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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[+]

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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. 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 a clear 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, travel restrictions and suspension of non-essential activities. Social-distancing policies have had extensive implications on the labour market that have gone beyond just income shocks: lockdown measures have impacted many sectors of the economy and workforce, deeply altering working conditions and jointly 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 fill this gap and extend prior research on symptoms of depression related to the COVID-19 crisis by analysing the mental health consequences of job disruption across different European countries taking advantage of the heterogeneity of employment policies at country-level. To this aim, European countries were clustered into three macro-regions characterised by high, intermediate and low employment regulatory protection, using the Employment Protection Legislation (EPL) aggregate score.

The EPL summarizes the strictness of regulation of individual and collective dismissals of regular workers and the regulation on temporary contracts across OECD countries (OECD, Employment Outlook 2020). Previous literature has found that EPL strictness influences workers' perception of job insecurity that, in turn, may influence their psychological well-being, see e.g. Caroli & Godard, (2016); Clark & Postel-Vinay, (2005); Sverke et al., (2002).

This study focuses on older workers (aged 50 and over) exploiting 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. The COVID-19 pandemic has been extremely challenging for older workers who were exposed to a twin threat: a higher risk of adverse effects from the COVID-19 and the reduced labour demand as a consequence of the shutdown policies. Previous research has shown that, 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).

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 spectre 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 older 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) (Clark & Postel-Vinay, 2005). 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 labour markets and different levels of job security.

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 render 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 characteristic known to be associated with job disruption and individuals’ mental health condition (Caliendo & Kopeinig, 2008). This analysis uses the propensity score matching method (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.

The present results are robust under different specifications of the propensity score model, which reveal a clear EPL gradient: job disruption has 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 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.

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. The 8th wave of SHARE is a regular wave 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 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.

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 enables a detailed examination of how older workers' psychological well-being may have been 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.[1]

The empirical strategy used 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).[2] Hence, individuals who were employed (permanent and

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

[2] 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

temporary workers) before the COVID-19 outbreak are included while self-employed individuals are excluded.[3]

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 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 three sub-indicators EPR, EPC and EPT respectively, assigning to them different weights: specifically, EPL can be obtained by the weighted sum of the sub-indicators for regular contracts (EPR, weight 5/12), temporary contracts (EPT, weight 5/12), and collective dismissals (EPC, weight 2/12). The EPC was weighted at 40 percent of the other two indexes to reflect the fact that "*the*

score concerns the regulation of temporary employment and refers to the rules regarding the types of work for which such 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.

[3] Employment information as provided by the variable *ep005* from the Employment and Pension (EP) module of the 8th wave of SHARE database was considered.

*collective dismissals measure*s *typically represent modest increments to the EPL requirements for individual dismissals*" (OECD Employment Outlook, 1999 – Ch. 2, Annex 2b, page 118).

The first column of Table 1 shows the overall EPL index that was used to stratify the sample into three clusters, 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

Analyzing the causal relationship between job disruption and older workers' mental health may be complicated by the presence of endogeneity among them. The treatment assignment (i.e. job disruption/loss) is not randomized among workers and the outcome of interest (mental health status) may be biased by differences in the characteristics that influence the selection into jobs. For instance, poor-health workers are perceived as more vulnerable being at higher risk in terms of COVID-19 adverse effects and so they might be even more affected by job disruption compared to those who did not suffer from pre-determined health conditions. 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 disruption. 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).

Propensity score matching explicitly looks for each untreated individual, a similar treated individual to be considered as its counterfactual, that is what would have happened to an individual belonging to the treatment group without the treatment. 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 with a single variable that is a function of all the variables. Analytically, this method models the probability of treatment (i.e. job disruption) e_i (x) for each worker as a function of all observable individual characteristics (confounders X) :

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

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. Outside the common support, no counterfactual exists.

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 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 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, some of the time, or hardly ever or never. 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 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 some of the time*" 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 some of the time*" (3) .

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 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).

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

$$
\begin{aligned}
&D = i \leftrightarrow \tau_{i-1} < W \le \tau_i \quad && i = 1, \dots, m_D \\
&A = j \leftrightarrow \xi_{j-1} < Z \le \xi_j \quad && j = 1, \dots, m_A \\
&S = k \leftrightarrow \gamma_{k-1} < U \le \gamma_k \quad && k = 1, \dots, m_S \\
&L = l \leftrightarrow \varsigma_{l-1} < V \le \varsigma_l \quad && l = 1, \dots, m_L
\end{aligned}
$$

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

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

These thresholds where estimated using the marginal distributions of the indicators, see Olsson (1979) Section 3 Case 2; the correlation matrix, estimated by ML, was then 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 (highest level of psychological distress that worsened during the COVID-19 outbreak) to aid in interpretation of the 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*").[4] 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 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: these two dimensions were

[4] 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.

strictly related to 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 Ministerial with a Decree on 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.[5]

The COVID-19 pandemic has brought the importance of digital skills for workers forcing many production activities towards 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 workers, the model was specified to include 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*

[5] 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.

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 model considered the COVID-19 Government Response Stringency Index (SI) from the Oxford Coronavirus Government Response Tracker (OxCGRT) (Hale et al., 2021).[6] 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.

From the Covid-19 SHARE questionnaire it was possible to know 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 by 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.[7] Finally, each respondent was matched on the relative change in the SI stringency index of her 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 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

[6] 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.

[7] 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.

itself and the associated lockdown, we also included information on their health status before the outbreak (8th wave of SHARE). 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 will not be 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). [8]

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 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

[8] 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.

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).[9]

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 (see Subsection 4.1).

4. Results

Table 3 shows pre-matching statistics 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).

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[10].

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

[10] 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.

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 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. ATTs were computed by adopting two matching methods: 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 worsened symptoms of psychological distress. These findings also reveal the presence of an EPL gradient: in the group of countries characterized by stronger 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 significance level considered. The magnitude of the ATT, even if not statistically different from 0, is lower in magnitude than in the stronger regulation countries cluster (with an increase of psychological distress index in our sample of interest of about 1.8% for those workers who faced a job disruption).[11] 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 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

[11] The sample size in the analysis is limited, and it is linked to the availability of 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.

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 but higher than in countries characterized by a lower EPL and a greater labour market flexibility where 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 remains very similar to those related to the baseline model presented in Section 3 (7.5%).[12]

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' 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]

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

[12] 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.

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 of the relationship between COVID-19 job disruption and older workers' psychological distress taking into account of 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 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 clear 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 European countries with higher Employment Protection legislation.

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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	No. of treated off support	Probit Pseudo R2 before matching	Probit Pseudo R2 after matching	p > Chi2 before matching	p > Chi2 after matching	Median Bias before matching	Median Bias after matching	%reduction in median bias
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	1,060
EPL=2	0.0184	0.015	0.0167	0.016	1,997
EPL=3	0.0842***	0.023	0.0780***	0 .021	568

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	918
EPL=2	0.0255	0.026	0.0196	0.026	1,835
EPL=3	0.107***	0.027	0.102***	0.036	520

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	1,060
EPL=2	0.0183	0.016	0.018	0.015	1,997
EPL=3	0.0749***	0.024	0.0714***	0.023	568

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	1,060
EPL=2	0.0210	0.0152	0.0167	0.0165	1,997
EPL=3	0.0788***	0.0222	0.0781***	0.0202	568

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 change2	-6.61e-06**	2.94e-06
EPL macro areas	0.240***	0.0481
Observations: 3625		
R2: 0.0770		