordered variable generated on the basis of the number of weeks of interruption: taking value 0 if there was no interruption, 1 if the respondent stopped their working activity for at most 8 weeks and taking value 2 if the interruption was longer than 8 weeks. The control variables are the same as in the previous specifications.

## 4. Results

### 4.1 Occupation, work interruption and work arrangements during the pandemic

Table 2 reports the marginal effects of the probability of work interruptions for three specifications. The first column - model 1 - is a more parsimonious specification in which, besides occupation variables, we include gender, age and region of residence. In model 2, we also control for education, information technology skills, type of employment and health status while the third specification also includes interaction variables between gender and the occupation category.

TABLE 2 HERE

By considering the “unsafe and unessential” group as the baseline category, the marginal effects for all the others are negative and significant, pointing to a lower probability of work interruptions. The “safe and essential” occupations display a larger impact, with a 10.2% lower probability of experiencing interruptions, followed by the “safe and unessential” ones, which is 6.8% less likely to undergo any interruptions. The other three categories show very similar impacts on the probability of work interruptions (about 4.2% lower than the baseline). It is interesting to observe that in the first wave of the pandemic the “safety” dimension seems to have prevailed over being an “essential” occupation (i.e. performing key tasks). While the “safe and essential” was by far the job group less likely to undergo work interruptions, the other categories range from “safe and unessential”, “partially-safe and essential”, “partially safe and unessential” to “unsafe and essential” in increasing order of probability of stopping.

One could argue that our grouping of job characteristics is arbitrary and may conceal useful information, also because it is based on a criterion which reflects the COVID-19 shock in making some jobs more relevant than others and some safer than others. In order to show that our proposed grouping preserves the value of the original information, we carried out a robustness check (see Table 3) by estimating equation (1) in relation to forty dummies, one for each job sub-major. In this specification, we choose “teaching professionals” as the baseline group because it is fairly homogenous in terms of within-group composition, as well as work arrangements options. Indeed, most teaching activities continued remotely in almost every European country during the pandemic. With respect to the baseline group, the coefficients indicate that jobs belonging to other sub-majors had significantly higher probabilities of temporary or permanent work interruptions. Larger and statistically significant effects are associated to occupations related to tourism and hospitality, while jobs in “subsistence agricultural activities” were associated to a lower probability of work interruptions. These results are in line with our main specifications.

TABLE 3 HERE

For the length of work interruptions, Table 4 reports the marginal effects of an ordered Probit regression for two specifications (with and without gender-occupation interaction variables). All job categories are less likely to experience longer work interruptions (columns 2 and 3) and more likely to go through brief episodes (less than 1 week) or no activity stop (column 1) with respect to “unsafe and unessential” jobs. The results are consistent with those found in the estimation of the probability to stop working. As a robustness check we also perform a Tobit regression model using the number of weeks of interruption as a continuous dependent variable. The results support our findings and are available as supplementary information.

TABLE 4 HERE

The second goal of our analysis is to evaluate the impact of jobs’ characteristics on the probability of having worked from home partially - or totally - during the first wave of the pandemic. Table 5 presents the estimates obtained by using the six job categories previously defined. With respect to the category “unsafe and unessential”, individuals engaged in “safe and essential” jobs display about a 36% higher probability of having worked from home (column 2). A similar effect is also found in the third regression where interaction terms between gender and job groups are included.

TABLE 5 HERE

It is interesting to note that in the latter specifications the “partially safe and essential” occupations display a smaller and less significant impact on the probability of working from home with respect to the partially safe and unessential category. The other explanatory variables generate the expected regression coefficients: homeworking is positively related to the level of information technology skills<sup>6</sup>.

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<sup>6</sup> We cross-check our results by running a probit specification with a battery of 40 occupational dummies. The results of these regressions are consistent with the findings above.

## 4.2 A focus on women and the role of education

This model allows us to address several issues, which are currently the object of debate for researchers and policy makers. Do women pay a higher price than men in terms of work interruptions during the pandemic? Does education have a mitigating role vis-à-vis the negative Covid-19 shock? As an additional point of attention, we can check if public-sector employees are less affected by the shock as many economists and social scientists have argued.

By recalling that particular care should be paid in drawing general conclusions - our sample looks at workers aged 50 and over - we can provide answers to the above questions. When introducing a “female dummy” in the above models, we find that women in our age groups are about 3.7% more likely to experience work interruptions with respect to men, and longer work breaks (by 1.7% more for interruptions between 1 to 8 weeks, and by 2% more for episodes longer than 8 weeks). When we include interaction terms (i.e. we multiply the female dummy with the six job categories), we find a significant increase in the probability of having experienced work interruptions for women engaged in “unsafe and unessential” jobs. Women in this occupational group are 9.3% more likely to experience a job interruption during the pandemic. Moreover, we estimate larger probabilities of experiencing longer interruptions (about 4% higher between one and eight weeks and about 5.3% for breaks longer than eight weeks). Concerning the type of work arrangements: homeworking is more likely to occur for women. This effect seems to be mostly driven by “partially safe and unessential” jobs: we estimate a likelihood to have switched to teleworking for women in this category of 11.2% higher. Hence, our results confirm that women are more heavily affected by the crisis in terms of labour market outcomes.

We find that education has a clear mitigating role for the negative labour market effects of the pandemic. A level of education lower than high school is associated to a higher probability to stop working and a larger probability to undergo longer work interruptions. Finally, our results also highlight differences between workers in different types of employment. Public-sector employees are associated with a significantly lower probability of work interruption with respect to the private-sector employees (about 8.3% lower), while being self-employed increased the occurrence of such an event by 6.9%. Moreover, public-sector employees are characterised by a 4.1% lower probability to have experienced work interruptions between 1 to 8 weeks and 4% smaller likelihood of breaks longer than 8 weeks. We find an opposite and significant effect for self-employed workers. Finally, both public-sector employees and self-employed workers were more likely to have worked from home than private sector employees.

## 5. Conclusions

This paper evaluates the impact of job characteristics on two main labour outcomes which emerged during the COVID19 crisis: (i) the probability of having experienced work interruptions, coupled with the length of such interruptions and (ii) the probability of having switched to home

working. Assessing the determinants of these labour market outcomes is of great policy relevance as suitable interventions can be designed to prevent important economic consequences at individual level and welfare losses for the European society at large. The key finding of our research effort is that job characteristics play a major role for workers aged 50 and over in Europe, even controlling for other relevant determinants of labour supply, such as education, geographical location and the traditional demographic and “human capital” variables used in the literature.

The novelty of our paper rests on the richness of the SHARE data, which allows us to retrieve information on panel respondents before the COVID-19 outbreak took place and to relate such information to the reported level of activity during the lockdowns. The most salient feature of our work is the use of the newly coded occupations reported in SHARE and classified according to their 3-digit ISCO08 code. The level of detail provided by the occupational classification allows us to classify jobs into six categories based on two dimensions: the degree of safety in terms of exposure to the Coronavirus and the essential (or unessential) nature of the job. A further important feature of the SHARE data is the heterogeneity across countries, so that we benefit from the variability in labour markets arrangements (lockdowns) across EU regions during the Pandemic.

We find that for workers in the age group 50 and over, the “safety dimension” of their job played a major role in determining both the probability of working continuously during the pandemic and the length of work breaks. Workers who experienced job interruption (and longer work breaks) were engaged in “unsafe and unessential” occupations, followed by those in the “unsafe and essential” group. A clear policy implication of our finding is that labour market arrangements should facilitate the more vulnerable jobs, devoting more resources to increasing the safety of these occupations, which in some cases are also engaged in the production of essential goods or services.

Furthermore, occupations which are unsafe and not essential are characterized by longer job interruptions, possibly ending up into long-term unemployment experiences, which could jeopardize the chances for these workers to return to the labour market after the end of the crisis. Policies aimed at protecting work during the pandemic should prioritize occupational groups which are more at risk of suffering these long term consequences.

The COVID-19 shock has also made clear that employers and institutions might need to plan a rearrangement of the work force. We show that a possible line of intervention has to do with the nature of the tasks performed, so that it might be necessary to re-design the production process where more vulnerable workers (due to age and co-morbidities) are moved to less risky tasks.

We also investigate the transition of workers to teleworking: with respect to the baseline category- “unsafe and unessential” jobs - all the remaining occupations are associated with higher probabilities of switching to teleworking. Once controlling for the occupational characteristics, the IT skills appears a crucial determinant of performing the job at home. This finding calls for more investment in IT infrastructure as well as for training of adult workers.

In addition, our results contribute to an ongoing debate on gender differences in labour market outcomes. Women aged 50 and over have been more heavily affected by the pandemic because they are more likely to experience job interruptions and for longer periods. A possible explanation supported by our data is that jobs which rely on close physical interaction with customers (hence “unsafe”) such as, retail activities, accommodation or services to the person and which have been hit harder by the recent sanitary situation, are performed mainly by women. Our results help disentangling an important dilemma: on the one hand, women are more exposed to negative labour market experience, but, on the other hand, because they are more likely to work in the public sector

they are less affected by the negative Covid-19 shock (OECD, 2020b). We show that even controlling for the sector of employment, women are more likely to experience job interruptions and confirm that women represent a particularly vulnerable group during the crisis. A policy implication clearly emerges: labour market arrangements should not only improve the safety of jobs where women are typically involved, but also help women in performing tasks from home, for example through training programs.

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Table 1. Sample composition by country and job category

	Observations (number)	Safe & Essential (%)	PartiallySafe & Essential (%)	Unsafe & Unessential (%)	Safe & Unessential (%)	PartiallySafe & Unessential (%)	Unsafe & Unessential (%)
<b>Germany</b>	537	4.28	7.82	23.46	27.37	14.71	22.35
<b>Sweden</b>	222	6.76	10.36	29.73	26.58	10.36	16.22
<b>Spain</b>	94	5.32	10.64	23.40	17.02	10.64	32.98
<b>Italy</b>	416	5.29	6.73	20.91	33.65	9.13	24.28
<b>France</b>	218	5.50	7.34	32.11	26.15	12.84	16.06
<b>Denmark</b>	484	6.40	8.47	21.07	32.85	15.70	15.50
<b>Greece</b>	339	5.01	6.78	22.42	30.09	13.57	22.12
<b>Switzerland</b>	284	5.63	5.28	23.24	29.23	15.85	20.77
<b>Belgium</b>	634	6.47	6.31	27.76	25.08	10.09	24.29
<b>Israel</b>	243	4.12	6.58	25.93	37.45	9.88	16.05
<b>Czech Republic</b>	254	5.91	8.27	26.77	20.87	14.96	23.23
<b>Poland</b>	576	3.47	10.24	23.61	13.89	24.65	24.13
<b>Luxembourg</b>	77	3.90	9.09	19.48	42.86	12.99	11.69
<b>Portugal</b>	123	6.50	5.69	18.70	15.45	15.45	38.21
<b>Slovenia</b>	235	6.38	11.06	21.70	25.96	12.77	22.13
<b>Estonia</b>	1,019	4.91	10.89	22.67	22.87	14.03	24.63
<b>Croatia</b>	223	3.14	9.87	24.66	16.14	17.04	29.15
<b>Lithuania</b>	338	2.66	15.38	23.08	21.30	14.20	23.37
<b>Bulgaria</b>	182	1.65	9.34	19.23	17.03	19.78	32.97
<b>Cyprus</b>	85	2.35	8.24	20.00	27.06	11.76	30.59
<b>Finland</b>	377	6.90	11.94	25.99	26.26	12.20	16.71
<b>Latvia</b>	187	3.74	12.30	26.20	14.44	13.37	29.95
<b>Malta</b>	104	3.85	5.77	20.19	22.12	8.65	39.42
<b>Romania</b>	147	4.76	4.76	24.49	12.24	19.05	34.69
<b>Slovakia</b>	266	1.50	11.28	25.19	12.78	14.29	34.96

Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary.

**Table 2. Probability of work interruptions**

	<i>Work Interruption model 1</i>	<i>Work Interruption model 2</i>	<i>Work Interruption model 3</i>
Age	0.001	-0.000	-0.000
Female	0.025**	0.037***	0.036***
Unsafe&Unessential ( <i>baseline</i> )			
Safe&Essential	-0.157***	-0.102***	-0.105***
PartiallySafe&Essential	-0.049**	-0.045*	-0.055**
Unsafe&Essential	-0.074***	-0.042**	-0.040**
Safe&Unessential	-0.092***	-0.068***	-0.068***
PartiallySafe&Unessential	-0.046**	-0.042**	-0.047**
High School Education ( <i>baseline</i> )			
Less than High School	-	0.043**	0.043*
Higher than High School	-	-0.035***	-0.034**
Major Illness	-	0.034	0.035
Self-evaluated IT-skills: Excellent/Very good ( <i>baseline</i> )			
Good	-	0.010	0.010
Fair	-	0.013	0.013
Poor	-	0.023	0.024
I never used a computer	-	-0.005	-0.001
Private Employee ( <i>baseline</i> )			
Public Employee	-	-0.083***	-0.082***
Self-Employed	-	0.069***	0.069***
1.female#Safe&Essential	-	-	-0.003
1.female#PartiallySafe&Essential	-	-	0.002
1.female#Unsafe&Essential	-	-	0.018
1.female#Safe&Unessential	-	-	0.028
1.female#PartiallySafe&Unessential	-	-	0.013
1.female#Unsafe&Unessential	-	-	0.093***
<i>Macro Regions</i>	YES	YES	YES
N	7662	6914	6914
Pseudo-r2	0.0528	0.0757	0.077
Log pseudolikelihood	-3.458	-3.074	-3.069

Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary. Notes: marginal effects of probit models are reported. \* p<0.05, \*\*p<0.01, \*\*\*p<0.001



**Table 3. Work interruption outcome by occupation (ISCO08-2 digit)**

	Model 1	Model 2
23.Teaching professionals ( <i>baseline</i> )		
11.Chief Executives, Senior Officials and Legislators	0.056	0.027
12.Administrative and Commercial Managers	0.066*	0.031
13.Production and Specialized Services Managers	0.044	0.013
14.Hospitality, Retail and Other Services Managers	0.281***	0.216***
21.Science and Engineering Professionals	0.061*	0.021
22.Health Professionals	0.011	-0.006
24.Business and Administration Professionals	0.027	-0.002
25.Information and Communications Technology Professionals	0.096*	0.075
26.Legal, Social and Cultural Professionals	0.066**	0.048
31.Science and Engineering Associate Professionals	0.106***	0.079**
32.Health Associate Professionals	0.102***	0.082*
33.Business and Administration Associate Professionals	0.073***	0.047*
34.Legal, Social, Cultural and Related Associate Professi..	0.110**	0.085*
35.Information and Communications Technicians	0.171*	0.144*
41.General and Keyboard Clerks	0.037	0.013
42.Customer Services Clerks	0.118**	0.101*
43.Numerical and Material Recording Clerks	0.078**	0.044
44.Other Clerical Support Workers	0.060	0.056
51.Personal Service workers	0.296***	0.233***
52.Sales Workers	0.175***	0.122***
53.Personal Care Workers	0.120***	0.096***
54.Protective Services Workers	0.116**	0.095*
61.Market-oriented Skilled Agricultural Workers	0.022	-0.039
62.Market-oriented Skilled Forestry, Fishery and Hunting	0.053	-0.014
63.Subsistence Farmers, Fishers, Hunters and Gatherers	-0.046	-0.083**
71.Building and Related Trades Workers (excluding Electr.)	0.121***	0.047
72.Metal, Machinery and Related Trades Workers	0.186***	0.138***
73.Handicraft and Printing Workers	0.268***	0.227***
74.Electrical and Electronic Trades Workers	0.135**	0.103*
75.Food Processing, Woodworking, Garment and Other Craft.	0.181***	0.128***
81.Stationary Plant and Machine Operators	0.137***	0.092*
82.Assemblers	0.101	0.067
83.Drivers and Mobile Plant Operators	0.187***	0.144***
91.Cleaners and Helpers	0.157***	0.118***
92.Agricultural, Forestry and Fishery Labourers	0.120	0.047
93.Labourers in Mining, Construction, Manufacturing and T..	0.155***	0.109**
94.Food Preparation Assistants	0.322***	0.296***
95.Street and Related Sales and Services Workers	0.403**	0.277*
96.Refuse Workers and Other Elementary Workers	0.065	0.043
<i>Macro Regions</i>	YES	YES
<i>Additional Variables</i>	NO	YES
N	7717	6963

Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary. Notes: marginal effects of probit models are reported. \*p<0.05, \*\*p<0.01, \*\*\*p<0.001

**Table 4. Ordered Probit models for the length of work interruption**

	Length of Work Interruption			Length of Work Interruption		
	0 weeks	Between 1 and 8 weeks	More than 8 weeks	0 weeks	Between 1 and 8 weeks	More than 8 weeks
Age	-0.0002	0.0001	0.0001	-0.0002	0.0001	0.0001
Female	-0.037***	0.017***	0.020***	-0.036***	0.016***	0.020***
Unsafe&Unessential ( <i>baseline</i> )						
Safe&Essential	0.104***	-0.051***	-0.054***	0.107***	-0.052***	-0.055***
PartiallySafe&Essential	0.043*	-0.019*	-0.023*	0.051*	-0.023*	-0.028*
Unsafe&Essential	0.041**	-0.018**	-0.022**	0.040*	-0.017*	-0.022*
Safe&Unessential	0.071***	-0.033***	-0.038***	0.071***	-0.033***	-0.039***
PartiallySafe&Unessential	0.046**	-0.021**	-0.025**	0.051**	-0.023**	-0.028**
High School Education ( <i>baseline</i> )						
Less than High School	-0.033*	0.015*	0.018*	-0.033*	0.015*	0.018*
Higher than High School	0.037***	-0.018***	-0.019***	0.036**	-0.017**	-0.018**
Major Illness	-0.035*	0.016*	0.019	-0.035*	0.016*	0.019
Self-evaluated IT-skills:						
Excellent/Very Good ( <i>baseline</i> )						
Good	-0.006	0.003	0.003	-0.006	0.003	0.003
Fair	-0.002	0.001	0.001	-0.002	0.001	0.001
Poor	-0.008	0.004	0.004	-0.005	0.004	0.004
I never used a computer	0.008	-0.004	-0.004	0.004	-0.002	-0.002
Private Employee ( <i>baseline</i> )						
Public Employee	0.082***	-0.042***	-0.041***	0.081***	-0.041***	-0.040***
Self-Employed	-0.065***	0.028***	0.038***	-0.065***	0.028***	0.037***
1.female#Safe&Essential	-	-	-	0.004	-0.002	-0.002
1.female#PartiallySafe&Essential	-	-	-	-0.004	0.002	0.002
1.female#Unsafe&Essential	-	-	-	-0.026	0.012	0.014
1.female#Safe&Unessential	-	-	-	-0.020	0.011	0.010
1.female#PartiallySafe&Unessential	-	-	-	-0.014	0.007	0.007
1.female#Unsafe&Unessential	-	-	-	-0.093***	0.040***	0.053***
Macro Regions	YES	YES	YES	YES	YES	YES
N	6878			6878		
Pseudo-r2	0.0601			0.061		
Log pseudolikelihood	-3.838			-3859		

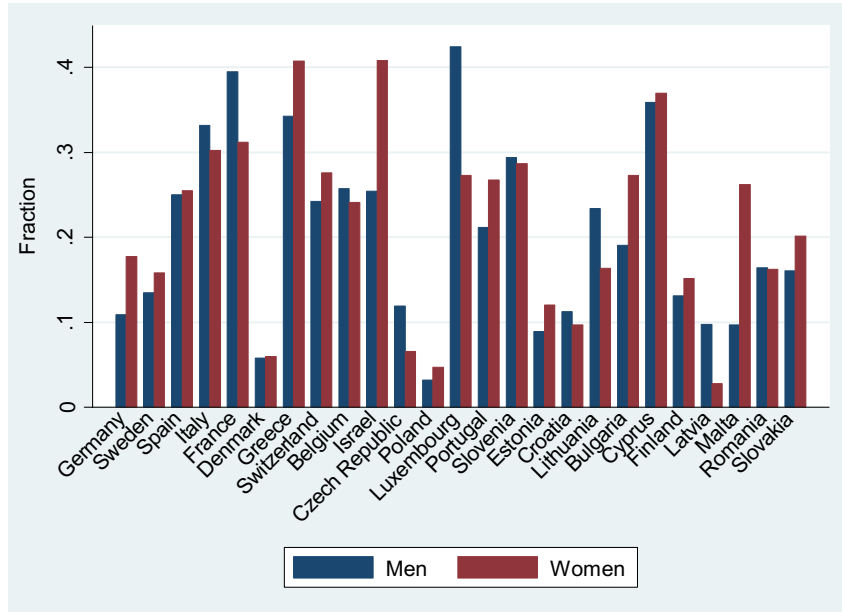
Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary. Notes: marginal effects of an ordered probit model are reported. \* p<0.05, \*\*p<0.01, \*\*\*p<0.001

**Table 5. Probit models for the work from home probability**

	Work from Home <i>model 1</i>	Work from Home <i>model 2</i>	Work from Home <i>model 3</i>
Age	0.004***	0.004***	0.004***
Female	0.054***	0.036***	0.037**
Unsafe&Unessential ( <i>baseline</i> )			
Safe&Essential	0.622***	0.363***	0.367***
PartiallySafe&Essential	0.059**	0.050*	0.053*
Unsafe&Essential	0.113***	0.026	0.023
Safe&Unessential	0.337***	0.204***	0.207***
PartiallySafe&Unessential	0.051***	0.053**	0.066***
High School Education ( <i>baseline</i> )			
Less than High School	-	-0.030	-0.032
Higher than High School	-	0.197***	0.193***
Major Illness	-	0.0011	-0.010
Self-evaluated IT-skills: Excellent/Very good ( <i>baseline</i> )			
Good	-	-0.068***	-0.068***
Fair	-	-0.174***	-0.174***
Poor	-	-0.225***	-0.226***
I never used a computer	-	-0.277***	-0.277***
Private Employee ( <i>baseline</i> )			
Public Employee	-	0.099***	0.098***
Self-Employed	-	0.073***	0.070***
1.female#Safe&Essential	-	-	0.083
1.female#PartiallySafe&Essential	-	-	0.049
1.female#Unsafe&Essential	-	-	0.057*
1.female#Safe&Unessential	-	-	-0.014
1.female#PartiallySafe&Unessential	-	-	0.112***
1.female#Unsafe&Unessential	-	-	0.026
<i>Macro Regions</i>	YES	YES	YES
N	7522	6792	6792
Pseudo-r2	0.1247	0.2268	0.229
Log pseudolikelihood	-4146	-3331	-3324

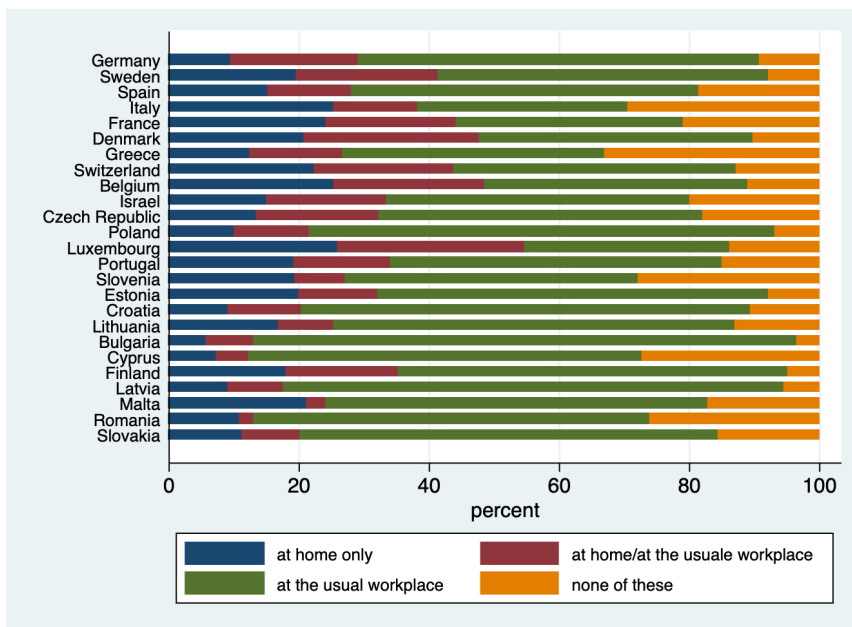
Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary. Note: marginal effects of probit models are reported. \* p<0.05, \*\*p<0.01, \*\*\*p<0.001

**Fig. 1** Fractions of work interruption by country and gender



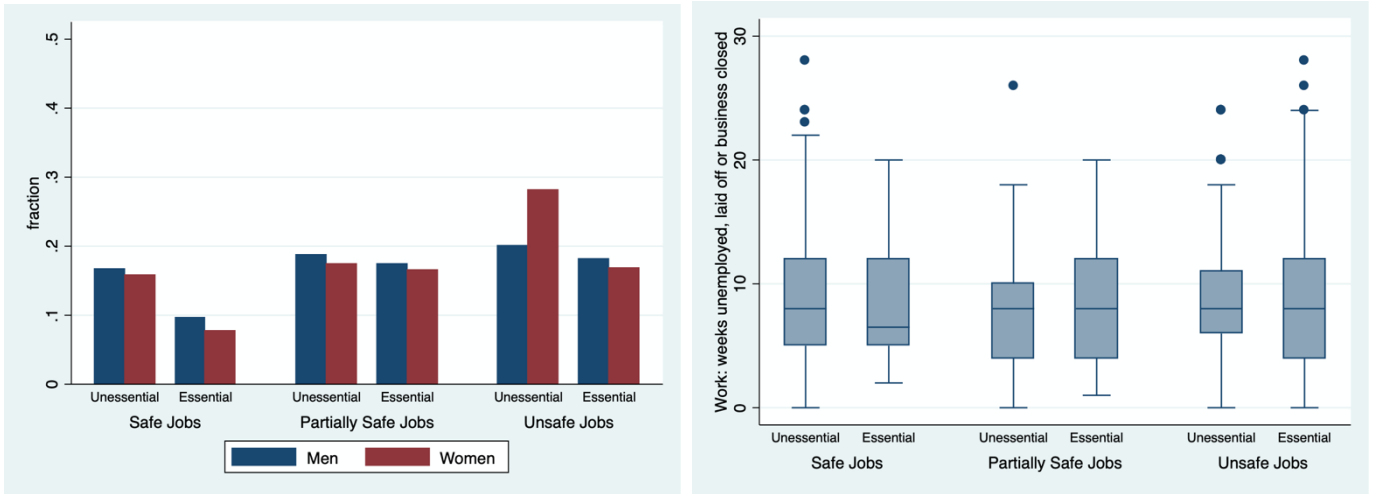
Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary.

**Fig. 2** Working arrangements after the pandemic outbreak



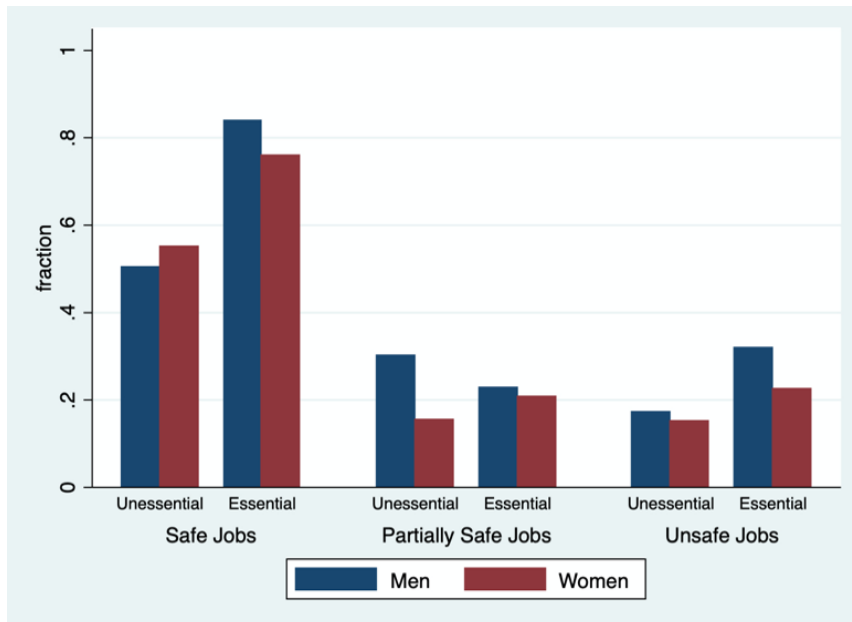
Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary.

**Fig. 3** Fraction of work interruptions (left panel) and length of work interruptions (right panel) by *relevance* (essential/unessential) and *safeness* (safe/partially safe/unsafe)



Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary.

**Fig. 4** Fraction of homeworking - by *relevance* (essential/unessential) and *safeness* (safe/partially safe/unsafe)



Data: Preliminary SHARE wave 8 release 0. Conclusions are preliminary.