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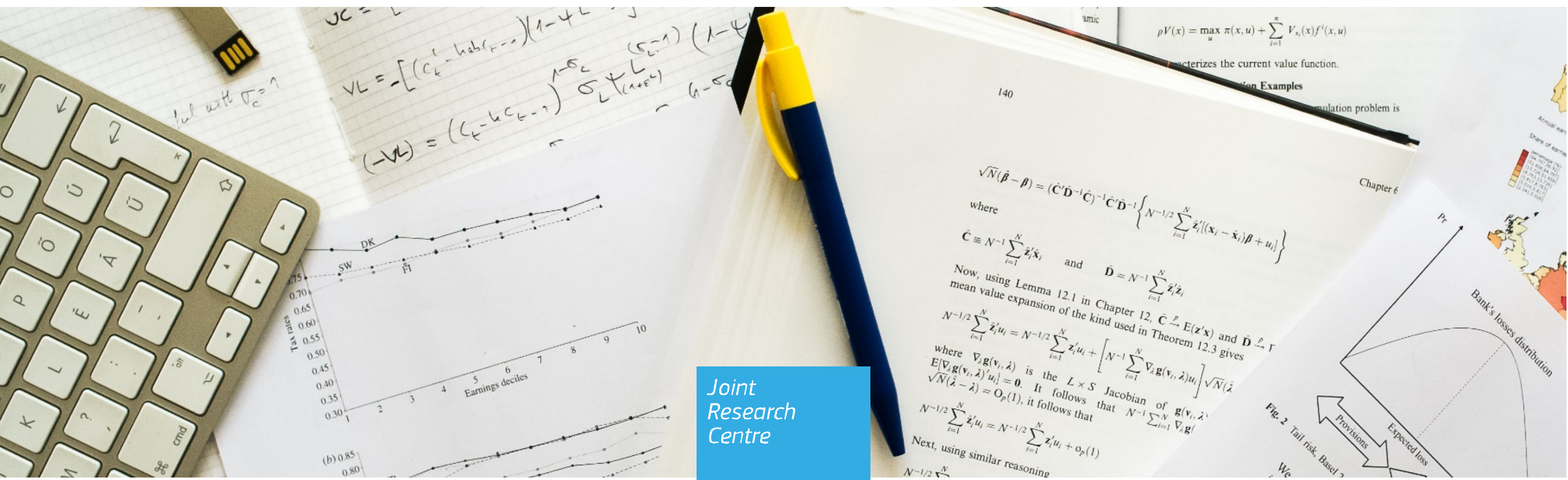

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The Role of Employment Protection Legislation Regimes in Shaping the Impact of Job Disruption on Older Workers' Mental Health in Times of COVID-19[+]

Cinzia Di Novi[*] Paolo Paruolo[*], Stefano Verzillo[*]

Abstract

This study exploits individual data from the 8th wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) and the SHARE Corona Survey to investigate the mental health consequences of COVID-19 job disruption across different European countries. It focuses on older workers (aged 50 and over) who were exposed to a higher risk of infection from COVID-19 and were also more vulnerable to the risk of long-term unemployment and permanent labour market exits during economic downturns. The relationship between job disruption in times of COVID-19 and older workers' mental health is investigated using differences in country-level employment legislation regimes in Europe. European countries are clustered into three macro-regions with high, intermediate and low employment regulatory protection regulations, using the Employment Protection Legislation (EPL) aggregate score proposed by the OECD. Results reveal an EPL gradient: job disruption has a positive and significant impact on older workers' psychological distress especially in those countries where EPL is more binding. The present findings suggest possible mitigating measures for older unemployed in the European countries with higher Employment Protection Legislation.

Keywords: European Countries; COVID-19 pandemic; job disruption; mental health; older workers, EPL

JEL classifications: I14; I18; J08

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Introduction

The SARS-CoV-2 emerged in Wuhan - China in late 2019 and quickly spread globally reaching pandemic proportions. At the beginning of the pandemic no medicines or vaccines were available; governments introduced different forms of non-pharmaceutical interventions (NPIs) worldwide, including mandatory lockdowns, mobility restrictions and suspension of non-essential activities. Social-distancing policies had extensive implications on the labour market beyond income shocks, impacting many sectors of the economy and workforce in an heterogeneous way, altering working conditions and affecting workers' overall well-being. Many workers lost their jobs, others switched to remote working conditions and were forced to combine paid work with other family responsibilities, with an increasing stress stemming from the attempt to meet competing demands (Kniffin et al., 2020). The suspension of non-essential productive activity, loss of income and job insecurity are aspects that may have played a crucial role in worsening mental health conditions of workers facing the pandemic scenario (Donnelly & Farina, 2021).

Despite the COVID-19 pandemic having taken a heavy toll on workers' distress, there is still limited evidence on robust quantification and measurement of this issue in a cross country perspective. This study aims to contribute to this area of research on symptoms of depression related to the COVID-19 crisis by analysing the mental health consequences of job disruption across different European countries. Specifically, this study considers the extent to which pre-existing country-level employment policy contexts, measured through Employment Protection Legislation (EPL) aggregate score proposed by the OECD, may shape the impact that job disruption, caused by the COVID-19 pandemic, may have had on workers' mental health conditions.

The EPL is a key labour market institution that summarizes the strictness of regulation of individual and collective dismissals of regular workers (i.e., the set of regulations that limit employers' ability to dismiss without cost) and the regulation on temporary contracts (i.e., the set of regulations on the use of fixed-term and temporary work agency contracts) across OECD countries (OECD, Employment Outlook 2020). A greater degree of EPL strictness may proxy for a higher rigidity of labour markets, which works through several underlying driving factors including lower inflow and outflow from unemployment, lower turnover and job relocation, longer unemployment spells (Saridakis & Cooper, 2016; Boeri and van Ours, 2021); previous literature has found that all these factors contribute to influence workers' perception of job insecurity (i.e., an individual's assessment about the risk of being dismissed and the chances of moving into a new job) that, in turn, may affect their psychological well-being see e.g. Caroli & Godard, (2016); Clark & Postel-Vinay, (2005); Sverke et al., (2002).

The COVID-19 pandemic has led to sharp reduction in labour demand in many sectors of economic activity in Europe. Despite public interventions to limit the impact of COVID-19 job disruption on job losses in many European countries, such as short-time working schemes or freeze on firings, the long COVID-19 crisis has raised the risk that the increase in the unemployment levels might substantially persist in the near future. A more binding EPL in this situation can act as a "double-edged sword": while protecting workers by reducing their risk of job loss, it might also reduce the outflow rate from unemployment for those who faced a job disruption and lost their job, increasing difficulties in finding another secure employment with similar working conditions (for instance a similar wage) and exacerbating the feeling of job uncertainty (Clark & Postel-Vinay, 2005).

Previous literature claimed that labour market rigidity is particularly harmful for vulnerable workers, such as such as young, unskilled, or female workers increasing barriers to labour market entry and re-entry (Avram, 2020; Cho & Newhouse, 2013). Lessons from previous recessions, however, showed that older workers too have significant difficulties in returning back to employment in case of job loss especially in more rigid labour markets. Even though older workers are less likely to be made unemployed compared to younger ones during economic downturns, unemployment shocks may have persistent effects on the employment of older workers who are highly vulnerable to long term unemployment or permanent labour market exits (Kirsten & Heywood, 2007; Crawford & Karjalainen, 2020; Goda et al., 2021).

The COVID-19 pandemic, and the resulting recession, have been comparatively more challenging for older workers hitting them much harder than other vulnerable groups and much harder than during past recessions; indeed older workers were exposed to a twin risk: a higher probability of adverse effects from the COVID-19 and the reduced labour demand as a consequence of the shutdown policies (Bui et al. 2020). The fear of becoming permanently unemployed or employed at a lower wage in the years preceding retirement may carry a markedly higher burden on older workers' psychological well-being which -in principle- may differ between countries that have different a labour market rigidity and different levels of job security.

This study focuses on workers aged 50 and over and exploits the individual-level data from the 8th wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) until its suspension in March 2020 and the SHARE Corona Survey fielded from June to September 2020. To test whether labour market rigidity has the ability of shaping the impact of job disruption on older workers' mental health, European countries were clustered into three macro-regions characterised by high, intermediate and low employment regulatory protection, following the same classification proposed by OECD based on the EPL aggregate score.

Investigating the causal relationship between job disruption and older workers' mental health faces the challenge of systematic differences in the underlying characteristics of workers who experienced a job disruption and workers who did not that make a direct comparison of these groups potentially problematic. In order to account for potential endogeneity in the relationship between job disruption and workers' mental health, each worker who experienced a job disruption was matched with a worker who did not on several characteristics known to be associated with job disruption and individuals' mental health condition (Caliendo & Kopeinig, 2008). This analysis uses propensity score matching (Rosenbaum and Rubin, 1983), which enables one to construct well-balanced control groups. The mental health of matched workers was then compared to estimate the average effect of job disruption due to COVID-19 pandemic in European countries.

The present results are robust under different specifications of the propensity score model, and under different construction of the dependent variable. An EPL gradient is found in all specifications: job disruptions had a positive and significant impact on older workers' psychological distress especially in the countries characterized by a more binding employment regulatory protection and hence a more rigid labour market. The sensitivity of the results was also tested to different groupings of countries through a leave-one-out procedure (where each country in the group characterized by a more binding EPL was excluded one-at-a-time) as well as via sequentially adding countries with a lower EPL score to the cluster with highest EPL. All results present an EPL gradient.

The EPL is an aggregate variable that may be influenced by several institutional, societal and labour market characteristics. Because of data limitations, it was not possible to investigate which of these factors was more important in driving the present results. These aspects may be addressed in future research using more detailed data sources.

The remainder of the paper is organized as follows: Section 2 describes the data and the structure of the EPL sub-samples; Section 3 illustrates the empirical model, while the results are presented in Section 4. Concluding remarks are reported in Section 5. The Appendix report additional results.

2. Data

This study makes use of a representative sample of individuals drawn from the 8th wave of the Survey of SHARE and the SHARE Corona Survey.[1] The 8th wave of SHARE is a regular wave

[1] The Survey of Health, Ageing and Retirement in Europe (SHARE), co-ordinated by the Mannheim Research Institute for the Economics of Aging (MEA), is the most ample and complete European study about ageing. SHARE is subdivided into modules (each one identified by two letters) dedicated to collecting detailed information on a wide variety of aspects, among which the health status, the socioeconomic characteristics of people aged 50 + in Europe. The target population

collecting information on the health, demographic and socio-economic status of individuals who are 50 years old and over through Computer-Assisted Personal Interviews (CAPI). The interviews started in October 2019 and were interrupted because of the outbreak of the COVID-19 pandemic in March 2020 when approximately 70% of the panel respondents across Europe had already been interviewed (see also Bertoni et al., 2021). A sub-sample of the 8th wave SHARE panel respondents was then interviewed from June to September 2020, via a Computer Assisted Telephone Interview (CATI), partly to collect a set of basic information as in the regular SHARE questionnaire and partly to elicit information on life circumstances in the presence of COVID-19.[2]

The data collected with the latter questionnaire provide a detailed picture of how individuals were coping with the health-related and socio-economic impact of COVID-19. It also includes the most important life domains for the target population and specific questions about the COVID-19 infection and life changes during the lockdown i.e. physical health (general health before and after the COVID-19 outbreak, infections and COVID-19 related symptoms); mental health (anxiety, depression, sleeping problems and loneliness before and after the COVID-19 outbreak); health behaviour (social distancing, mask wearing etc.); SARS-CoV-2 testing and hospitalisation; changes in work and the respondents' economic situation (Scherpenzeel et al., 2020). Combining data from the new SHARE Corona Survey questionnaire with existing information on respondents from the 8th wave of SHARE interviews provides a detailed record of how older workers' psychological well-being was affected by the COVID-19 crisis.

This study focused on older workers aged between 50 and over, according to the country-specific statutory retirement eligibility ages, drawn from the Mutual Information System on Social Protection (MISSOC) tables.[3]

The empirical strategy uses the employment protection legislation index (EPL), which measures the strictness of employment protection for permanent and temporary contracts and relies on three components as measured by the OECD: rules affecting the individual and collective dismissal of workers with regular employment contracts (EPR and EPC respectively) and institutions governing temporary employment (EPT).[4] Hence, individuals who were employed (permanent and

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of SHARE is defined both in terms of households and in terms of individuals. The interviewers observed families with at least one person and the individuals born before 1969 who speak the official language of the country and who, during the time of the survey, do not live abroad or in an institution like a prison, as well as their spouse/partner, independently of age.

[2] SHARE Corona Survey adds only the information on the Covid-19 aspect in addition to already obtained information for the same persons from SHARE.

[3] See https://www.missoc.org/missoc-database/comparative-tables/.

[4]The EPR, EPC and EPT indexes were drawn from the 2020 OECD database in the last available versions (OECD, Employment Outlook, 2020). The EPR score relies on four categories of regulation: procedural requirements, notice and severance pay, the regulatory framework for unfair dismissals and enforcement of unfair dismissal regulation. The EPT score concerns the regulation of temporary employment and refers to the rules regarding the types of work for which such

temporary workers) before the COVID-19 outbreak are included, while self-employed individuals are excluded.[5]

Since the OECD measure of EPL is not available for non-OECD members, the sample was further restricted excluding respondents from Bulgaria, Cyprus, Malta and Romania. Respondents from Croatia were also excluded, since the most recent EPL score for this country dates back to 2015. Finally, respondents from the Netherlands were also excluded from the sample, because information on occupations was not collected after the 6th wave of SHARE, and similarly for Hungary and Israel, because of limited within-country variation in the variables of interest.

Once conditioning on having no missing value on any dependent variable and/or covariate, the final sample consisted of 3.625 observations (out of 6.645 workers) across 19 European countries, namely: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Latvia, Lithuania, Luxembourg, Poland, Slovenia, Slovakia, Spain, Sweden and Switzerland.

2.1. EPL sub-samples

Following Boeri and van Ours (2021), an overall indicator of labour market rigidity of a country was constructed, using simultaneously the strictness of permanent contract (EPR), regulation on temporary contract (EPT) and the strictness of collective dismissal (EPC); the weighted average of these three indicators provides the EPL overall index. The EPL index is a cardinal overall indicator ranging from 0 to 6, which summarizes at the country level, the degree of rigidity of labour legislation and procedures, with a higher value indicating a more stringent regulation of employment and, consequently, a more rigid labour market with lower turnover and unemployment spells which tend to last longer (OECD Employment Outlook, 1999).

The EPL index was calculated according to the approach adopted by the OECD, which combines the three sub-indicators EPR, EPC and EPT respectively with the formula

$$EPL = (5\ EPR + 5\ EPT + 2\ EPC)/12 \qquad (1)$$

The EPC has a lower weight (equal to 40% of the other two weights) to reflect the fact that "*the collective dismissals measures typically represent modest increments to the EPL requirements for individual dismissals*" (OECD Employment Outlook, 1999 – Ch. 2, Annex 2b, page 118).

contracts are allowed, the number of possible renewals and the maximum cumulative duration. The EPC is related to the specific requirements for collective dismissals and includes all additional costs beyond those applicable for individual dismissal. Each indicator is measured on cardinal scores that are normalised to range from 0 to 6, with higher scores representing stricter regulation.

[5] Employment information as provided by the variable *ep005* from the module EP of the 8th wave of SHARE database was considered.

The first column of Table 1 shows the overall EPL index that was used to stratify the sample into three clusters, following the same classification proposed by OECD namely: low employment regulatory protection countries (Switzerland, Denmark and Austria) with an EPL score lower than 2; intermediate employment regulatory protection countries (Lithuania, Germany, Sweden, Finland, Slovenia, Poland, Latvia, Estonia and Belgium) with an EPL score ranging between 2 and 2.5; high regulatory protection countries (Slovak Republic, Czech Republic, Greece, Spain, France, Luxembourg and Italy) with an EPL score higher than 2.5 (OECD, Employment Outlook 2020).

[Table 1 about here]

3. Identification Strategy

Analysing the causal relationship between job disruption and older workers' mental health may be complicated by the presence of endogeneity. The treatment assignment (i.e. job disruption/loss) is not randomized among workers and the outcome of interest (mental health status) may be affected by characteristics that influence the selection into job disruptions. For instance, poor-health workers are perceived as more vulnerable because at higher risk in terms of COVID-19 adverse effects. Workers who deliver essential services continued to do their jobs also in the countries that adopted lockdown measures and so were less exposed to job disruptions. Moreover, the burden of the COVID-19 job disruption had an asymmetric impact and mainly fell on vulnerable workforce groups, such as women and lower-educated and lower-skilled workers (Pouliakas & Branka, 2020).

This potential endogeneity problem can be corrected by matching each worker who experienced job disruption (the "exposed/treated") with a worker who did not (the "control/untreated") on each characteristic known to be associated with job disruption and mental health conditions (Caliendo & Kopeinig, 2008). This matching was performed by using a propensity score matching, as formalized by Rosenbaum & Rubin (1983).

For each treated individual, propensity score matching explicitly looks for a similar untreated individual to be considered as its counterfactual. The propensity score matching technique produces two balanced groups, one of workers who experienced job disruption and one of workers who did not: the propensity score substitutes a collection of confounding variables X with a single variable e – the probability of treatment – that is a function of all the variables:

$$e_i(x) = \Pr(D_i = 1 \mid X = x) \qquad (2)$$

where D_i is an indicator variable that individual *i* belongs to the "job disruption group". The common support is considered restricting the attention to the set of data points belonging to the intersection of the supports of the propensity score distribution among treated and controls.

The identification of the Average Treatment Effect on the Treated (ATT) relies here on the validity of the Conditional Independence Assumption (CIA), namely that the potential treatment outcomes are independent of the assignment mechanism for any given value of a vector of observable characteristics, (*X*) i.e. selection-on-observables (Ichino et al., 2008). In this specific case, CIA implies that selection into a job disruption is solely based on observable variables included in the propensity score model. Thus, it would be crucial to cover all relevant factors that may have influenced a job disruption and the workers mental health over the period of observation, i.e. first wave of COVID-19 pandemic.

3.1 Workers' mental health

In order to measure the deterioration of workers' mental health related to the pandemic itself, four self-reported psychological distress symptoms were considered, based on the SHARE Corona Survey: worsened depressed mood; worsened anxiety symptoms; worsened sleep problems; worsened loneliness. Specifically, respondents were asked the following questions: "*In the last month, have you been sad or depressed?*", "*In the last month, have you felt nervous, anxious, or on edge?*", *"Have you had trouble sleeping recently*?", respectively, with yes or no answer options. For loneliness, respondents were asked "*How much of the time do you feel lonely?*", with response options being often, sometimes, or hardly ever or never.[6]

Concerning depressed mood, anxiety symptoms and sleep problems, if the answer was "*yes*", respondents were also asked "*Has that been more so, less so, or about the same as before the outbreak of Corona?*". Based on their answers, it was possible to create three different indicators, on a four-point scale, ranging from "*no symptoms*" to "*more so*", that capture worsened symptoms (worsened depressed mood, anxiety symptoms, or sleep problems). Responses were coded so that "*no*

[6] The SHARE Corona Survey includes four indicators of mental health distress, namely depressed mood, anxiety, sleep problems and loneliness. The model considered depressive mood and anxiety since they are the key symptoms of mental health disorder (see Kalin, 2020). Moreover, the model also considered the other two additional symptoms: insomnia and feeling lonely. According to the previous literature there exists a strong link between sleep problems and mental illness and insomnia may also exacerbate the symptoms of other mental conditions (Garcia-Prado et al., 2022; Nutt et al., 2008). Previous researches has also recognized an increased risk of mental health problems associated with loneliness. Feeling lonely in particular has increased during the pandemic due to mobility restrictions, social isolation and lockdown measures introduced to tackle the spread of the Coronavirus (Santini et al., 2020). Table 2A in the Appendix shows the correlation matrix for the four self-reported psychological distress symptoms.

symptoms" was the lowest end (0) of the scale and "*more so*" was the highest (3). Worsened loneliness was assessed by the SHARE Corona Survey among those responding "*often or sometimes*" to the first question; these respondents were also asked "*Has that been more so, less so, or about the same as before the outbreak of Corona*?". A three point scale was constructed ranging from "*hardly ever or never*"(1) to "*often or sometimes*" (3).

All the above described outcomes are measures of the worsening of mental health during the COVID-19 outbreak and are not simply indicators of the existence or absence of symptoms; this allows to take into account of the higher risk of being negatively affected by job disruption by workers who experienced depressive symptoms before the pandemic.

In order to obtain a single score that reflects overall mental health/psychological distress, a synthetic continuous indicator of psychological distress is constructed by extracting the first common factor from the correlation matrix estimated by polychoric correlations on the basis of the discrete indicators described above, see Olsson (1979). The polychoric correlation matrix is estimated using Maximum Likelihood (ML) for the latent unobserved continuous variables corresponding to the four ordinal variables: worsened depressed mood (D); worsened anxiety symptoms (A); worsened sleep problems (S); worsened loneliness (L), each with four ordered categories respectively.

The ordinal variables D, A, S and L are assumed to be observed indicators of latent, continuous and normally distributed variables W, Z, U and V. The values of D, A, S and L are defined through W, Z, U and V as

$$\begin{array}{ll} D = i \leftrightarrow \tau_{i-1} < W \leq \tau_i & i = 1,\ldots,m_D \\ A = j \leftrightarrow \xi_{j-1} < Z \leq \xi_j & j = 1,\ldots,m_A \\ S = k \leftrightarrow \gamma_{k-1} < U \leq \gamma_k & k = 1,\ldots,m_S \\ L = l \leftrightarrow \varsigma_{l-1} < V \leq \varsigma_l & l = 1,\ldots,m_L \end{array} \tag{3}$$

where $\tau, \xi, \gamma, \varsigma$ are thresholds such that

$$\begin{array}{c} -\infty = \tau_0 < \tau_1 < \ \ldots \tau_{m_{D-1}} < \tau_{m_D} = \infty \\ -\infty = \xi_0 < \xi_1 < \ \ldots \xi_{m_{A-1}} < \xi_{m_A} = \infty \\ -\infty = \gamma_0 < \gamma_1 < \ \ldots \gamma_{m_{S-1}} < \tau_{m_S} = \infty \\ -\infty = \varsigma_0 < \varsigma_1 < \ \ldots \varsigma_{m_{L-1}} < \varsigma_{m_{DL}} = \infty \end{array} \tag{4}$$

These thresholds were estimated using the marginal distributions of the indicators, see Olsson (1979) Section 3 Case 2, while the correlation matrix was estimated by ML. The latter was used to extract the first factor using standard factor analysis. The score of the first factor was then standardised to lie between 0 (absence of symptoms or worsened symptoms of psychological distress) to 1 (presence of symptoms of psychological distress that worsened during the COVID-19 outbreak) to facilitate the interpretation of results.

3.2 The propensity score model

A Probit model was used as a baseline specification for the individual propensity score. The dependent variable is a binary variable that takes a value of 1 for respondents who experienced job disruption and 0 otherwise. The variable was constructed according to the question "*Due to the Corona crisis have you become unemployed, were you laid off or have you had to close your business?*" with yes and no as the available answer options.

This Probit model controls for a rich set of individuals' demographic and socio-economic characteristics. For demographics, respondent's sex and age (entered as a continuous variable) were included. Concerning workers' family status, controls included respondents' family size and an indicator of individuals' ability to meet their work and family commitments measured before the COVID-19 outbreak (8th wave of SHARE). The indicator relies on the following question: "*How often do you think that family responsibilities prevent you from doing what you want to do*?". Response choices were coded according to a four-point Likert scale: "*often*", "*sometimes*", "*rarely*" and "*never*". This information was treated as a dummy variable with value one if respondents reported "*often*" or "*sometimes*" and zero otherwise ("*rarely*" and "*never*").[7] Marital status was categorized into four 0-1 dummy variables, namely: single, married, widowed, divorced or separated.

The International standard classification of education (Isced) was used to classify the education variable. Three levels of education were considered and categorized into three dummy variables: low education (no educational certificates or primary school certificate or lower secondary education); medium education (upper secondary education or high school graduation); high education (university degree or postgraduate).

Because the income variable in the SHARE database has many missing values and is not reliable, an indicator was added on the household's ability to make ends meet before the COVID-19 outbreak (8th wave of SHARE). Participants were asked to think about the household's total monthly income and rate the degree to which they felt able to make ends meet: "*with great difficulty*", "*with some difficulty*", "*fairly easily*" or "*easily*". This information was treated as a dummy variable with

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[7] This variable was included in order to take into account the respondents' ability to combine work and family responsibilities: maintaining a boundary between work and non-work activities has become particularly challenging during the COVID-19 pandemic and this might have influenced workers mental health conditions.

value one if respondents reported "*with great difficulty*" or "*some difficulty*" and zero otherwise ("*fairly easily*" or "*easily*").

Occupation characteristics were also exploited. First of all, workers were distinguished between those belonging to "essential" and "non-essential" sectors, as defined in the first wave of the COVID-19 pandemic. Indeed, to contain the spread of the coronavirus, at the beginning of March 2020, many European countries imposed a nationwide lockdown limiting the free circulation of people and prohibiting "non-essential" services and activities; only precisely defined sectors deemed as "essential" were excluded from any mobility restriction and allowed to fully operate to ensure the production of primary goods and essential services.

Italy was the first country in the EU that issued the list of "essential"/"non-essential sectors". To ensure continuity of operations of essential functions, the Italian Government advised that critical infrastructure workers were permitted to continue working, despite the mobility restrictions in place. The "essential workers" list was drawn up by the Prime Minister Decree of March 22, 2020 and then adopted by the majority of European countries (see also Bertoni et al., 2021; Fana et al., 2020). Job sectors were divided into "essential"/"non-essential" relying on the 2-digit Nomenclature of Economic Activities (NACE): workers employed in agriculture, hunting, mining, quarrying, utilities, transport and storage, public administration, education and health sectors were considered as "essential", while workers employed in manufacturing, construction, wholesale and retail, hotels and restaurants, financial intermediation, real estate, community workers sectors were considered as "non-essential". Accordingly, a binary variable was constructed with value one if workers were employed in one of the sectors classified as "essential" and zero otherwise. To construct this variable the 2-digits NACE code was used, which is available in the 8th wave of SHARE.

Among the occupation characteristics included in the 8th wave of SHARE, respondents were split according to whether they were employed in the public sector (with private sector as reference category), and to whether respondents were part-time workers or workers with multiple jobs.[8]

The COVID-19 pandemic has highlighted the importance of digital skills for workers; many production activities were staffed working from home (WFH) during the outbreak. However, even before the pandemic, many workers (especially the oldest ones) lacked the digital skills necessary to perform their job from home: those unable to work remotely, unless deemed essential, might have faced a significantly higher risk of job disruption. To take into account the digital divide among

[8] SHARE also includes a variable (ep811) that allows distinguishing between workers hired with a fixed-term contract from those hired with permanent contracts. This variable was not included in the model because of too many missing values. According to Eurostat (2021) workers on temporary contracts, who were less protected by pandemic support schemes, accounted for the large majority of employment losses in all quarters of 2020; however, this phenomenon mainly concerned youth employment rather than the oldest ones.

workers, the model includes an indicator of respondents' computer skills. Participants were asked, "*How would you rate your computer skill? Would you say they are ...*". For the response, a five-point scale was used, ranging from poor to excellent. An additional category was "*I never used a computer*". Responses were coded so that "*I never used a computer*" was the lowest end (0) of the scale and "*excellent*" was the highest (5).

Along with demographics and workers socioeconomic characteristics, the observable confounders include the COVID-19 Government Response Stringency Index (SI) from the Oxford Coronavirus Government Response Tracker (OxCGRT) (Hale et al., 2021).[9] This index captures the day-to-day variation in the containment and closure policies adopted by national governments worldwide to tackling the pandemic; the index scores between 0 and 100, with a higher score indicating a more stringent response. The SI relies on the following measures: closings of schools and universities, closings of workplaces, cancelling public events, limits on gatherings, closing of public transport, orders to "shelter-in-place" and otherwise confined at home, restrictions on internal movement between cities/regions, restrictions on international travel, presence of public info campaigns.

The Covid-19 SHARE questionnaire reports the interview month of each respondent. The average value of the SI was computed over the month of the interview in the respondents' country of residence. Then, this value was compared with the value of the SI in the same country on March, 12 2020 (the day after WHO declared COVID-19 as a pandemic) to compute the relative change in the SI which takes into account the potential mitigation/tightening in the COVID-19 restrictions over time, from the beginning of the pandemic, that might have affected job disruption and respondents mental health conditions.[10] Finally, each respondent was matched on the relative change in the SI stringency index of their country of residence on the month of interview. The model included the relative change in the SI and the relative change in the SI squared to allow for a nonlinear relationship between the relative change in the SI, job disruption and workers mental health.

The local virus spread might also be a key factor in determining mental health issues and job disruption. Therefore, the model considered a variable related to the COVID-19 experience and the spread of COVID-19 among respondents' contacts. This dummy indicator has value one if a respondent or anyone close to a respondent had suffered from the Coronavirus or was hospitalized

[9] Free publicly-accessible data collected by the OxCGRT was used; it is available here: https://www.bsg.ox.ac.uk/research/research-projects/ covid-19-government-response-tracker.

[10] By March, 12 2020 all European countries put in place a set of containment measures, with a large gap persisted between countries that adopted the tightest restrictions and the countries that adopted the loosest over time. This gap might have contributed to widening cross-country heterogeneity in economic conditions and inequality in job disruption and workers psychological distress.

due to the infection or anyone close to a respondent died after being affected by the Coronavirus, and 0 otherwise.

Since the risk of severe COVID-19 increases as the number of underlying medical conditions increases in a person, those who suffer from poor health might be more exposed compared to the others to a job disruption. To account for the respondents' health conditions unrelated to the pandemic itself and the associated lockdown, information on their health status before the outbreak (8th wave of SHARE) was also included. The health-related variables include a binary indicator of general health i.e. the self-assessed health (SAH), and a binary indicator of chronic health condition. SAH in particular, is supported by literature that shows the strong predictive relationship between people's self-rating of their health and mortality or morbidity (Idler & Benyamini, 1997; Kennedy et al., 1998). Moreover, self-assessed health correlates strongly with more complex health indices, such as functional ability (Unden & Elofosson, 2006).

The following standard self-assessed health status question was asked: "*Would you say that in general your health is: excellent, very good, good, fair, poor.*" Since the answers cannot simply be scored (for example as 1, 2, 3, 4, 5) because the true scale is not equidistant between categories (O'Donnell *et al*., 2008) according to previous literature (see, for instance, Contoyannis & Jones, 2004; Balia & Jones, 2008; Di Novi, 2010), the multiple-category responses was dichotomized and a binary indicator was constructed with value 1 if individuals reported that their own health was *fair* or *poor*, and zero otherwise (*excellent*, *very good*, or *good*). Since SAH may suffer from individuals reporting heterogeneity, a more objective indicator of health that is constructed through responses to fairly precise questions about specific chronic conditions is also included in the model (see also Di Novi, 2010; Caroli & Godard, 2016). [11,12]

3.3 Empirical strategy

The baseline empirical model was run first on the full sample. Labour market regulation was considered by means of the EPL index categorized as a scale ranging from 1 to 3 where 1 refers to the cluster of countries characterized by the lowest employment regulatory protection and 3 to the

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[11] The indicator of chronic conditions relied on whether respondents suffer from at least one of this conditions: high blood pressure; high blood cholesterol; stroke; diabetes; chronic lung disease; asthma; arthritis, osteoporosis; cancer; peptic ulcer; Parkinson's disease; cataracts; hip fracture; or other conditions.

[12] In order to test for misspecification (that may lead to estimation bias) in the propensity score model, the linearity restriction was also relaxed in several cases to capture the existence of potential non-linear effects, by including age squared, family size squared, and by including the indicator of respondents' computer skills and the EPL macro areas in the form of six and three dummies respectively. The results remain robust also under this specification of the model and are shown in the Table 3A in the Appendix.

cluster of countries with the highest regulatory protection. Then, in order to test the presence of an EPL gradient in the effect of job disruption on workers' mental health, the analysis was performed by stratifying the sample into three macro-regions according to the EPL index.

Table 2 sets out a full description of the variables used in the model.

[Table 2 about here]

Once the propensity score was calculated, statistical matching was performed so as to form twin data that differ in terms of the job disruption status alone and not in terms of any of the other observed characteristics. Since the sample consists of comparatively few workers who experience job disruption in relation to many untreated ones, Kernel and Radius (with caliper 0.05) matching were chosen as the matching algorithms. These techniques use the maximum amount of data and, in the case of Radius matching, the imposition of a tolerance threshold avoids the risk of bad matches (Caliendo and Kopeinig 2008; Imbens and Wooldridge, 2009).[13]

Country fixed effects are not included in the baseline specifications for reasons of parsimony. However, results are shown to be robust to the inclusion of country fixed effects instead of the EPL index categorized as a scale, as discussed in Subsection 4.1 below.

4. Results

Table 3 shows the pre- and post- matching sample means and standard deviations for the variables used in the model (41% male; mean age of 59 years).

[Table 3 about here]

Note that the psychological distress index (based on four self-reported worsened symptoms i.e. worsened depressed mood; worsened anxiety symptoms; worsened sleep problems; worsened loneliness) and the proportion of workers who experienced a job disruption are higher in the countries characterized by a more stringent employment regulation (EPL cluster=3) that also show, on average, the lowest increase of the SI from the beginning of the COVID-19 pandemic and the lowest Coronavirus local spread according to the data (i.e. proportion of respondents or individuals close to respondents who suffered from the Coronavirus or were hospitalized due to the infection or individuals close to a respondent who died after being affected by the Coronavirus).

[13] The estimation was carried out using the PSMATCH2 program for STATA developed by Leuven and Sianesi (2003).

The results of the baseline Probit model for propensity score matching (see Section 3) are provided in the Appendix (see Table 1A). A higher EPL (i.e. a more stringent regulation of employment) is found to be associated with a higher probability of job disruption. The likelihood of experiencing job disruption is also positively associated with a worsened SI, a larger local Covid spread, a lower socioeconomic status and with part-time jobs. Respondents employed in essential activities and those employed in the public sector are significantly less likely to suffer from job disruption, as expected. Unhealthy individuals are less likely to have faced a job disruption too[14].

The covariate balancing test included in Table 4 shows that the matching is effective in removing differences in observable characteristics between workers who experienced job disruption (treated group) and those who did not (the counterfactual/control group).

[Table 4 about here]

In particular, the median absolute bias is reduced by approximately 72%-88% for the full sample depending on the matching technique and by 64%-89% in the analysis by EPL clusters depending on the matching technique and the EPL cluster. The Pseudo R-squared after matching is always close to zero, correctly suggesting that the covariates included in the model have no explanatory power in the matched samples. The Chi square test (i.e. the bivariate test for joint significance) conducted before and after matching proves that the propensity score removed bias due to differences in covariates between treatment and control groups.

Table 5 shows the average effects of job disruption (ATTs) as measured on individuals' psychological distress index indicator for the full sample and for the EPL sub-samples, adopting the two matching methods of Kernel and Radius Matching. Only observations within the common support were used in the matching procedure.

[Table 5 about here]

Starting from the full sample, the present results show that experiencing a job disruption had a positive and significant impact on worsening symptoms of psychological distress. These findings also reveal the presence of an EPL gradient: in the group of countries characterized by stronger

[14] Concerning pre-existing health conditions, it is interesting to note that there is a discrepancy between countries characterized by a stronger and weaker employment protection: in countries with the highest EPL only, those who suffered from bad health also reported a higher probability of job disruption given also their higher vulnerability to risk associated to the Coronavirus. This was not the case in countries characterized by intermediate and lower employment protection legislation.

employment regulation (EPL cluster = 3 in Table 5) job disruption significantly affected individuals' mental health conditions; specifically, the ATT is significant at 1% level and positive.

A worker who experienced a job disruption in a country characterized by a more stringent regulation of employment and, consequently, a more rigid labour market, showed an increase of the psychological distress index of about 8.4%; for workers who live in the group of countries characterized by an intermediate regulation (EPL cluster = 2 in Table 5) the effect of job disruption on worsened symptoms is not significantly different from zero at any conventional significance level.

The magnitude of the ATT, even if not statistically different from 0, is lower in magnitude in the more-strongly regulated countries cluster (with an increase of psychological distress index in the sample of interest of about 1.8% for those workers who faced a job disruption).[15] Moreover, job disruption appears not to have a significant effect on reporting worsened symptoms of psychological distress also in the group of countries characterized by a lower level of employment protection (EPL cluster=1 in Table 5).

4.1 Sensitivity checks

Different specifications of the propensity score model were entertained in order to check to what extent ATT estimates were sensitive to the choice of specification. Firstly, the model was re-run using a different dependent variable in the Probit model for the propensity score that takes into account the length of job disruption. The SHARE Corona Survey provides information about the length (in weeks) of job disruption, based on the question: "*How long were you unemployed, laid off or did you have to close your business*?". The model was re-estimated by setting the threshold at 8 weeks, equal to the median value of the variable and excluding from the sample workers who experienced job disruption for 8 weeks or less (9.3 % of the full sample) (see also Brugiavini et al. 2021). Then, the propensity score was computed through a Probit model for those who experienced more than 8 weeks of job disruption, using the same specification as described in Section 3. The sample included 3,287 observations. The number of workers who reported more than 8 weeks of job disruption (7.4% of the full sample) is higher in countries characterized by a more stringent EPL: 12.2% of workers who live in countries with a more binding EPL experienced a job disruption against 5.2% and 6.9% of workers living in countries characterized by an intermediate and a low employment

[15] The sample size in the analysis is restricted to the available survey data. Larger sample sizes, such as the ones obtainable with access to administrative data, could help in better gauging the significance of these effects.

regulatory protection respectively. Table 6 shows ATTs for the full sample and for the EPL cluster sub-samples.

[Table 6 about here]

Starting again from the full sample, the longer the job disruption the heavier the psychological burden. As before, a longer job disruption seems to have an adverse influence on worsened psychological distress symptoms in particular in countries where EPL is more binding where the magnitude of the effect is higher: in these countries a worker who experienced a job disruption for more than 8 weeks presents an increase of the psychological distress index of about 10.7% compared to a worker who did not and the ATT is again significant at 1% level. In the intermediate employment regulatory protection countries, the ATT is not significant at any significance level and its magnitude (about 2.5%) is again lower than in the high employment regulatory protection countries. In countries characterized by a lower EPL and a greater labour market flexibility the ATT remains not statistically different from zero.

The model was re-run by including in the Probit model for the propensity score the country fixed effects to control for countries heterogeneity, instead of the EPL index. The results are shown in Table 7.

[Table 7 about here]

Even though the model is less parsimonious, the ATTs remain very similar to those related to the baseline model presented in Section 3 (7.5%).[16]

The model was finally estimated to replace the relative change in the SI of each country with the absolute value of the SI of the country by March, 12 2020. Indeed, at the beginning of the COVID-19 pandemic a rather negative scenario applied to countries more severely hit by the Coronavirus spread that adopted more stringent restrictions and longer-lasting lockdowns such as Czech Republic, France, Italy, Spain and Slovakia. These countries are all included in the first high regulatory protection countries cluster. So, one may argue that the negative and stronger impact of job disruption on individuals' mental health conditions may have been driven by stringency of the initial restrictions that countries introduced to curb the spread of the virus rather than the differences in the countries'

[16]All observed controls used in the propensity score matching analysis satisfy again the balancing property. For the sake of brevity Tables showing the additional balancing tests are not included, but they are available from the authors upon request.

labour specific institutional arrangements and employment structures. The results of this sensitivity analysis are shown in Table 8, and are once again in line with the ones of the baseline specification (7.8%).

[Table 8 about here]

Robustness of the ATTs was checked by performing additional stress tests with respect to different groupings of countries. The main specification followed the classification proposed by OECD using EPL thresholds values of 2 and 2.5. Firstly, to empirically assess the importance of this problem, a leave-one-out test for the EPL=3 group was performed, where each country in the group was excluded one-at-a-time. Results are represented on the left panel of Figure 1, where coefficients are sorted from the exclusion of the country with highest EPL (on the left) to the exclusion of the country with lowest EPL (on the right) within the group. The exclusion of one country does not have a relevant impact on the estimated coefficient, and variations in the confidence intervals are not ordered in the same way as the EPL score, something one would expect if differences between specifications were truly random. This suggests that the main results are robust with respect to the exclusion of any specific country from the EPL=3 group.

Moreover, the robustness of the results was also tested to the number of countries included in the stronger EPL group. The main model was also re-estimated sequentially adding the next set of countries with highest EPL in the EPL=2 group. The resulting coefficients are reported in the right panel of Figure 1 labelled "Add in", where the coefficients correspond to adding all countries with EPL greater or equal to the one of the country on the horizontal axis to the EPL=3 group. The results show the presence of a EPL gradient, where addition of countries with lower EPL decreases the dimension of the estimated ATT as expected.

[Figure 1 about here]

As a further sensitivity analysis, the baseline model was also tested considering each of the four self-reported psychological distress symptom as a proper dependent variable. Specifically, the model was re-run treating the four self-reported psychological distress symptoms (namely worsened depressed mood; worsened anxiety symptoms; worsened sleep problems; worsened loneliness) as binary indicators of workers' mental health conditions.[17]

[17] As stated before (see Subsection 3.1), in the SHARE Corona questionnaire, respondents were asked about their depressed mood, anxiety symptom and sleep problems in the month before the interview and whether these symptoms/problems have worsened, improved, or remained the same since the beginning of the pandemic. Based on their answers, it was possible to create three different dummy indicators that capture worsened symptoms/problems: worsened

For loneliness, respondents were asked "*How much of the time do you feel lonely?*", with response options being often, sometimes, or hardly ever or never. Worsened loneliness was assessed by the SHARE Corona Survey among those responding "*often or sometimes*" to the first question; these respondents were also asked "*Has that been more so, less so, or about the same as before the outbreak of Corona*?". A binary variable that takes value one if they answered "*often or sometimes*" and zero otherwise ("*hardly ever or never*") was constructed.

Table 9, that include the ATTs of this sensitivity analysis, shows, once again, the existence of an EPL gradient: the ATTs in this case capture the probability of suffering from psychological distress symptoms that tend to be higher in the countries characterized by a higher EPL where job disruption appears to significantly affect the key symptoms of mental health disorder: namely worsened depressed mood and worsened anxiety symptoms (see footnote 6), at 1% level, with an increase in the probability of suffering from these conditions of about 12% and 15% compared to those workers who do not experience a job disruption.

[Table 9 about here]

5. Concluding Remarks

The COVID-19 crisis has come with an extraordinary level of economic uncertainty that profoundly affected many sectors of the economy and working conditions: many workers, especially those employed in non-essential activities, have been faced with a new set of challenges including workforce reductions, substantial income losses and fear of becoming permanent unemployed in the near future.

Using data from the 8th wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) and the SHARE Corona Survey, this study aimed at investigating the impact of job disruption on older workers psychological well-being, providing additional insights into the psychological status of, and strain on, older workers during the COVID-19 outbreak.

The main contribution of this paper consisted in analysing the relationship between COVID-19 job disruption and older workers' psychological distress taking into account the labour market differences, in particular in terms of rigidity and job security levels, across European countries. Indeed, while job disruption and the related job loss and income shocks during the COVID-19 pandemic have been relatively extensive across the European countries, their mental health

depressed mood, anxiety symptoms, or sleep problems were considered as present if respondents reported "*more so*" and absent otherwise ("*less so or about the same*").

consequences on workers may vary due to differing labour market contexts. This paper considers the extent to which pre-existing country-level employment policies shape the impact that COVID-19 job disruption may have had on workers' mental health conditions focussing in particular on the Employment Protection Legislation (EPL) aggregate score, which summarizes the strictness of employment regulation and the overall labour market rigidity.

Results reveal a EPL gradient: job disruption has a positive and significant impact (about 8%) on older workers' psychological distress especially in the countries with more binding EPL that might have acted as a "double-edged sword" increasing the job security for older workers who did not suffer from any job disruption but increasing at the same time the uncertainty for those who have experienced layoffs given its potential to reduce the outflow rate from unemployment.

The present findings suggest possible mitigating measures for older unemployed in the EU countries with higher Employment Protection legislation. The precise form of these measures depends on different feasibility factors across countries that do require additional analysis.

This study does have limitations. While the paper took advantage of uniquely combined information about job disruption and mental health of elderly workers in several OECD countries collected by the 8th wave of SHARE and SHARE Corona Survey, it does face important limitations due to the reduced sample size available for this analysis. Once elderly workers within the survey population for which full information is available (e.g. no missing information on any considered variable) were selected, the sample ended up with around 3.700 observations from 19 countries which do not allow to estimate country-specific treatment effects which would allow to explore deeply the EPL gradient found in the paper and its determinants.

Moreover, the unique information about job disruption at worker level was collected for the first time in the SHARE Corona Survey, preventing any possible benchmark of the estimated ATTs at country level with similar data before the COVID-19 pandemic (e.g. estimating the additional mental health burden due to a job disruption experienced during the Covid-19 times). In this respect, it is not possible to test for COVID-19 pandemic specificities on the mental effects of job disruptions.

Despite these limitations this paper provides insights regarding the short-term consequences on workers mental health of job disruptions during the COVID-19 outbreak and contributes to the body of research on the negative associations between such disruptions and the psychological well-being of the older workers.

The EPL is an aggregate variable that may be influenced by several institutional, societal and labour market characteristics. Because of data limitations, it was not possible to investigate which of these factors was more important in driving the present results; these aspects are left to future research using more detailed data sources.

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TABLES

Table 1 - Countries by Strictness Employment Protection Legislation (EPL)

Country	*EPL*	*EPR*	*EPC*	*EPT*
Switzerland	1.58	1.61	1.69	1.5
Denmark	1.99	1.94	2.18	1.96
Austria	2.00	1.8	2.14	2.17
Lithuania	2.11	2.24	2.24	1.92
Germany	2.21	2.33	2.61	1.92
Sweden	2.21	2.54	2.72	1.67
Finland	2.22	2.48	2.75	1.75
Slovenia	2.30	2.32	2.68	2.13
Poland	2.31	2.39	2.36	2.21
Latvia	2.36	2.71	2.89	1.79
Estonia	2.41	1.93	2.04	3.04
Belgium	2.48	2.71	2.68	2.17
Slovak Republic	2.53	2.33	2.46	2.75
Czech Republic	2.66	3.03	3.05	2.13
Greece	2.70	2.54	2.55	2.92
Spain	2.71	2.43	2.43	3.1
France	2.96	2.68	3.25	3.13
Luxembourg	3.09	2.54	2.66	3.83
Italy	3.24	2.86	3.19	3.63
Average	2.42	2.39	2.55	2.41

Source: OECD, Employment Outlook 2020 and authors own elaboration. Scores are rounded to two decimals.

Table 2 - Variables Description

Variable name	***Description***	***Data Sources***
Psychological distress index	Continuous scale between 0 (no symptoms of psychological distress) to 1 (presence of symptoms of psychological distress that worsened during the COVID-19 outbreak)	SHARE Corona Survey
Job Disruption	1 if unemployed, were you laid off or has had to close her business because of the COVID-19 outbreak	SHARE Corona Survey
Age	Continuous variable	SHARE Corona Survey/ Mutual Information System on Social Protection (MISSOC)
Male	1 if Male, 0 otherwise	SHARE Corona Survey

Marital Status	Single - 1 if single, 0 otherwise Married - 1 if married, 0 otherwise Widowed - 1 if widowed, 0 otherwise Divorced/separated - 1 if divorced/separated, 0 otherwise	SHARE Wave 8
Family Size	Number of household members	
Ability to meet work and family commitments	1 if family responsibilities prevent her from doing what her want to do (often or sometimes), 0 otherwise	SHARE Wave 8
Education	Low education - 1 if lowly educated, , 0 otherwise Medium education - 1 if medium educated, 0 otherwise High education -1 if highly educated, 0 otherwise	SHARE Wave 8
Occupation	Essential Workers — 1 if employed in an essential sector, 0 otherwise Public Sector — 1 if employed in the public sector, 0 otherwise Part-time — 1 if part-time worker, 0 otherwise Multiple Jobs — 1 if worker with multiple jobs, 0 otherwise	SHARE Wave 8
Computer skills	Scale ranging between 0 (never used a computer) and 5 (excellent computer skill)	
Ends not meeting	1 if able to make ends meet with great difficulty or with some difficulty; 0 otherwise	SHARE Wave 8
SAH	1 if her health is poor or fair, 0 otherwise	SHARE Wave 8
Chronic conditions	1 if suffers from at least a chronic condition, 0 otherwise	SHARE Wave 8
COVID-19 spread	1 if anyone close had suffered from the Coronavirus, and/or was hospitalized due to the infection, and/or died after being affected by the Coronavirus; 0 otherwise	SHARE Corona Survey
COVID-19 Government Response Stringency Index (SI) relative change	Relative change in the SI between 12 March 2020 and the month of the interview date	Oxford Coronavirus Government Response Tracker (OxCGRT)
EPL macro-areas	1 corresponds to low employment regulatory protection, 2 to intermediate employment regulatory protection, 3 to high regulatory protection.	OECD Employment Outlook (2020)

Table 3 - Descriptive Statistics

Variables	*Full Sample*		*EPL=1*		*EPL=2*		*EPL=3*	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*
Psychological distress index	0,12	0,22	0,098	0,19	0,11	0,21	0,15	0,26
Job Disruption	0,16	0,37	0,13	0,33	0,13	0,33	0,24	0,43
Age	59	3,3	60	3,1	59	3,2	59	3,3
Male	0,41	0,49	0,42	0,49	0,4	0,49	0,41	0,49
Single	0,079	0,27	0,072	0,26	0,085	0,28	0,074	0,26
Married or Couple	0,75	0,43	0,75	0,44	0,73	0,44	0,78	0,41
Divorced	0,13	0,33	0,15	0,36	0,13	0,34	0,11	0,31
Widowed or Separated	0,042	0,2	0,026	0,16	0,05	0,22	0,035	0,18
Family Size	2,3	0,99	2,1	0,76	2,3	0,98	2,6	1,1
Ability to meet work and family commitments	0,29	0,45	0,24	0,43	0,27	0,44	0,36	0,48
Low education	0,11	0,31	0,097	0,3	0,069	0,25	0,2	0,4
Medium education	0,51	0,5	0,46	0,5	0,53	0,5	0,51	0,5
High education	0,38	0,48	0,44	0,5	0,4	0,49	0,29	0,45
Essential Workers	0,24	0,42	0,14	0,35	0,3	0,46	0,17	0,37
Public Sector	0,39	0,49	0,43	0,5	0,4	0,49	0,36	0,48
Part-time	0,13	0,34	0,17	0,38	0,13	0,34	0,11	0,31
Multiple Jobs	0,071	0,26	0,13	0,33	0,074	0,26	0,037	0,19
Computer skills	2,8	1,2	3,3	1,1	2,7	1,2	2,6	1,4
Ends not meeting	0,16	0,37	0,046	0,21	0,14	0,35	0,27	0,44
SAH	0,2	0,4	0,1	0,31	0,27	0,44	0,13	0,33
Chronic conditions	0,61	0,49	0,55	0,5	0,67	0,47	0,53	0,5
COVID-19 spread	0,19	0,39	0,31	0,46	0,18	0,39	0,15	0,36
COVID-19 Government Response Stringency Index (SI) relative change	0,64	0,81	0,61	0,32	0,94	0,93	0,099	0,32
N	3625		568		1997		1060	

Source: SHARE wave 8 and SHARE Corona Survey and authors own elaboration. Means and standard deviations are rounded to two decimals.

Table 4 - Results of Covariate Balancing Tests

No. of Treated	No. of treated	No. of controls	treated off	Pseudo R2	Pseudo R2	before	after	before	after	in median
Kernel Matching										
Full sample	581	3043	1	0.077	0.007	0.000	0.940	9.6	2.7	72%
EPL=1	70	497	1	0.205	0.012	0.000	1.000	16.6	4.2	75%
EPL=2	257	1740	0	0.062	0.012	0.000	0.989	6.4	2.3	64%
EPL=3	254	806	0	0.078	0.004	0.000	1.000	12.6	3.3	74%
Radius Matching										
Full sample	581	3043	1	0.077	0.001	0.000	1.000	9.6	1.2	88%
EPL=1	70	497	1	0.205	0.009	0.000	1.000	16.6	2.7	84%
EPL=2	257	1740	0	0.062	0.002	0.000	1.000	6.4	1.1	83%
EPL=3	254	806	0	0.078	0.001	0.000	1.000	12.6	1.4	89%

Table 5 - Average Treatment Effect on Treated (ATT) - psychological distress index

	Kernel matching		Radius Matching		N.Obs
	ATT	SE	ATT	SE	
Full Sample	0.0526***	0.012	0.0487***	0.013	3,625
Analysis by Cluster					
EPL=1	0.0206	0.032	0.0143	0.046	568
EPL=2	0.0184	0.015	0.0167	0.016	1,997
EPL=3	0.0842***	0.023	0.0780***	0 .021	1,060

Table 6 - Average Treatment Effect on Treated (ATT) - psychological distress index for job disruption for more than 8 weeks

	Kernel matching		Radius Matching		N.Obs
	ATT	SE	ATT	SE	
Full Sample	0.0673***	0.018	0.0587***	0.018	3,287
Analysis by Cluster					
EPL=1	-0.0168	0.054	-0.0159	0.058	520
EPL=2	0.0255	0.026	0.0196	0.026	1,835
EPL=3	0.107***	0.027	0.102***	0.036	918

Table 7- Average Treatment Effect on Treated (ATT) - psychological distress index with countries fixed effects

	Kernel matching		Radius Matching		N.Obs
	ATT	SE	ATT	SE	
Full Sample	0.044***	0.014	0.0402***	0.012	3,625
Analysis by Cluster					
EPL=1	0.0178	0.036	0 .0166	0.043	568
EPL=2	0.0183	0.016	0.018	0.015	1,997
EPL=3	0.0749***	0.024	0.0714***	0.023	1,060

Table 8- Average Treatment Effect on Treated (ATT) – Stringency Index as by March, 12 2020

	Kernel matching		Radius Matching		N.Obs
	ATT	SE	ATT	SE	
Full Sample	0.0522***	0.0116	0.0472***	0.0119	3,625
Analysis by Cluster					
EPL=1	0.0179	0.0396	0.0144	0.0399	568
EPL=2	0.0210	0.0152	0.0167	0.0165	1,997
EPL=3	0.0788***	0.0222	0.0781***	0.0202	1,060

Figure 1

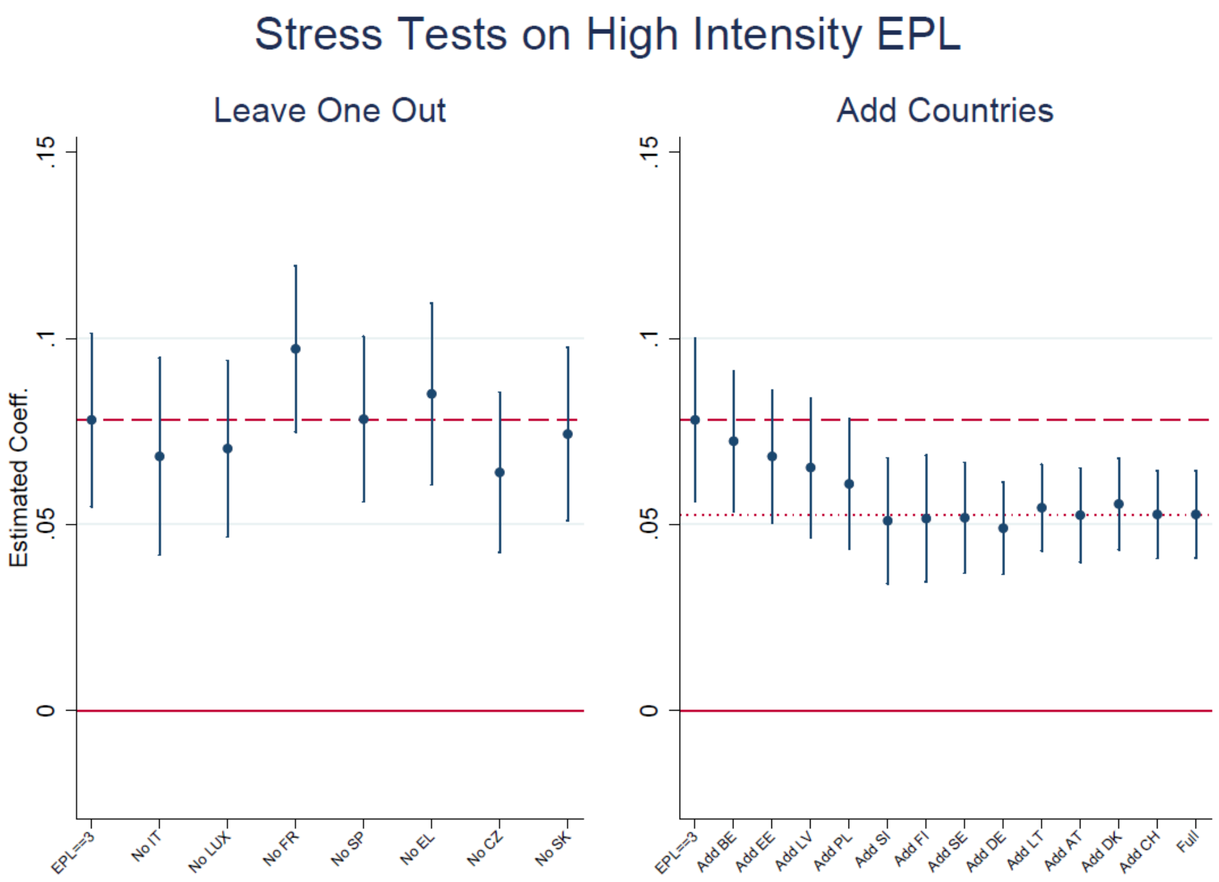

Table 9 - Average Treatment Effect on Treated (ATT) – for each self-reported psychological distress symptoms

	Kernel Matching		Radius Matching		
	ATT	SE	ATT	SE	N.Obs
Full Sample					
worsened depressed mood	0.0714***	0.0166	0.0682**	0.02	3,625
worsened anxiety s	0.0826***	0.0193	0.0807***	0.0205	3,625
worsened sleep problems	0.0332**	0.0127	0.0331**	0.0138	3,625
worsened loneliness	0.0426**	0.0143	0.0386**	0.0151	3,625
Analysis by Clusters					
EPL=1					
worsened depressed mood	0.0462	0.0609	0.0429	0.0657	568
worsened anxiety	0.2686	0.0548	0.0262	0.0585	568
worsened sleep problems	0.0714	0.0474	0.0744	0.0495	568
worsened loneliness	- 0.2344	0.0415	-0.0328	0.0493	568
EPL=2					
worsened depressed mood	0.0256	0.0253	0.0218	0.0238	1,997
worsened anxiety	0.0552*	0.0292	0.0548**	0.0271	1,997
worsened sleep problems	0.009	0.0181	0.1124	0.1722	1,997
worsened loneliness	0.039**	0.0175	0.0389**	0.0176	1,997
EPL=3					
worsened depressed mood	0.1161***	0.0324	0.1129***	0.0298	1,060
worsened anxiety	0.1522***	0.0367	0.1492***	0.0370	1,060
worsened sleep problems	0.0407*	0.0225	0.0378	0.0242	1,060
worsened loneliness	0.0518*	0.0286	0.0476*	0.0262	1,060

APPENDIX

Table 1 A – Probit model for the propensity score matching (baseline model; full sample; dependent variable: job disruption)

Variables	*Coefficient*	*Std. err.*
Age	0.003	0.009
Male	-0.056	0.057
Single	0.118	0.098
Divorced	-0.126	0.087
Widowed or Separated	-0.057	0.136
Family Size	0.014	0.029
Ability to meet work and family commitments	0.046	0.058
Low education	0.132	0.080
High education	-0.178**	0.063
Essential Workers	-0.189**	0.071
Public Sector	-0.421***	0.061
Part-time	0.228**	0.076
Multiple Jobs	-0.054	0.109
Computer skills	-0.016	0.023
Ends not meeting	0.419***	0.067
SAH	-0.147**	0.070
Chronic conditions	-0.043	0.057
COVID-19 spread	0.247***	0.066
Stringency Index (SI) relative change	0.002**	0.001
Stringency Index (SI) relative change^2	-6.61e-06**	2.94e-06
EPL macro areas	0.240***	0.0481
Observations: 3625		
Pseudo R^2: 0.0770		

Table 2 A – Correlation matrix self-reported psychological distress symptoms

	worsened depressed mood	*worsened anxiety*	*worsened loneliness*	*worsened sleep problems*
worsened depressed mood	1			
worsened anxiety	0.4700	1		
worsened loneliness	0.3198	0.2519	1	
worsened sleep problems	0.3795	0.3088	0.2201	1

Table 3A - Average Treatment Effect on Treated (ATT) - psychological distress index – misspecification test

	Kernel matching		Radius Matching		N.Obs
	ATT	SE	ATT	SE	
Full Sample	0.0511***	0.0115	0.0478***	0.0127	3,625
Analysis by Cluster					
EPL=1	0.0157	0.04	0.0122	0.0443	568
EPL=2	0.0181	0.0147	0.0175	0.0154	1,997
EPL=3	0.0793***	0.0211	0.0750***	0 .0255	1,060

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