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Unsafe Jobs, Labour Market Risk and Social Protection

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Abstract

This paper proposes a new classification of occupations based on the extent to which they put workers at risk of being infected with aerial-transmitted virus. We expand on previous work that mainly focused on the identification of jobs that can be done from home by providing a more nuanced view of infection risks and by identifying jobs that, although impossible to be done from home, expose workers to a low risk of infection. We label jobs that cannot be done from home and that present a high risk of infection as “unsafe jobs”. We combine our classification of epidemiological risk with a list of “essential activities” that have been carried out even during the most severe lockdown measures, obtaining a taxonomy of jobs exposed to different degrees of contagion and labour market risk. Using both survey and administrative data, we show that this taxonomy successfully predicts job-related epidemiological risk and labour market outcomes (such as sick leaves, COVID-19-related work injuries, recourse to short-time work schemes and work-from-home). We then apply our taxonomy to labour force survey data from 28 countries and find that unsafe jobs are very unequally distributed across different types of workers, firms, and sectors. More vulnerable workers (women, youngster, low educated, immigrants, and workers on fixed-term contracts) are over-represented in this pool, and therefore more at risk of suffering from the economic consequences of a prolonged pandemic. We finally discuss possible paths to reform social protection systems, so that they can better support workers during the labour market adjustments that are likely to be spurred by the COVID-19 pandemic.

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1. Introduction

Following the outbreak and the extended duration of the COVID-19 pandemic, epidemiological risk is gaining an enormous importance as a dimension of workers' safety. Such risk is unevenly distributed across jobs and workers. In this paper, we provide a method to classify occupations according to the risk of contagion. We expand on the previous literature that almost exclusively looked at the feasibility of working from home by analysing other dimensions of risk, notably considering the frequency of interactions with co-workers and customers. Starting from O*NET data, which describe the characteristics of jobs at the current level of technology and in the pre-pandemic scenario, we classify jobs in four categories by gradually relaxing some safety constraints. This gives a more nuanced characterisation of the epidemiological risk of occupations, encompassing working from home and various degrees of physical proximity required to work.

Our classification is necessarily based on the ways jobs were carried out at the onset of the pandemic. It is therefore subject to change, to the extent that the set of tasks constituting a given occupation changes in response to technological progress or to other events, including the COVID-19 pandemic itself. While the classification will therefore need to be updated in the future, the methodology offered in this paper will remain a useful tool for policy analysis well beyond the contingency of the COVID-19 pandemic.

By using the information contained in the O*NET survey, and building on previous work by Boeri, Caiumi and Paccagnella (2020) and Dingel and Neiman (2020), we classify jobs in four mutually exclusive categories, characterised by decreasing degree of safeness. Safest jobs are those that can be done from home, followed by jobs that only require infrequent contacts with co-workers, and then by those which also require infrequent contacts with customer. The last, residual category contains all other jobs, which we label "unsafe". We argue that the risks associated to jobs with a mild degree of risk (*infrequent contacts with co-workers and infrequent contacts with co-workers and customers*), although higher than those associated with jobs that can be carried out in from home, are still low enough to make them feasible even in a context where a virus is spreading at large scale. Each job is classified in a given category if the average response of workers to a set of O*NET items is above (or below, depending on how the question is phrased) a pre-defined threshold. Drawing on data from the US Current Population Survey (CPS) and on harmonised labour force survey data for European countries (EU-LFS), we estimate the share of jobs falling in these four categories for 28 countries. Roughly 50% of jobs belong to the residual category of unsafe jobs, although large cross-country variation exists, notably in the share of jobs that can be done from home. This nuanced characterisation of job safety is one of the main contributions of this paper and has clearly important policy implications.

We then combine our classification of health risk with a list of essential occupations that have been carried out even during the most severe lockdown measures (Fasani and Mazza, 2020). This allows us to interact epidemiological risk with labour market risk, i.e. the risk that health policy measures prevent a worker from carrying out his or her job during a pandemic. By combining the two dimensions of risk – epidemiological and labour market – we develop an eightfold taxonomy of jobs with different degrees and types of risk. We validate such a classification with labour market and job-related health risk administrative and survey data *during the pandemic* for the countries for which such data are available (Italy, UK and the US).

We then examine in detail the characteristics of workers holding unsafe jobs in essential and non-essential activities. We find that the most economically vulnerable workers, i.e., women, low-educated workers, immigrants, low-wage workers, workers on temporary contracts, and part-timers, are over-represented in unsafe jobs. Moreover, we show that about 60 percent of unsafe jobs are in non-essential occupations: firms restructuring in these sectors may lead to a dramatic drop in labour demand hitting these twice-vulnerable workers. We therefore discuss reforms of

labour and social policies that – in addition to a better targeting of the vaccination campaign to job-related contagion risk – could deal with these new dimensions of economic vulnerability.

Our contribution to the literature on the labour market consequences of the COVID-19 pandemic is threefold. First, we consider a broader definition of *potentially* hazardous and non-hazardous jobs: we focus not only on jobs that can be done from home, but we also identify jobs that, while requiring physical presence on the workplace, can easily comply with physical distancing protocols as they involve only infrequent contacts with other persons. Second, we evaluate whether our classification predicts *actual* labour market and job-related health risks during the pandemic. Third, we characterise the heterogeneity in the distribution of such risks across many workers, jobs and firm characteristics in 28 countries, and we discuss the implications in terms of the design of labour market and social policies dealing with these new dimensions of workers' vulnerability.

The remainder of the paper is structured as follows. Following the literature review in Section 2, we present our methodology to classify jobs according to their level of infection risk in Section 3. In Section 4, we combine our classification with a list of essential jobs, and we validate our taxonomy with actual data on job-related health risk and labour market outcomes. In Section 5, we analyse heterogeneity in the incidence of such risks according to a large number of jobs and workers characteristics in 28 countries. Section 6 discusses the implications of our results for labour market and social policies dealing with the pandemic and its legacies. Section 7 concludes the paper.

2. Identifying Unsafe Jobs

Since the first appearance of the pandemic, the literature on the economic consequences of COVID-19 has been growing rapidly. A number of studies have attempted to estimate the share of jobs that can be performed at home or remotely, and which are therefore compatible with the most restrictive lockdown measures put in place to contain the pandemic. In what follows, we focus only on the papers that are most related to our setup and analysis, but we acknowledge there is a vast research in this field.¹ The earliest papers that attempted this exercise, and which have been developed simultaneously and independently, are Boeri, Caiumi and Paccagnella (2020) and Dingel and Neiman (2020). The latter focuses on the US and relies on the O*NET surveys to estimate the feasibility of working from home; the former expands the perspective by taking into account also jobs entailing only sporadic personal interactions. In this paper, we expand on Boeri,

¹ Among the extensive literature, we highlight the following papers. Alipour, Falck and Shüller (2020) quantify the workers who can work from home in Germany in about 56 percent of the labour force despite only half of them actually did: among the most vulnerable groups, there are low-skilled and low-wage earners. In an early attempt to analyse the impact on COVID-19 on the Italian labour market, Barbieri, Basso and Scicchitano (2020) use the Italian equivalent to O*NET (Sample Survey of Professions), to identify the sectoral characteristics in terms of exposure to infection and disease, physical proximity and possibility to work from home. Different from this paper, however, Barbieri et al. build only relative measures of proximity risks and disease exposure and do not quantify the absolute number of workers at risk. Adams-Prassl et al. (2020) study heterogeneity within-occupations in the feasibility of working from home. Using large surveys from the US and UK, they find that the share of tasks that can be done from home is not constant across workers within occupations or industries: their ability to work from home varies both across and within occupations and sectors. Another aspect that has been explored is the impact of lockdown across different type of workers. Yassenov (2020) provides evidence of the distributional effects of stay-at-home orders caused by the pandemic in the United States: workers with lower wages, lower levels of education, young, ethnic minorities and immigrants are less likely to work in occupations for which working from home is feasible. Using survey data from the project REPEAT for a number of OECD countries, Foucault and Galasso (2020) documents unequal lockdown effects across categories of workers. Low-educated workers, blue collars and low-income service workers were more likely to have suspended working activities and low-educated workers less likely to work from home. Over the lockdown weeks, a higher share of workers become active from home: highly educated workers and white collars benefitted the most from such adjustments.

Caiumi and Paccagnella (2020) by further analysing multiple dimensions of risks and provide evidence for different countries with a special focus on the employment effects of the pandemic and the subsequent challenges for labour market protections.

Mongey, Pilossoph and Weinberg (2020) also classify jobs in terms of feasibility of working from home and proximity with other people. They empirically validate their classifications with data from the American Time Use Survey (ATUS), which contain information on the habits of workers before the pandemic.² Linking such indicators with information from the Bureau of Labor Statistics Current Population Survey (BLS CPS) and the Panel Study of Income Dynamics (PSID), they conclude that workers in occupations that cannot be done remotely and work in physical proximity with other are more likely to be economically vulnerable (i.e. they are less likely to have a college degree, to have health insurance, to have liquid assets, to be white, to be US natives). They also find that metropolitan areas (MSA) with lower shares of employment in work-from-home jobs before COVID-19 experienced smaller declines in mobility, as measured using mobile phone data, and that those predicted to be employed in low work-from-home jobs experienced greater declines in employment with respect to pre-pandemic months. As in much of the literature on tasks (Acemoglu and Autor, 2011; Dingel and Neiman, 2020), our classification is based on arbitrary choices of the questions and the thresholds imposed. Yet it differs substantially from Mongey et al. (2020), among others, who inherently calculate relative measures by taking as reference values the median of an (arbitrary index) weighted by occupational employment. In this sense, the advantage of our categorisation is that of providing absolute measures of safeness that can be used to quantify the workforce vulnerable to the COVID-19 labour market crisis. Our procedure leads us to identify, for instance, the *most* unsafe jobs within an economy, rather than a set of unsafe jobs in relative terms. Relative categorization, instead, would be particularly problematic in performing comparisons across countries (as we do), because the very same occupation, even if carried out under the same working conditions in two different countries, could be classified differently just because of differences in the occupational composition of each economy.

Attempts to categorise occupations across multiple countries have also been made, although mostly with a focus on developing economies. Saltiel (2020) looks at ten low- and middle-income countries, using data from the World Bank Skills Toward Employability and Productivity (STEP) survey (as information from O*NET surveys may not be representative of the task content of occupations in developing countries). He finds that in the ten countries analysed only 13% of workers can work from home and that the feasibility of working from home is higher in high-paying occupations, and for workers who have higher levels of education, a formal contract, and higher household wealth. Gottlieb, Grobovšek and Poschke (2020) analyse how the share of workers that can work from home varies with a country's income level. They build a micro level dataset for 57 countries and find that the share of workers in urban areas that can work from home is about 20% for poor countries, while it is about twice as high in rich countries. This is largely due to the higher share of self-employed workers not able to work remotely in poor countries. Our paper complements these works by looking at the richest economies, but also extend the dimensions of risks to provide a more comprehensive analysis of the impact of COVID-19 on the labour markets. In an early attempt to associate workers' safety risk and actual contagion, Lewandowski (2020) estimates country-specific levels of COVID-19 spread (from the Johns Hopkins CSSE) and social contacts and diseases exposure indicators (built from O*NET and the European Working Condition Survey data). Analysing 26 EU countries, he finds that higher levels of occupational exposure to contagion are positively correlated with faster growths in COVID-19 cases and deaths, in particular for workers aged 45-64. Our classification of occupations predicts

² Hensvik, Le Barbanchon and Rathelot (2020) rely on the American Time Use Survey (ATUS) and compute the share of hours actually worked at home in different occupations and industries. They conclude that 15% of total working hours are carried out from home and that workers in high-skilled occupations work more hours at home than workers in less skilled occupations.

an array of employment outcomes in 2020, including leave of absence due to medical reasons for those jobs associated to a higher proximity on the workplace (unsafe jobs).

Closely related to our work, a set of papers focused on the unequal effects of the pandemic on different groups of workers. Alon et al. (2020a, 2020b) show that women are suffering the most in terms of unemployment during the pandemic recession also because of childcare needs. Borjas and Cassidy (2020) use CPS data and find that the negative employment shock caused by the pandemic in the United States hit immigrants severely. They argue that this can be explained by the fact that the rate of job loss rose for immigrants more than it did for natives (partly because immigrants are less likely to work in occupations that can be performed remotely) and that job-finding rate for unemployed immigrants fell compared to natives. OECD (2020a) also documents that in the sectors most affected by the COVID-19 containment measures, non-standard forms of employment are over-represented. Fasani and Mazza (2020) focus on immigrants in the European Union. They find that in EU27 13% of immigrants are employed in “essential” occupations that were not affected by the most restrictive lockdown measures. Migrants account for 20 percent or more of employment in occupations like cleaners and helpers, labourers in mining and construction, personal care workers, and food processors. We expand on this line of research by including an array of different dimensions and by providing preliminary evidence on the ex post consequences of the first pandemic wave by looking at data from different countries. To do so, we also borrow from Fasani and Mazza the classification of “essential” occupations and interact it with our own classification to provide a broader picture on the health and employment risks for workers.

Finally, another line of research looks closely at the potential for reallocation of workers hit by the pandemic crisis. Using data from the Survey of Business Uncertainty (SBU), Barrero, Bloom and Davis (2020) quantify the short-term impact of the pandemic on workers’ reallocation, and conclude that the COVID-19 shock caused 3 new hires for every 10 layoffs. According to the authors much of this impact will persist, with 42% of recent layoffs that will become permanent job losses. They also develop forward-looking excess job reallocation measures (the difference between job turnover and net employment growth), which rise sharply after the beginning of the pandemic. Hensvik, Le Barbanchon and Rathelot (2021) examine the impact of COVID-19 on job search by analysing vacancies posted online in Sweden. They find heterogeneity in the negative impact of the pandemic across industries and occupations, with occupations characterised by less home-working suffering more. At the same time, they find that job seekers search less intensively and redirect their search towards high home-working or more resilient occupations. The policy implications of our paper are intertwined with the reallocation that will occur during the transition and the post-pandemic recovery: the evidence from this stream of the literature complements our findings on workers exposed to higher health and economic risks.

3. Classifying ex-ante epidemiological risk

In this paper, we classify jobs, defined as fine occupation categories, in four mutually exclusive group of risk within the context of the COVID-19 pandemic. We define safe jobs as those that can be carried out with a minimal risk of being infected and of spreading the virus. The first three groups are based on a gradual definition of safety and the last is built as a residual containing jobs that do not satisfy any definition of safeness, not even the least restrictive one, and thus can be deemed “unsafe”.

The first group contains all occupations that can be potentially performed remotely. These jobs do not require workers to leave their homes, nor to interact with co-workers or customers in

person. This measure provides the most restrictive definition of safety, as it essentially reduces the risk of work-related contagion to zero.³

The second category relaxes slightly these constraints by adding jobs that require at most a low level of physical proximity on the workplace. Arguably, these jobs do not pose significant risks to workers' health under a pandemic. Job-related contagion risk arises mainly from (rather infrequent) interactions with co-workers.

The third category still requires a low level of physical proximity, but allows for the inclusion of jobs that involve some interactions with external customers. The need to interact with external customers potentially increases the size of the network the worker is exposed to, which is clearly an important element to consider in the context of a pandemic. These jobs are likely characterised by an element of "mobility", either because the workers have to visit customers, or because customers have to visit the workers.⁴

We sketch here the procedure used to build our classification: the methodological details including the questions considered and the conditions imposed are reported in Annex A. To assign occupations to these four categories, we rely on data from the U.S. Department of Labor O*NET survey, which contains information on the most distinctive traits of each job in the United States. Building on the work of Dingel and Neiman (2020), and on our previous classification of occupations (Boeri, Caiumi and Paccagnella, 2020), we first select 27 questions from the "Work context" and "Work Activities" sections of O*NET database that, according to our judgment, provide information on the feasibility of working from home. As in Dingel and Neiman (2020), we classify a job as not doable from home if the average response of workers to an item is above (or below, depending on how the question is formulated) a pre-determined threshold. The answers to each item can take values ranging from 1 to 5, where higher values denote a stronger intensity or higher frequency of the trait under scrutiny. If any such condition is not satisfied, we classify a job as not suitable for remote working. For instance, if the average answer for a given occupation to the question "How frequently does your current job require electronic email?" is lower than 3.0 (where 3.0 represents the option "once a month or more but not every week"), we consider that job as not suitable for remote working; we therefore exclude it from the *category home/remote working*.

The second category (*low physical proximity*) includes those jobs that cannot be carried out from home, but entail low physical proximity and limited exposure to customers and to the public.⁵ The

³ In our classification, jobs that can be performed from home also include occupations whose conditions might not be considered as safe once the presence on the workplace of full workforce will be restored. However, anecdotal evidence tells us that in the future both the share of people performing working tasks remotely and the frequency with which such arrangements will be allowed will increase. The impact of the pandemic is likely to be long-lasting on this aspect, so that making a further distinction within jobs that can be performed from home do not add much depth for the purposes of a reallocation analysis. Also, even several months after the start of the pandemic, the vast majority of people whose jobs can potentially be done from home continue to be encouraged, when not forced, to do so (when it is not the case, often rotating schemes for the personnel are in place, which greatly reduce contagion risk on the workplace).

⁴ Any job that cannot be done from home presents an additional risk factor related to commuting, which mechanically increases the risk of infection by increasing human interactions. Unfortunately, the data we use do not contain information on commuting habits (although we do look at some rough proxy such as whether people live in urban or rural areas). This additional risk is therefore very difficult to quantify, also because it varies significantly in ways that are difficult to predict with available data, such as whether the worker use private or public transportation, how much time is spent in commuting, and whether the travel takes place at peak or off-peak hours.

⁵ To identify the jobs belonging to the second and third *categories (infrequent contacts with co-workers, and infrequent contacts with co-workers and customers)*, we complement the set of questions used for the *remote working category* with two other questions on physical proximity and contacts with public and customers from O*NET. In particular, we use the question from the Work context section – "How physically close to other people are you when you perform your current job?" (Q21) – and from the Work activities section – "How important is performing for or working directly with the public to the performance of your current job?" (Q32). We use a 3.5 threshold for question

third category (*infrequent contacts with co-workers and customers*) further relaxes this criterion by allowing jobs reporting higher values for “Performing for or working directly with public”, as such jobs may also require substantial exposure to external persons, while still maintaining low physical proximity. On the contrary, any job that does not meet the criteria outlined above or that, even when meeting those criteria, is potentially exposed to diseases or infection (according to high value answers to the O*NET question “Work section – Average respondent says they are exposed to diseases or infection at least once a month”) is classified as unsafe.⁶

Having classified all occupations in one of these four categories for each job in the 5-digit SOC classification, we then aggregate them into 3-digit occupational codes as follows. First, we map O*NET occupations to SOC occupations through simple averages whenever the correspondence is not 1-to-1. Then we proceed with mapping from SOC to ISCO, again following Dingel and Neiman (2020): ideally, each SOC would map to a unique ISCO, so that we could simply calculate the ISCO categories as a weighted average of SOC categories, using the BLS counts as the weights. However, given the many-to-many mapping, this approach would put disproportionate weight on those SOCs that happen to map to a larger number of ISCOs. To address this issue, when a SOC maps to multiple ISCOs, we allocate the SOC’s BLS weight across the ISCOs in proportion to the ISCOs’ employment shares in Europe.⁷ Thus, for each ISCO 3-digit code, we obtain a coefficient ranging from 0 to 1 proxying the employment share in each category of risk/safeness: each ISCO occupation is then associated to the group with the highest employment share.

For the US data, instead, we convert the occupational codes of the CPS to SOC codes, and we link then our taxonomy directly at the SOC level, without walking through the ISCO classification.⁸ One caveat to this approach is that we start from the characteristics of US jobs, namely technology and labour market conditions, and we map these to European jobs. This exercise necessarily entails some measurement error as long as technology differs across countries

Q21 corresponds to “Work more distant than arm’s length”, and a 3.0 threshold for question Q32 corresponds to “Performing for or working directly with public is important”.

⁶ While it is true that the selection of survey questions to build any classification may be subject to arbitrary decisions, our choice is not completely independent from scientific evidence on the spread of the pandemic. With the questions available in O*NET, we were able, for instance, to assign greater contagion risk to jobs requiring contacts with people from outside the usual set of co-workers and to assign to unsafe jobs occupations where the workplace distance between co-workers is less than arm’s length.

⁷ For instance, if a particular SOC has 100 US employees and is associated with two ISCOs that have respective totals of 3000 and 1000 employees in a EU-LFS, we allocate 75 of the SOC’s US employees to the larger ISCO and 25 to the smaller one. Those values of 75 and 25 are then used as that SOC’s weight when calculating the average across all SOCs within each ISCO for that country. Lastly, it must be noted that this process makes the resulting ISCO classification specific to Europe. We use data from the Employment Projections (EP) program by the U.S. Bureau of Labor Statistics for the crosswalk as it provides the most comprehensive collection of occupation-level data in the US. For this purpose, we focus on the base-year only (2018 in our case) whose data are actual employment figures derived from the OES program, CES program, QCEW and CPS. Indeed, the advantage of using EP program’s data is to cover the universe of US occupations hinging on a combination of sources: nonfarm wage and salary employment is covered by OES, CES and QCEW, whereas agricultural industry employment, self-employed workers, and workers in private households are covered by the CPS.

⁸ In general, our analysis entails several crosswalks across classifications of occupations. The CPS classifies occupations using the official Census Codes. The 2010 version of the Census Code was replaced in the CPS starting in 2020 by the 2018 version. The Census Codes are mapped 1-to-1 into the SOC classification using the crosswalk provided by the US Census. Similar to the Census Codes, the SOC2010 classification was updated in 2018 and the CPS implemented the new version in 2020. We map SOC2018 into SOC2010 using the crosswalk provided by the US Census. However, the SOC codes used in the Census crosswalk are an aggregate version of the complete SOC2010 classification (which instead is used to crosswalk to ISCO). Consequently, we convert this classification into the granular version of SOC. This is a one-to-many matching and we assume that each aggregate SOC code is equally split (in terms of number of workers) into the granular SOC codes it corresponds to. As far as the SOC2010-to-ISCO08 conversion is concerned, this is a many-to-many matching: again, we assume that when the same SOC is mapped into multiple ISCOs, it equally splits; while, when more than one SOC are mapped into a single ISCO code we do a summation (or a weighted average).

and European occupations are carried out differently with respect to US ones. Thus, our results need to be interpreted as if the US occupational technology was in place for each labour market analysed. This crosswalk from O*NET to European labour markets is rather common in the literature on “task-approach” to labour markets (Goos, Manning and Salomons, 2009).

Some occupations exemplify well the categories that we identified.⁹ Examples of occupation classified as safest as they belong to the *remote working category*, are information and communications technology service managers (ISCO 133), finance professionals (241) and sales and purchasing agents and brokers (332). Occupations belonging to the second safest group (*low physical proximity*) are mixed crop and animal producers (613), blacksmiths, toolmakers and related trades workers (722), wood processing and papermaking plant operators (817). In the third category (*infrequent contacts with co-workers and customers*) we have social and religious professionals (263) and heavy truck and bus drivers (833). Finally, a few examples of “unsafe” occupations are medical doctors (221), primary school and early childhood teachers (234), nursing and midwifery associate professionals (322), food preparation assistants (941), and waiters and bartenders (513).

We would like to highlight two features of our classification. First, we opted for employing job categories rather than a single continuous score, which would have required to introduce an ad-hoc threshold along its distribution in order to distinguish between safe and unsafe jobs, making even more difficult to characterise the set of safe jobs with multiple dimensions of risk. Second, it is important to clarify upfront that this classification is necessarily based on the way jobs were carried out in “normal times”, i.e. before the outbreak of the COVID-19 pandemic. This exercise is therefore informative as to the number of jobs that will likely not require any major organisational change. It is certainly possible that jobs that we are now classifying as unsafe will be reorganised in ways that allow them to be performed at lower the risk of contagion, although we are not yet in a position to assess the effects of these changes on productivity. A good example is primary school teachers: we classify them as “unsafe”, because O*NET data tell us that performing this job involves daily physical contacts with a large number of people, and still many teachers have managed to switch to online lectures in many of the countries that have implemented prolonged lockdown measures.

It is then natural to ask how many workers fall in the different categories we built. To answer this question, we applied our classification of occupations to labour force survey data for 2019 for EU countries (harmonised EU LFS data) and for the United States (CPS, averaging the 2019 12 monthly waves).¹⁰

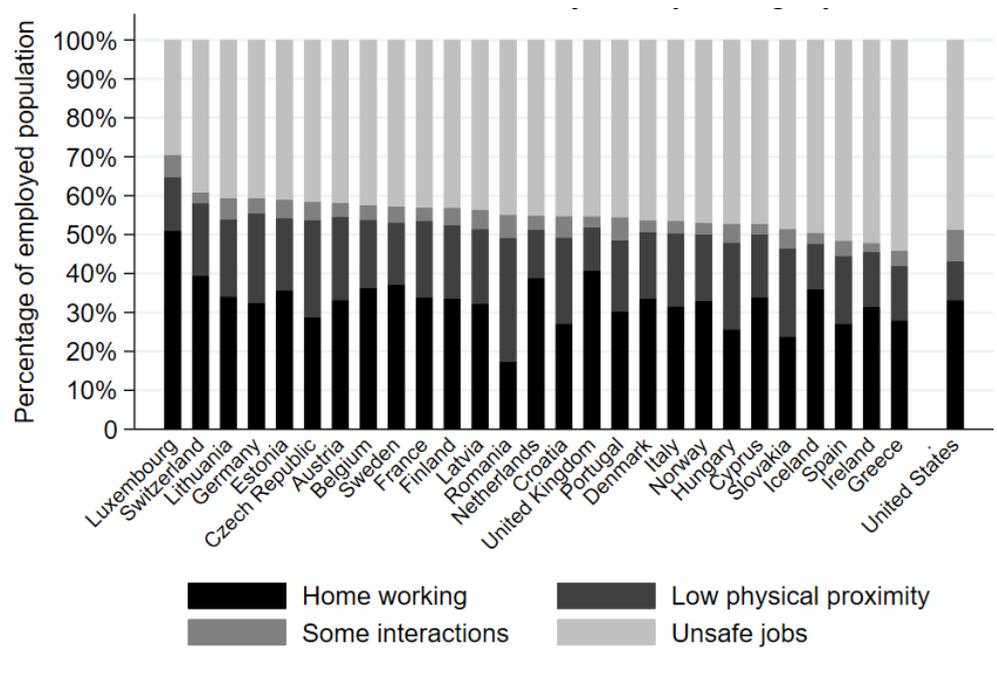
For each country, Figure 1 reports the share of workers (either employees or self-employed persons) holding jobs that can be carried out from home (dark black portion of the bars), that involve limited interactions with co-workers (dark grey portion) or with co-workers and customers (light grey), and the residual category of unsafe jobs. The share of workers on jobs that can be performed from home ranges from less than 20% in Romania to 50% in Luxembourg, with a weighted average of 33% for the whole sample. The two intermediate categories of jobs that cannot be carried out from home, but involve a limited number of personal interactions provide employment to a relatively small fraction of the workforce (from 10% in the US and 11% in the United Kingdom to 32% in Romania, and from 2% in Ireland to 6% Romania and 8% in the US, respectively). “Unsafe” jobs are majoritarian in Spain, Ireland and Greece and are less than a third of employment in Luxembourg (with a weighted average of 47% for the whole sample). Due to

⁹ Detailed information on category coefficients for all ISCO 3-digit codes can be found in Annex A.

¹⁰ We could not exploit data from Bulgaria, Malta, Poland and Slovenia due to missing information on many of the dimensions analysed. The final sample is composed of 28 countries: Austria, Belgium, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania Luxembourg, the Netherlands, Norway, Portugal, Romania, the Slovak Republic, Spain, Sweden, Switzerland, the United Kingdom and the United States.

the limited relevance of the two intermediate categories, in the remainder we will often concentrate on the two extreme categories of safe and unsafe jobs.

Figure 1. Shares of jobs by category and country



Note: The figure shows the percentage of workers holding a job belonging to the different categories of our taxonomy across the 28 countries of the sample. Data refer to 2019. Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

4. Comparing ex-ante and ex-post epidemiological and labour market risk

As stressed at the outset, our classification provides an assessment of potential job-related health risk. One year after the pandemic hit OECD countries, it is possible to compare these ex-ante risk assessments with actual, ex-post outcomes. This is important to evaluate the predictive power of our classification, and to possibly use it in identifying measures that can mitigate the work-contagion trade-off as well as in orienting the vaccination campaign. Information on actual job-related epidemiological risk often becomes available when most decisions on actions to contain the pandemic (e.g. lockdowns) and on the priorities for the vaccination campaign have already been made. It is important to know if ex-ante risk assessments can offer a guidance to Governments confronted with such hard decisions.

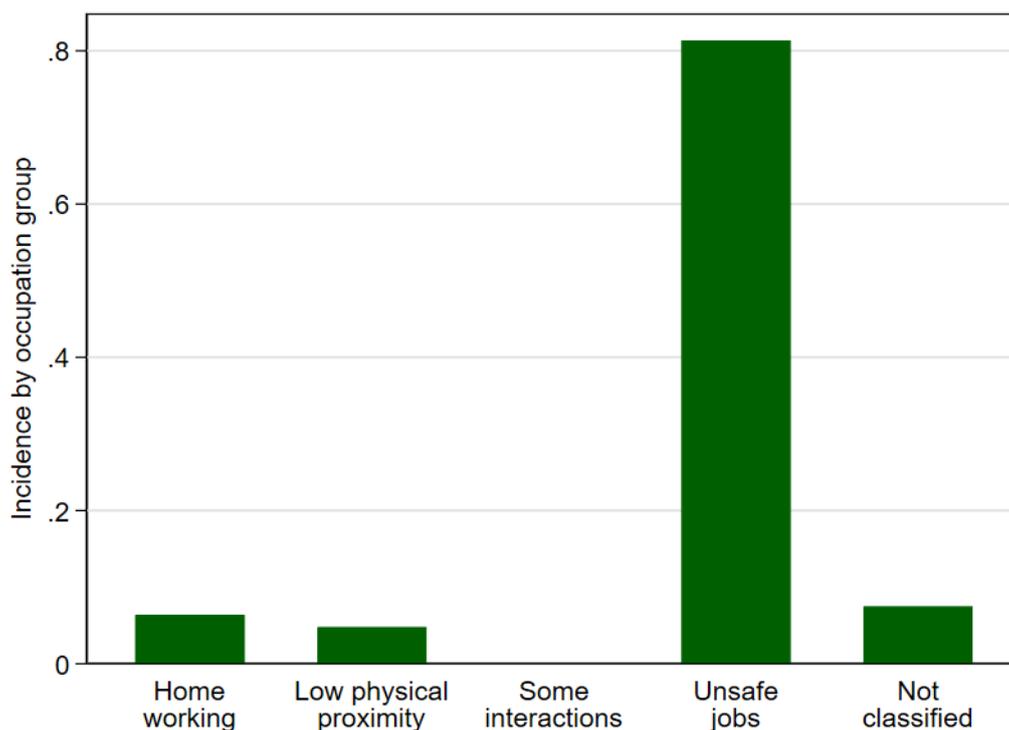
In this Section, we draw on information from multiple data sources and on the limited set of countries for which data on ex-post job-related epidemiological risk are available. In particular, we use administrative data from the Italian Work Injury Insurance (INAIL) and from the Italian Social Insurance (INPS) administrations that were extracted for the first time for this study. We also draw on household survey data on Italy, United Kingdom and the United States providing detailed information on the use of remote working, reduction in working hours, sick leave and wage adjustment during the pandemic.

It is clearly very hard to evaluate whether a person contracted the virus on the workplace or elsewhere. Administrative data on claims for COVID-related fatal and non-fatal injuries provide the best basis for such assessment. We were able to gain access to Italian data provided by INAIL

(the entity running the work accidents social insurance) at a sufficiently high level of disaggregation by occupation. INAIL must carefully check the requirements for insurance protection as the consequences and side effects must be compensated: these data provide therefore the best available information on illnesses contracted at work. While the data are limited to one country, Italy is also the OECD country with the longest history of pandemic and administrative data on COVID-related work injuries, and these data seem to track pretty well the evolution over time of the pandemic. According to such data, job-related contagion seems to have played a non-negligible role in the spread of the virus: out of about 220,000 new infections registered between March and May 2020 (i.e., during the first peak of the pandemic), about one-fifth originated work injury claims.¹¹

Figure 2 displays the incidence of COVID-19 work injury claims processed by the Italian national Work Injury Insurance administration in 2020 according to the four categories of ex-ante job-related epidemiological risk defined in the previous section. There is clearly a very strong concentration of risk in the category of (ex-ante) unsafe jobs defined by our classification. About 81% of all injuries concern 11 occupations in this category that represent 24.7% of total employment in Italy. Claims for workers in occupations that, according to our classification, can be carried out remotely or involve limited interactions with co-workers and customers are fairly negligible.

Figure 2. COVID-19 related work injuries by ex-ante job-related epidemiological risk



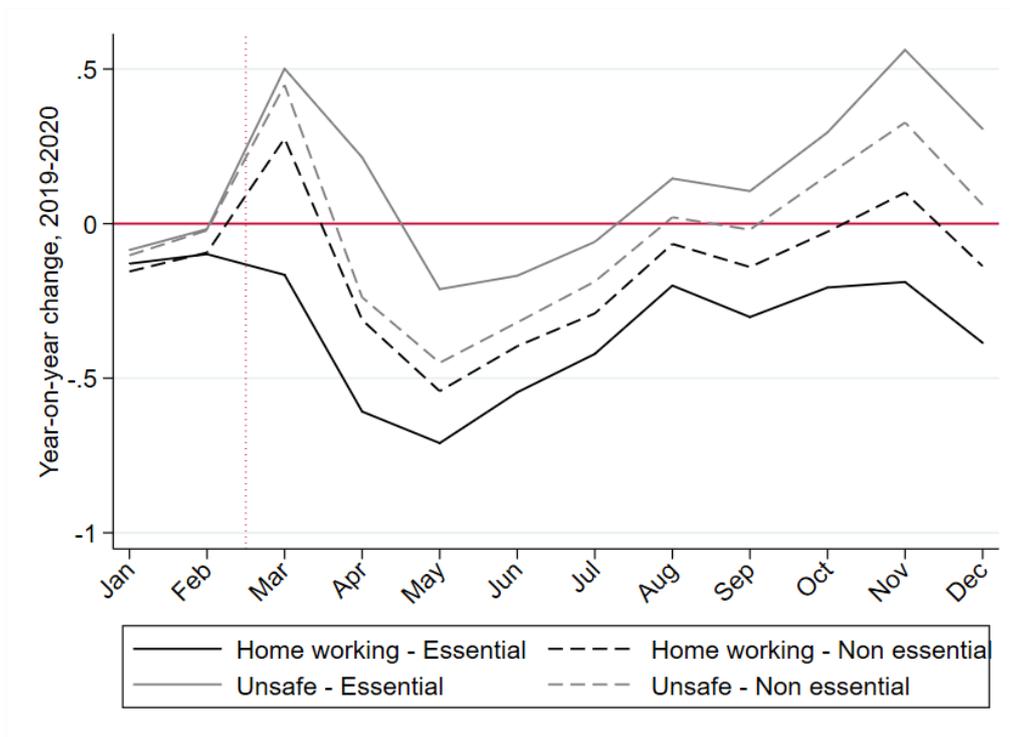
Note: The figure shows the share of work injuries as reported in the claims data collected by the Italian Work Injury Insurance administration (INAIL) between January 2020 and January 2021. The occupation codes have been aggregated according to our taxonomy. Source: INAIL COVID-19 claims.

¹¹ The contagion data are available from the National Health Institute (ISS) at https://www.epicentro.iss.it/coronavirus/bollettino/Infografica_29maggio%20ITA.pdf (in Italian, last accessed on March 18, 2021). The work injury report due to COVID-19 are published by INAIL at <https://www.inail.it/cs/internet/comunicazione/news-ed-eventi/news/news-denunce-contagi-covid-31-maggio-2020.html> (in Italian, last accessed on March 18, 2021).

Another source of information on the actual spread of the virus among workers comes from sickness benefit claims to the Italian Social Insurance administration (INPS). This data source presents three limitations. The first issue is that privacy rules prevent to have information on the nature of the illness inducing the sickness benefit claim. We deal with this problem by taking the difference with the reported sickness leave claims over the same month in 2019. The implicit assumption is that the time profile of this difference captures the effects of the pandemic, in terms of both the spread of the virus among workers and the use of remote working to reduce the risk of contagion. The second problem is that INPS data are available only by sector, as occupations are not reported in the sickness benefit claims to social security. We had therefore to transform our occupation-based into a sector-based classification of risk by calculating the occupational distribution across sectors (obtained from the Italian Labour Force Survey) and assigning each sector to any of the four category of risk of our taxonomy based on the prevalent occupation group in that sector. The third problem is perhaps the most serious: the coverage of social insurance in the case of sickness benefits, unlike work injury claims, is not conditional on where the person was infected, i.e., whether at the workplace or elsewhere. Hence, we can attribute the different incidence of sickness leave to job-related epidemiological risk only insofar as the non-job related contagion risk is distributed uniformly across workers over the four categories of our classification. As this is probably unrealistic (as persons operating remotely or benefitting from short-time work and leaves of absence are likely to be infected only outside their usual workplace), we bring in another dimension of heterogeneity across jobs, notably the distinction between essential and non-essential activities.

We draw on a list of essential occupations developed by Fasani and Mazza (2020), which identifies the occupations that need to be performed even during a pandemic in order to keep citizens healthy, safe and fed. The list of such “key” occupations can be found in Table A.4 in Annex A.

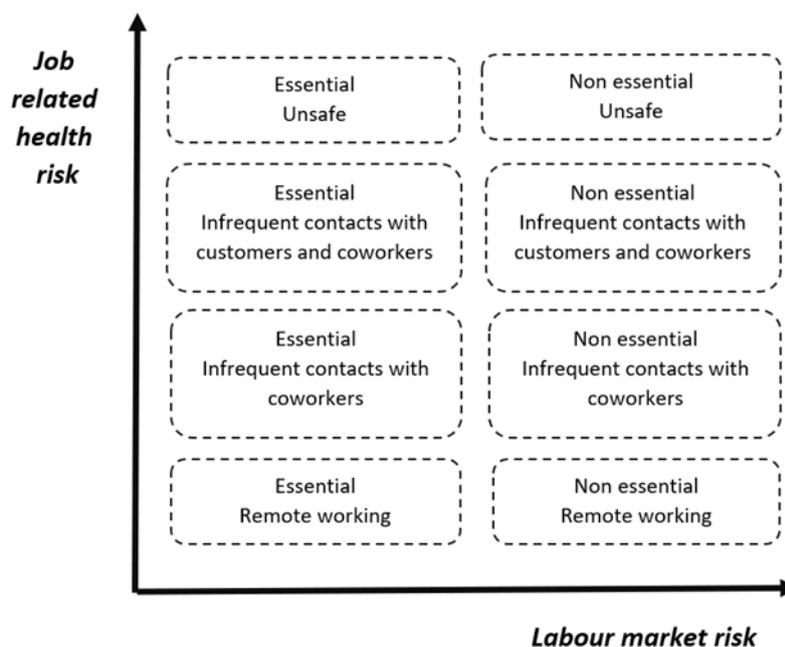
With the above caveats in mind, Figure 3 shows the evolution of average daily sickness benefit claims across four groups of sectors depending on the incidence of safe versus unsafe occupations and on the relevance of essential or non-essential activities in these sectors. Sickness leaves appear to replicate the two waves of the pandemic: there is a peak in March-April 2020 and then again in November of the same year. More importantly, sectors with most jobs that can be carried out from home according to our classification display a lower number of sickness benefit claims with respect to same month in 2019 throughout the entire 2020, and the decline is more marked since February, that is, after the pandemic outbreak. The opposite happens for unsafe jobs, notably for unsafe jobs in essential occupations, which register a strong increase with respect to the same month of 2019 during the two waves of the pandemic.

Figure 3. Sickness benefit claims by job-related epidemiological risk

Note: The figure shows the year-on-year (2020 on 2019) relative variation in sickness benefits for each month as reported in the claims data collected by the Italian Social Insurance administration (INPS). The sectors are classified according to our taxonomy based on the most prevalent occupation group calculated from the Labour Force Survey data. The definition of “essential” and “non essential” occupation is taken from Fasani and Mazza (2020) as described in the text. The vertical dotted line shows the date of the first COVID-19 case in Italy. Source: INPS sickness benefits claims.

Labour Force Survey (LFS) data also offer valuable information on ex-post job-related epidemiological risk. An advantage of LFS data is that they cover a wider range of labour market outcomes (as well as workers’ and jobs’ characteristics), thus allowing to validate our classification against a number of theoretical predictions. One obviously important outcome is the extent to which workers were actually able to work from home during the pandemic. Another outcome is the recourse to short-time work schemes, which are a reasonable proxy for the labour market risk generated by health policy measures. Ex-post job-related epidemiological risk has relevant interactions with working hours reductions, which took place suddenly and at unprecedented levels during the pandemic. Most OECD countries introduced severe lockdown measures to contain the spread of the pandemic, closing down entire sectors, subsidizing short-time work on a large scale as well as extending parental leave (also to cope with school closures), and other forms of leave of absence. Only firms providing a well-defined range of essential services were allowed to operate at full capacity throughout the pandemic. Even where severe lockdown measures were not undertaken, the fear of contagion kept consumers away from a wide range of non-essential activities concentrating work reductions therein.

While comparing ex-ante and ex-post epidemiological and labour market risk we will draw once more on the distinction between essential and non-essential activities transforming de facto our fourfold classification of job-related epidemiological risk into an eightfold taxonomy of risks, as visually characterised in Figure 4.

Figure 4. Taxonomy of occupations, health and labour market risks

Note: The figure shows the eightfold taxonomy of job-related epidemiological and labour market risk as described in the text.

We expect working from home to increase during the pandemic in those activities that can potentially be carried out remotely, independently of whether or not they contribute to essential services. Lockdown measures and the fear of contagion are likely to have concentrated working time reductions in terms of short-time work schemes and leaves of absence in non-essential and unsafe jobs. Sick leaves can be expected to have increased most notably in essential and unsafe jobs. In presence of a rigid (derived) labour demand for these sectors and contracting labour supply due to the fear of contagion, wages could also have increased in essential and unsafe jobs.¹²

These predictions can be tested based on LFS data for Italy and the UK and CPS data for the US covering the second quarter of 2019 and of 2020, thus comparing the middle of the first wave of the pandemic with the same quarter the year before. We estimate a simple linear probability model on the outcomes of interest as follows:

$$y_{i,o,t} = post_t + \sum_j \beta^j risk_{i,o}^j + \sum_j \gamma^j (post_t * risk_{i,o}^j) + \delta essential_{i,o} + \varphi (post_t * essential_{i,o}) + X_{i,o,t}' \vartheta + \varepsilon_{i,o,t} \quad (1)$$

where i stands for the individual, o for the occupation, j indicates the category of risk according to our classification (the omitted group is *home working*; we aggregated the two intermediate groups of occupation for easing the reader). $post$ is an indicator equal to 1 for the second quarter of 2020 (and 0 for the second quarter of 2019), and X are individual and job characteristics.¹³

¹² There is evidence that workers are redirecting search away from risky occupations (Hensvik, Le Barbanchon and Rathelot, 2021).

¹³ We include as controls individuals' age and its square, dummies for the level of education also interacted with age and its square, dummies for immigrant status, gender, the number of children (also interacted with gender), sector and working time arrangement, whether part-time or full time (the coefficients are not reported, but available upon request). The table does not report also the estimated effects on the risk group not interacted with the post dummy

The data come from three different sources, and we did our best to select variables that are as comparable as possible across countries. In particular, short-time work schemes are designed differently in the three countries: for Italy, that has long-established STW, we use an indicator for the *Cassa integrazione guadagni*; for the United Kingdom, which introduced the scheme during the pandemic, we use a dummy indicating whether the respondent has worked fewer hours than usual because of layoff, short time, or interrupted work for economic reasons; finally, for the US, we use a dummy that, following CPS guidelines, identify workers on temporary layoff, i.e. individuals on layoff or absent from work, who either already know the date in which they will be recalled to work or that expect to be recalled within six months.

The definition of sick leave is more comparable across countries, as we use a dummy indicating whether the worker was absent from work (in the UK, worked fewer hours than usual in the reference week), because of illness or personal health issues.

Unfortunately, information on working from home is available in the US data only starting in May 2020: as a consequence, we cannot interact it with the post dummy in Equation 1. The associated coefficients in Table 1 thus refer to occupation categories, not interacted with the post dummy.

The results of this exercise are presented in Table 1. We then run the same set of regressions on separate subsamples of essential and non-essential workers, and we present those results in Table 2.

Four sets of results are worth highlighting. First, in all countries there has been a substantial increase in the percentage of persons working from home. This phenomenon has been driven by workers having precisely those jobs that we classify as having the highest potential for remote working. For instance, in Italy the probability of working from home has increased by more than 30 percentage points (from a baseline level in 2019 of about 5%) and this boom is almost entirely explained by jobs that can be done in “remote working” according to our classification. In the UK the increase in remote working has been milder (+5 percentage points) and once more this development has been driven by those jobs that we classify as “remote working” jobs. For the US we cannot estimate the increase with respect to 2019, but for May and June 2020 the results clearly indicate that the probability of working from home is much higher for jobs that we classify as suitable for remote working.

Second, short-time work (STW) has also increased substantially in the aftermath of the COVID-19 outbreak in non-essential activities. The increase in this case is stronger in the UK (+26 percentage points) – a country without a tradition in STW and leaves of absence – than in Italy and the US. More importantly, the strongest increase in the use of these measures reducing working hours is observed in unsafe and non-essential jobs. In Italy and in the UK, the increase for this category of jobs is about 7-8 percentage points higher than for non-essential jobs that can be done from home (3 percentage points in the US, see Table 2).

Third, the large increase in sick leave observed in all countries has been driven everywhere by what we label as unsafe jobs in essential activities, and, to a lesser extent, by jobs that cannot be carried out in remote, but involve a limited number of interactions with co-workers and customers. In particular, in the US the increase in sick leave relative to the pre-COVID-19 period is about one percentage point higher than for jobs that can be carried out remotely. Interestingly, results from Italy are similar and even more striking: the increase in sick leave for workers in unsafe jobs is 5 percentage points higher than for home workers, twice as much for workers in low proximity jobs. For the UK, instead, the results on sick leave are more mixed and do not allow to depict a clear pattern.

because of space constraints. All the regressions are weighted by sample weights and standard are robust to heteroskedasticity.

Fourth, the results for wages in Italy show an interesting pattern: despite a general drop, essential occupations show a marked increase in hourly wages in the order of 3 percent in 2020. A similar pattern, but not statistically significant and smaller in magnitude can be observed also in the US. This result, although suggestive, based on just one quarter of data and available only for employees, is also in line with the predictions of our classification as we expect these wages to result from broadly unchanged labour demand (or even an increase in demand) and a decline in labour supply, due to the fear of contagion.

In interpreting this set of results across countries, one should not forget that the evolution of the pandemic has not been the same in all of them. Italy was most severely hit in the Spring, implemented very strict containment policies, and then had an extremely low incidence over the Summer, where most economic activities resumed as normal. The United States, on the contrary, were hit with a few months lag, and contagions were higher during the Summer. In the UK, the pandemic hit also with a lag, and cases remained at a higher level than Italy throughout the Summer. We can replicate the same set of regressions presented in Tables 1 and 2, looking at the third quarter of 2019 and 2020 (see Tables A6 and A7 in the Annex). Results for the probability of working from home, for short-time work schemes and for the incidence of sick leaves are mostly similar to those observed in the second quarter. On the contrary, we do not see any more an effect on wages in Italy, while we do see a (relative) increase in hourly wages for unsafe jobs in the United States.

Overall, the available evidence on job-related epidemiological risk as well as on labour market adjustment after the COVID-19 is broadly supportive of the predictive power of our classification of unsafe jobs. Our ex-ante risk assessments well capture the actual distribution of COVID-19 related work injuries and sick leave both in administrative and in survey data. When interacted with a list of essential activities to be carried out even during the most severe lockdown measures, our classification contributes to explaining the heterogeneity in labour market adjustment across different margins (shift to remote working, hours, leaves of absence and wages) during the pandemic.

Based on these findings we believe that characterising the distribution of unsafe jobs across worker and firm characteristics is particularly useful from a policy standpoint as the classification highlight areas of vulnerability that should be possibly addressed before such risks materialize.

Table 1. Ex-ante risk and ex-post labour market outcomes

		Work from Home	Short-time work	Sick leave	Log Wages
		(1)	(2)	(3)	(4)
Italy					
	Post	0.315** (0.006)	0.076** (0.003)	0.053** (0.003)	-0.017** (0.005)
	Post*Low proximity	-0.314** (0.007)	0.069** (0.005)	0.028** (0.004)	-0.022** (0.008)
	Post*Unsafe jobs	-0.303** (0.006)	0.068** (0.004)	0.043** (0.004)	-0.033** (0.007)
	Essential	-0.037** (0.003)	0.020** (0.002)	0.009** (0.002)	0.052** (0.005)
	Post*Essential	0.118** (0.005)	-0.068** (0.004)	-0.045** (0.003)	0.030** (0.007)
	R2	0.254	0.086	0.045	0.311
	N	95,432	95,432	95,432	72,012
	Mean of dep. var.	0.046	0.002	0.008	9.25
UK					
	Post	0.057** (0.004)	0.261** (0.006)	-0.033** (0.004)	0.009 (0.013)
	Post*Low proximity	-0.038** (0.006)	0.079** (0.012)	-0.003 (0.010)	0.014 (0.024)
	Post*Unsafe jobs	-0.051** (0.004)	0.071** (0.008)	-0.018** (0.006)	0.018 (0.018)
	Essential	-0.006* (0.003)	0.028** (0.003)	-0.000 (0.006)	0.022* (0.011)
	Post*Essential	0.002 (0.004)	-0.058** (0.008)	0.006 (0.007)	-0.006 (0.017)
	R2	0.093	0.168	0.040	0.382
	N	75,847	29,540	29,540	16,767
	Mean of dep. var.	0.057	0.003	0.077	15.70
US					
	Post		0.026** (0.001)	0.002** (0.001)	0.064** (0.010)
	Post*Low proximity	-0.181** (0.006)	0.005** (0.002)	0.006** (0.001)	0.002 (0.015)
	Post*Unsafe jobs	-0.222** (0.005)	0.029** (0.002)	0.007** (0.001)	-0.012 (0.013)
	Essential	0.008+ (0.004)	0.003** (0.001)	0.001 (0.001)	0.047** (0.008)
	Post*Essential		-0.011** (0.002)	-0.001 (0.001)	0.011 (0.012)
	R2	0.297	0.032	0.006	0.250
	N	80,643	289,522	289,522	64 806
	Mean of dep. var.	0.330	0.004	0.006	25.56

Notes: The table reports the estimated coefficients of equation (1) calculated on the Italian and the UK Labour Force Survey and on the US CPS. The sample period is the second quarter of 2019 and of 2020: the dummy post stands for the second quarter of 2020. Data on Work from Home for the US are only available for May and June 2020: the coefficients shown in the table are therefore not interacted with a post-Covid dummy. The occupation categories are those described in the text: the omitted category is remote working. We control for age and age square, the level of education also interacted with age and its square, immigrant status, gender, the number of children (also interacted with gender), sector and working time arrangement (part-time or full time; the coefficients are not reported, but available). The table does not report also the estimated effects on the risk groups not interacted with the post dummy because of space constraints. The mean of the dependent variable is computed as the baseline level in the 2nd quarter of 2019. All the regressions are weighted by sample weights and standard errors are robust to heteroskedasticity. * and ** denote significance at 5 and 10 percent level, respectively.

Table 2. Ex-ante risk and ex-post labour market outcomes for essential and non-essential jobs

	Work from Home		Short-time work		Sick leave		Wages	
	Non-essentials	Essentials	Non-essentials	Essentials	Non-essentials	Essentials	Non-essentials	Essentials
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Italy								
Post	0.288**	0.557**	0.073**	0.022**	0.052**	0.015**	-0.008	-0.014
	(0.006)	(0.013)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.012)
Post*Low Proximity	-0.256**	-0.474**	0.064**	0.064**	0.015**	0.038**	-0.031**	0.005
	(0.008)	(0.014)	(0.007)	(0.006)	(0.005)	(0.006)	(0.009)	(0.016)
Post*Unsafe Jobs	-0.264**	-0.450**	0.078**	0.043**	0.052**	0.024**	-0.048**	0.005
	(0.007)	(0.014)	(0.005)	(0.005)	(0.004)	(0.005)	(0.008)	(0.014)
R2	0.221	0.328	0.091	0.058	0.051	0.027	0.259	0.370
N	63260	32172	63260	32172	63260	32172	45734	26278
United Kingdom								
Post	0.055**	0.068**	0.259**	0.222**	-0.033**	-0.037**	0.016	-0.026
	(0.004)	(0.009)	(0.007)	(0.013)	(0.005)	(0.009)	(0.014)	(0.027)
Post*Low Proximity	-0.031**	-0.052**	0.053**	0.086**	-0.011	0.016	0.043	0.030
	(0.008)	(0.011)	(0.017)	(0.020)	(0.014)	(0.015)	(0.032)	(0.038)
Post*Unsafe Jobs	-0.047**	-0.064**	0.084**	0.034*	-0.020**	-0.006	-0.016	0.065*
	(0.005)	(0.009)	(0.010)	(0.016)	(0.008)	(0.012)	(0.021)	(0.033)
R2	0.077	0.115	0,16	0,132	0,018	0,024	0.363	0.369
N	50060	25787	19521	10019	19521	10019	11002	5765
United States								
Post			0.025**	0.018**	0.001*	0.002*	0.069**	0.056*
			(0.001)	(0.002)	(0.001)	(0.001)	(0.010)	(0.024)
Post*Low Proximity	-0.141**	-0.284**	0.003	0.008*	0.005**	0.006*	0.001	0.016
	(0.007)	(0.011)	(0.002)	(0.003)	(0.001)	(0.002)	(0.018)	(0.032)
Post*Unsafe Jobs	-0.201**	-0.262**	0.032**	0.024**	0.009**	0.005**	-0.021	0.008
	(0.005)	(0.010)	(0.002)	(0.003)	(0.001)	(0.002)	(0.015)	(0.027)
R2	0.261	0.385	0.033	0.027	0.004	0.005	0.250	0.248
N	55918	24725	201695	87827	201695	87827	44364	20442

Notes: The table reports the estimated coefficients of equation (1) calculated on the Italian and the UK Labour Force Survey and on the US CPS. The sample period is the second quarter of 2019 and of 2020: the dummy post stands for the second quarter of 2020. Data on Work from Home for the US are only available for May and June 2020: the coefficients shown in the table are therefore not interacted with a post-Covid dummy. The occupation categories are those described in the text: the omitted category is remote working. We control for age and age square, the level of education also interacted with age and its square, immigrant status, gender, the number of children (also interacted with gender), sector and working time arrangement (part-time or full time; the coefficients are not reported, but available). The table does not report also the estimated effects on the risk groups not interacted with the post dummy because of space constraints. All the regressions are weighted by sample weights and standard errors are robust to heteroscedasticity. * and ** denote significance at 5 and 10 percent level, respectively.

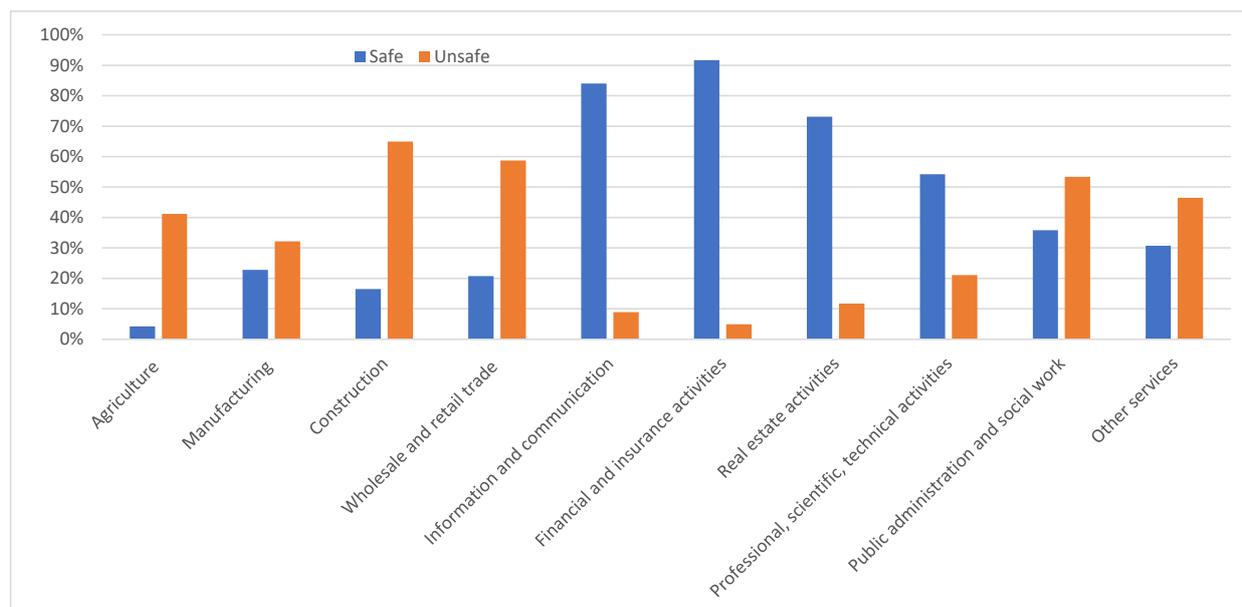
5. Identifying the most vulnerable groups

Since the beginning of the pandemic Governments have been struggling to mitigate the work-contagion trade-off, trying as much as possible to reconcile the overarching goal of reducing the pace of the contagion with the objective of minimising income losses of the workers and their families. In this context, they defined selective lockdown and income relief measures without often having sufficient information about the characteristics of the workers most in need of protection from health and labour market risk. The need for better targeting is still present in the current juncture as priority lists are defined for the vaccination campaign, and temporary short-time work schemes as relief measures are phased out. Encouraged by the results in the previous Section as to the correspondence between ex-ante and ex-post risk, in this Section we provide an assessment of the characteristics of workers more exposed to job-related contagion risk as well as on those who are more vulnerable to hours reductions and job loss.

The different degrees of contagion risk are not uniformly distributed across workers and firms: they depend on the technology of the profession, the structure of the firm and of the market they operate in, as well as the workers' characteristics and skills that are supplied and demanded in each job.

Figure 4 displays the distribution of safe and unsafe jobs across economic sectors, following the NACE Rev2 classification, pooling data from all EU countries in the sample.¹⁴ Histograms display the share of jobs of category i in sector j over total employment. The Figure shows that in sectors like “Financial and insurance activities”, “Professional, Scientific and Technical activities” and “Information and communication”, the share of jobs that can be done from home ranges from above 50 up to more than 90%. In these sectors, the share of jobs that can be considered unsafe according to our definition is negligible. At the other extreme of the distribution, sectors like “Human health and social work activities”, “Accommodation and food service activities” and “Households as employers” (shown in the graph within the broader groups of Public administration, Wholesale and retail trade and Other services) report the highest shares for unsafe jobs. Interestingly, these sectors are not always involved in lockdown measures as they provide essential services. For instance, in certain countries, restaurants and cleaners did not reduce their activities as much as schools.

¹⁴ We take a weighted average of the country-specific employment shares taking as weights the relative size of employment in each country and category. More detailed information at the sector and country level can be found in Annex A.

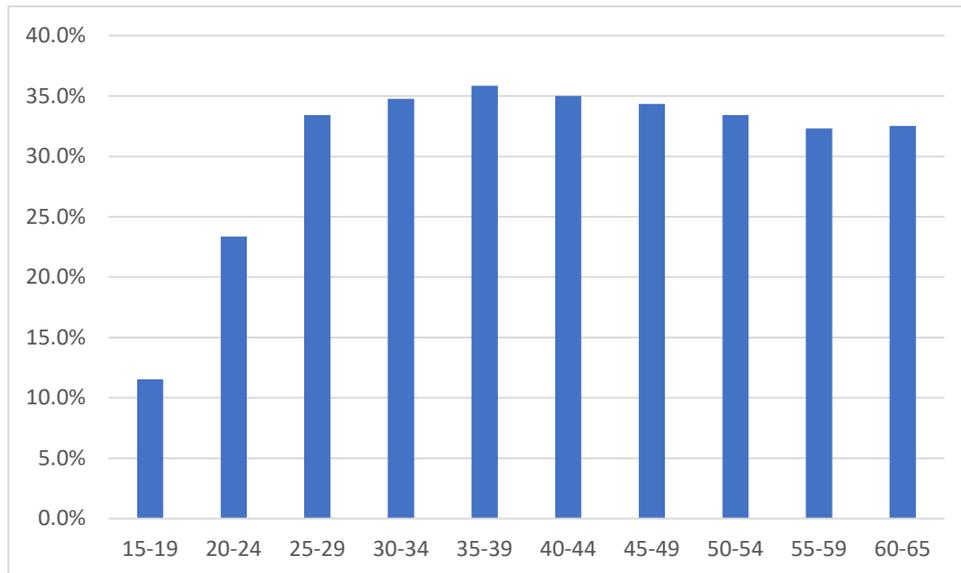
Figure 5. Share of safe (remote working) and unsafe jobs across sectors

Note: Distribution of jobs that can be performed from remote (safe) and unsafe jobs across sectors. Source: Eurostat Labour Force Survey 2019.

To better characterize workers and job characteristics associated to the ex-ante risk of contagion according to our classification, we pool the data from all countries in the sample and present simple conditional means (see Table 2).¹⁵ We separately present the same information for the US (see Table 3).

In Europe, young workers (15-24-year old) are over represented in unsafe jobs (the probability of observing them in unsafe jobs is between 8.7 and 15.2 percentage points higher than for any other age class) and underrepresented in any other job category. On the opposite, it is unlikely to see young people working in jobs that can be performed from home (the probability to observe a 25-plus worker in the remote working group is between 4.9 and 8.3 percentage points higher). As young workers are less likely to develop severe forms of the disease, their over-representation in epidemiologically hazardous occupations could reduce the risk of job-related infection and mortality during the pandemic. These patterns are observed also for the US (Table 3). The concentration of young workers in unsafe jobs may be related to selection effects: many occupations in the remote working group (such as professionals in business administration) require high levels of skills, and the more skilled individuals below age 24 are likely to be still in education. Another explanation is that young workers at the very beginning of their career are involved in lower ranked, often front-office, positions, involving frequent and risky contacts with customers. Indeed, the share of workers involved in safe occupations is steadily increasing with age up to the age of 39, and then stabilizes at about 35% (Figure 6).

¹⁵ The analysis is carried out as an unordered multinomial logit where the excluded category is the safest one, remote working. When pooling EU LFS data we control for country fixed effects. Table 1 reports the marginal effects. Information at the country level is available online. The results are robust if we run multivariate regressions including workers' and jobs' characteristics separately (available upon request).

Figure 6. Age structure in safe jobs

Note: Distribution of jobs that can be performed from remote (safe) across age groups. Source: Eurostat Labour Force Survey 2019.

Interestingly, this flattening in the age profile of the exposure to epidemiological risk is the by-product of a decline at older ages of the share of jobs that can be carried out in remote, and an increase of those that involve limited interactions, either with co-workers or customers. In most countries older workers are under-represented among the jobs that can be done from home. This can be also explained by the lower level of proficiency of older adults in the use of digital devices (OECD, 2015).

Women are over-represented at the two ends of the work-safety ladder, as they are more likely to be employed both in jobs that can be carried out remotely and in unsafe jobs. This indicates *inter alia* that it could be fairly misleading to confine the definition of safe jobs to those that can be carried out from home, as done by most of the literature reviewed in Section 2. The over-representation of women in unsafe jobs is widespread across countries.¹⁶

There is instead a monotonic relationship between the level of education of the workforce and exposure to epidemiological risk, as low-educated workers are largely over-represented in unsafe jobs. Unsafe jobs are over-represented among migrants. Indeed, as shown by Fasani and Mazza (2020), unsafe occupations like cleaners and helpers, mining and construction, machine and food processing operators are often dominated by foreign-born workers.

Another important dimension of potential risk relates to the place of residence of individuals.¹⁷ Higher population density is likely to increase the risk of infection, irrespective of the characteristics of jobs, as workers are for instance more likely to commute by public transportation. On the other hand, it is also possible that metropolitan and non-metropolitan areas have different occupational structures, and thus a different prevalence of safe or unsafe

¹⁶ This is partly due to the fact that occupations that are traditionally women-dominated, like nurses and primary school and early childhood teachers, feature unsafe jobs only.

¹⁷ In the US data, metropolitan areas are defined as areas with more than 100,000 individuals. The EU LFS provides a more granular description of areas.

occupations. Commuting is not captured in our data, but we can nevertheless look at the incidence of safe occupations according to population density in the place of residence.¹⁸

Metropolitan areas feature a higher share of jobs that can be done from home compared to the towns, suburbs and rural areas, jobs that need interactions with customers seem to be more evenly distributed across areas. Additionally, non-metropolitan areas have, on average, a higher share of jobs belonging to the unsafe jobs category (i.e. jobs that entail high physical proximity and exposure to customers and public). Likely, part of such jobs belongs to the agricultural sector, mostly present in rural and scarcely populated areas.

A better assessment of the economic vulnerability of the workers most likely to be at epidemiological risk and that could also be made redundant in case of a long lasting pandemic may come by analysing endogenous (to the labour market) characteristics such as job security and under-employment. Self-employed workers are both more likely to work in occupation suitable for remote working and in unsafe occupations with respect to employees. Self-employed in unsafe occupations are likely to be particularly vulnerable from an economic point of view the more severe is the drop in demand due to contagion concerns by customers. Analogously, job losses among employees are likely concentrated on fixed-term contracts, especially in European countries with strong employment protection legislations (this contract characteristics is not available in US data). These contracts are over-represented in the pool of unsafe jobs, and such evidence is consistent across all the countries under investigation.¹⁹ Part-timers are also disproportionately involved in unsafe occupations, as well as in rather safe occupations that require low physical proximity: according to EU LFS data they are frequently under-employed (just below one third of part-time was involuntary in the EU27 even in the buoyant labour market conditions of 2019).²⁰

Finally, similarly to what observed for education and other characteristics, firm size is inversely correlated with the risk of contagion. On-site jobs that require physical proximity and hence high contagion risk are more likely to be in small firms. On the opposite, it is up to 5.9 percentage points more likely to observe an occupation that could be performed from home in larger firms (50 employees or more).²¹

¹⁸ Clearly, the availability and usage of public transportation and the commuting habits of workers more in general are important dimensions that affect the risk of contagion: a specific analysis of these dimensions go beyond the scope of our paper.

¹⁹ The higher probability of unsafe jobs among workers with a temporary contract is present in all 27 countries analysed. Austria, Switzerland and Germany report the lowest probabilities, whereas Romania and Estonia the highest.

²⁰ Among the workers characteristics not reported in the Table because available only for a subset of workers, we would like to highlight that safer jobs are way over-represented at the top of the income distribution. This is especially true for jobs in the *home working category*, whose prevalence markedly increases as we move toward the upper quintiles of the earnings distribution. We also find a strong concentration of unsafe jobs in families of more than five members. Incidentally, large families may be at a serious disadvantage also when carrying out safe jobs: home is arguably a very poor substitute to the office if a large family lives in a small apartment, especially if children or other family members require assistance by those staying at home (e.g. because of school closures).

²¹ We coded self-employed as working in solo firms, thus being in 1-10 employees firms.

Table 3. Characteristics of workers in each occupation group in 27 European countries: marginal effects from an unordered multinomial logit

	Home working	Low physical proximity	Some interactions with customers	Unsafe jobs
	(1)	(2)	(3)	(4)
Age (15-24 omitted)				
25-39	.049 (.003)	.021 (.002)	.017 (.001)	-.087 (.003)
50-54	.080 (.003)	.026 (.002)	.024 (.001)	-.130 (.003)
55-65	.083 (.003)	.043 (.002)	.026 (.001)	-.152 (.003)
Gender (male omitted)				
Female	.059 (.001)	-.056 (.001)	-.034 (.001)	.031 (.002)
Education (college omitted)				
Primary	-.327 (.002)	.124 (.002)	.003 (.001)	.201 (.002)
Secondary	-.211 (.002)	.072 (.001)	-.009 (.001)	.148 (.002)
Native status (natives omitted)				
Foreign born	-.093 (.002)	.041 (.002)	-.001 (.001)	.053 (.002)
Urban status (metropolitan areas omitted)				
Town and suburbs	-.031 (.001)	.011 (.001)	.000 (.001)	.020 (.002)
Rural areas	-.057 (.002)	.027 (.001)	.007 (.001)	.023 (.002)
Empl. status (self-employed omitted)				
Employee	-.025 (.002)	.045 (.002)	.005 (.001)	-.025 (.003)
Full-time (omitted)				
Part-time	-.052 (.002)	.030 (.002)	-.006 (.001)	.028 (.002)
Contract (permanent omitted)				
Temporary	-.025 (.002)	-.007 (.002)	-.001 (.001)	.034 (.003)
Firm size FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Notes: The Table reports the marginal effects from an ordered multinomial logit where the probability of working in any of the four occupation groups is a function of individual, contract and firm characteristics. The firm size and sector fixed effects are not reported in the Table, but available in the equivalent online Appendix Table. The regressions are estimated on Eurostat Labour Force Survey data from 2019, controlling for country fixed effects.

Table 4. Characteristics of workers in each occupation group in the US: marginal effects from an unordered multinomial logit

	Home working	Low physical proximity	Some interactions with customers	Unsafe jobs
	(1)	(2)	(3)	(4)
Age (15-24 omitted)				
25-39	0.075 (0.002)	-0.002 (0.001)	0.016 (0.001)	-0.090 (0.002)
50-54	0.108 (0.002)	-0.002 (0.001)	0.029 (0.001)	-0.134 (0.002)
55-65	0.124 (0.002)	0.006 (0.002)	0.034 (0.001)	-0.164 (0.003)
Gender (male omitted)				
Female	0.041 (0.001)	-0.069 (0.001)	-0.024 (0.001)	0.052 (0.001)
Education (college omitted)				
Primary	-0.339 (0.003)	0.089 (0.003)	-0.006 (0.002)	0.256 (0.004)
Secondary	-0.178 (0.001)	0.044 (0.001)	0.006 (0.001)	0.127 (0.001)
Native status (natives omitted)				
Foreign born	-0.052 (0.002)	0.019 (0.001)	-0.022 (0.001)	0.055 (0.002)
Urban status (city omitted)				
Town and suburbs	-0.060 (0.002)	0.021 (0.001)	0.008 (0.001)	0.031 (0.002)
Rural areas	-0.034 (0.006)	0.013 (0.004)	0.013 (0.004)	0.009 (0.007)
Empl. status (self-employed omitted)				
Employee	-0.071 (0.002)	0.065 (0.001)	-0.006 (0.001)	0.012 (0.002)
Full-time (omitted)				
Part-time	-0.084 (0.002)	-0.013 (0.001)	-0.023 (0.001)	0.120 (0.002)
Sector FE	Yes	Yes	Yes	Yes

Notes: The Table reports the marginal effects from an ordered multinomial logit where the probability of working in any of the four occupation groups is a function of individual, contract and firm characteristics. The firm size and sector fixed effects are not reported in the Table, but available in the equivalent online Appendix Table. The regressions are estimated on the US CPS data from 2019. Differently from Table 2, we cannot control for country, temporary contract and firm size fixed effects.

The distribution of epidemiological risk can be better characterized by considering also the essential or non-essential nature of the unsafe jobs. Essential occupations have to be carried out even at peaks of the epidemic waves, and they were everywhere exempted from the lockdown measures. They employ 119.5 million workers in our sample, representing 32.5% of the total employment.²² About 60% of these essential workers (roughly 70 million people) hold a job that we classify as unsafe. Indeed unsafe jobs are over-represented in essential occupations. Norway is the country with the highest share of unsafe jobs among essential workers (66%), whereas Romania is the lowest (35%). Vice versa, activities that can be carried out remotely, are severely under-represented in essential occupations. We estimate that only 19% of essential workers have a job that can be performed remotely.

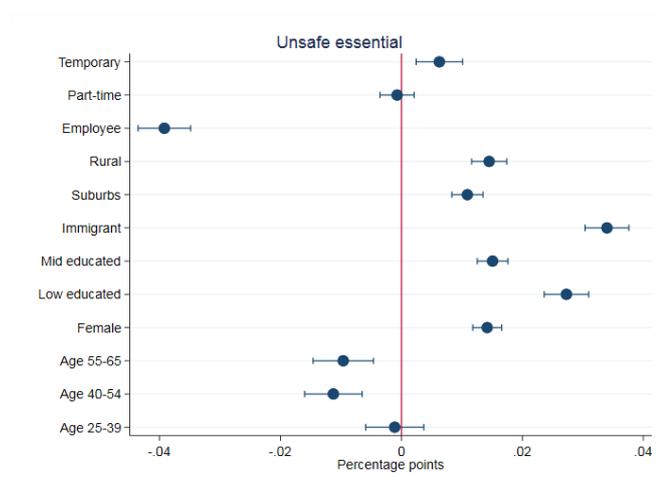
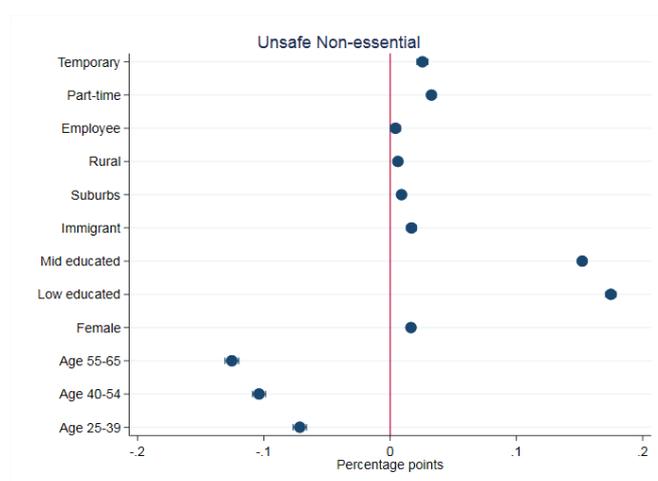
²² Information at the country level can be found in Table A5 in Annex A.

While workers in essential and unsafe jobs face the highest risk of being infected by the virus, workers in unsafe but non-essential jobs face the highest labour market risk. These workers are in fact most exposed to the risk of layoff or of forced reductions in their incomes, as their jobs are presumably among the first to be affected by the lockdown measures and among the last to be authorised to resume, or likely to face a substantial decline in demand. This is confirmed by our analysis of actual labour market outcomes in Section 3. According to our estimates, roughly 140 million workers in EU countries have a job in non-essential occupations, that is, about two thirds of the total EU employment; 58.5 million of them hold an unsafe job (27% of the total EU employment).

Figure 7, left panel shows the worker characteristics associated with being involved in unsafe essential occupations. In particular, it reports marginal effects from logit estimates of any given characteristics on the probability of having an unsafe and essential job relative to the reference group (native born male workers aged less than 24 highly educated self-employed living in cities). The fact of being migrant is the single most important factor affecting this probability: it increases by more than 3 percentage points with respect to the baseline. Low levels of education also increase the probability of having an unsafe and essential job. Women, persons living in peripheral areas and having a temporary contract are also over-represented in this group subject to a particularly high epidemiological risk. Unsafe and essential jobs provide employment above all to the youngsters and in the context of self-employment positions.

The key factor increasing the probability of being involved in unsafe and non-essential occupations is a low level of education (Figure 7 right panel). Ageing also in this case reduces the probability of being involved in unsafe jobs, but the effect is stronger than in the case of essential activities (being an older worker reduces the probability by about one percentage point with respect to the baseline). Female workers are also more represented than men in this group. Unlike the case of unsafe essential jobs, it is dependent employment and the fact of having a part-time position positively associated with the probability of having one of these risky jobs.

The sectoral composition of the two pools, not reported in the Figures, is also different. Unsafe essential jobs are concentrated in the health sector and in agriculture. Workers in unsafe and non-essential occupations are more likely to be employed in the retail, accommodation, entertainment and recreation, and in personal services as well as in the construction sector. In both cases small business is over-represented. This may have to do with the relative small size of firms in the hospitality industry, but may also have to do with the presence of fixed costs in organizing remote working. It is consistent with early evidence from real-time privately-owned data in the United States pointing to a concentration of job losses in small firms (Chetty et al. 2020).

Figure 7. Unsafe essential and non-essential jobs and individual characteristics**Panel A. Unsafe essential occupations****Panel B. Unsafe non-essential occupations**

Notes: The figures report the marginal effects of individual characteristics on the probability that a worker belongs to the unsafe essential occupation group (left panel) and to the unsafe non-essential occupation group (right panel). The regressions are estimated on the 27 countries available in the Eurostat European Labour Force Survey. The 95 percent confidence intervals reported are robust to heteroscedasticity.

6. Protecting Vulnerable Workers

The above analysis provide interesting evidence relevant for policy in light of the evolution of the pandemic towards normality. Our focus is here primarily on protection against labour market risk, which is concentrated on workers in unsafe and non-essential activities. The epidemic changed the traditional profile of vulnerable groups in the labour market, unfolding gaps in social security provision that have only partly been filled. Moreover such gaps will not be automatically closed by reducing the own infection risk of the workers involved: falls in demand putting at risk their job originate from the perception of consumers who may only partly feel reassured by the fact that they interact with persons who have been vaccinated.

The high prevalence of unsafe and non-essential jobs in small firms and among the self-employed poses a major challenge to labour market policies aimed at stabilizing employment over the cycle as these policies are often not tailored to the small business sector and the solo self-employed. Furthermore, plant closures, more frequent among small firms, would destroy at the same time firm-specific human, physical and relational capital. In Europe, small and medium enterprises (SMEs) have been among the main intended beneficiaries of the short-time work schemes introduced to mitigate the employment effects of the crisis. Indeed, STW schemes have been extended in several countries to cover also the small business sector (Giupponi and Landais, 2020), although the take-up rate among SMEs has been relatively low (OECD, 2020b). At the same time employment protection or even the banning altogether of layoffs introduced in some countries, may prove rather ineffective in this context as small firms may go bankrupt and are becoming unsustainable with the prolongation of the crisis.

At the same time, the over-representation of temporary workers among unsafe and non-essential activities challenges the insurance-based design of unemployment benefits in most countries. These workers often have relatively short contribution records and hence have, at best, access to unemployment benefit systems of very short duration. A similar problem arises with respect to school leavers who are being severely affected by the economic consequences of the pandemic, as also indicated by the overrepresentation in the most vulnerable pools of workers aged less than

24 before the pandemic. This also suggests that early retirement is not an option, even though it can appear tempting from a political point of view in countries with a large share of older voters.

In a number of countries, the policy response to these new challenges has been to extend the standard policy tools used to contain job losses – employment protection and short-time work – to small firms. A few countries (e.g., Greece, Spain and Italy), have banned economic layoffs, at least group layoffs, in all firms, not only those receiving subsidized STW. In almost all European countries, the coverage of STW has been extended to small business while funding subsidized working time reductions via general government revenues.²³ These measures were necessary during the lockdown, but can only be temporary. If protracted over time, they would hinder worker reallocation. Further considerations should also be devoted to unemployment benefit systems that typically offer a low coverage to temporary workers and solo self-employed. As the benefits' duration is proportional to the past contribution records, extensions of the duration of such schemes should thus be promoted, as moral hazard problems are second order during a pandemic.

Going forward, policy actors should seriously consider: i) better targeting the policies to the sectors, occupations and firms most hardly hit by the crisis; and ii) devising policies, such as combinations of STW and wage insurance, that could encourage the mobility of the workers that are twice vulnerable under the pandemic towards those occupations and sectors that may offer greater employment opportunities, such as the health and sanitation sectors.²⁴ Job creation will likely be stronger in the health sector and in those industries that serve the health sector also because of stronger public expenditures in these strategic activities. Such industries revolve around two main poles: the pharmaceutical industry and healthcare services. The first also encompasses the chemical industry, part of the packaging industry, research centres, logistics and pharmaceutical wholesale and retail trade. The second encompasses the supply of goods (manufacturing of hospital equipment and devices) and services (cleaners, hospital assistance and security, linen rental, food services), the management of special waste and the insurance sector.²⁵

Most of these job creators could demand mainly skilled workers, hence may not offer employment opportunities to the vulnerable groups described above. Still, there may be employment opportunities even for unskilled workers in essential activities and in new disinfection-related jobs created with the goal of containing the pandemic. The problem is that these jobs may carry with them significant health risk and offer relatively low wages, and hence may not be particularly appealing even to the long-term unemployed. To prevent this potential market disruption, public support in terms of wage subsidies (reducing the wedge between labour costs for the employer and take-home pay) or wage insurance (allowing workers to cumulate STW subsidies with wages in essential occupations) could be warranted when targeted to these sectors. Also, given that the activities that workers reallocated to different firms and sectors will be performing are likely to differ from those in their previous occupations, offering training courses could help make the transition smoother. Hiring incentives for firms able to absorb workers released by unsafe or less productive sectors could also support this reallocation. Finally, information campaigns about safety standards and other measures to mitigate health risk could also improve awareness among workers and employers and make wages more responsive to the actual risk faced by workers. Ultimately, the public sector could intervene directly into the market of essential goods and services whose productive capacity is about to be lost.

Careful considerations should be devoted to the digitalization process too. On-the-job training and retraining of unemployed adults to digital skills will play a major role in mitigating the negative effects of the pandemic on employment and productivity. Not only workers will move away from

²³ See OECD (2020) for a review of the economic initiatives undertaken so far by different countries.

²⁴ With “wage insurance” we refer to a measure complementing the wage of workers accepting to move to sectors offering lower wages compared to those of the initial employment.

²⁵ Estimates on the size and features of these industries are not possible with our data, which report only aggregate information in terms of economic sectors.

unsafe non-essential jobs to safe (and unsafe) essential jobs, but the organisation of all jobs is likely to change profoundly (Bloom and Prettner, 2020). A legacy of the pandemic will be the increase in remote working. On the supply side many workers became acquainted not only with the disadvantages but also with the advantages of home working. On the demand side, highly indebted firms will likely try to reduce fixed costs by forcing their employees to work from home at least a few days a week.

Digitalization will be important also among jobs that are unsafe under current technologies as there will be the need to have less physical proximity to avoid contagion risks. Thus, unlike previous recessions, we have quite a good understanding of the skills that are required to reduce job-related epidemiological risk. In particular, we know that proficiency in the use of digital devices is essential for remote working. Importantly, increasing reliance on remote working would have the further advantage of reducing mobility related health risk, which goes well beyond COVID-19: in many countries, most work-related injuries occur while commuting to work.

Finally, we shift to the epidemiological risk also in light of the start of the vaccination campaign. The evidence we provide could be useful to target subgroups of workers who are more likely to be involved in unsafe occupations. This has only partly been done so far. All countries have given priority in vaccination campaigns to workers in the health sector, and the police. In the definition of priority lists less attention would seem to have been paid so far to characteristics that significantly increase the probability of being in an unsafe working position, such as having a job in the retail sector. The overrepresentation of migrants in the pool of workers in unsafe and essential occupations also indicates that it is of paramount importance to provide health insurance coverage to these workers, who often have irregular working positions and sometimes are even illegal residents. Vaccination campaigns have clearly to take into account many other factors – such as differential mortality risks and the probability of infecting other persons – that are not considered in this paper.

7. Concluding Remarks

Overall, there is no evidence that COVID-19 is acting as a Great Leveller like the Black Death, the Russian revolution, and the World Wars (Scheidel, 2018). Job-related epidemiological risk is very unevenly distributed across sectors, occupations and firms. It also involves a rather specific worker profile, broadly corresponding to the same characteristics that even in normal times are associated with high job instability. On the basis of pre-pandemic information, about 50 percent of jobs were carried out in ways that would expose workers to significant risks of infections, and would therefore be considered “unsafe” during a pandemic. Some of these jobs provide essential goods and services, and cannot be discontinued, even at the peak of a pandemic wave. For this reason, all efforts should be made to make these jobs as safe as possible. Vaccination campaigns could target precisely the unsafe occupations in essential activities. So far this has been done only for workers in the health sector and the police. Many other workers (e.g., in the retail food distribution sector) are at high risk of contagion.

Turning to labour market risk, about 60 percent of unsafe jobs are in non-essential occupations. Firms offering these jobs will have to undergo major restructuring to reduce epidemiological risk. This may involve at least temporarily sizeable productivity losses and a dramatic drop in labour demand. As our analysis suggests, most of the workers involved in this restructuring had already a vulnerable position in the labour market before COVID-19. Thus, policies should target twice-vulnerable workers who are at a high risk of labour market related hardship.

Early retirement does not seem to be an option as these workers are spread all over the age distribution. Yet, for those workers who are close to the retirement age, an extended duration of unemployment benefits could provide a sort of bridging scheme to retirement.

The immediate policy response in most EU countries was to extend and facilitate the access to short-time work schemes (STW). Such measures, which allow workers to keep their job (and the right to be reinstated) while suffering hours (and salary) cuts, are a good way to preserve productive matches in the midst of an economic crisis (Boeri, Bruecker, Fucks-Schundenr and Mayer, 2011; Cahuc, Kramarz and Nevoux, 2018; Giupponi and Landais, 2020). However, they also hinder reallocation, as workers are usually not allowed to work while receiving the benefits. Workers on STW should instead be allowed to take up temporarily jobs in essential occupations – at least those in the private sector – without losing the option to go back to their original job when the emergency is over (Giupponi and Landais, 2020). More generally, STW should become as much as possible a wage insurance scheme, encouraging workers to take-up jobs paid less than their previous job. This will also encourage young workers to take up jobs in essential activities.

Publicly provided general training could also target these twice-vulnerable workers. In the current juncture, we have a better idea of the training needs than under previous recessions. There is also a better understanding among workers of the benefits associated to gaining the option to carry out some activities in remote. Nonetheless, it may be useful to establish that provision of income support in terms of STW or unemployment benefits is conditional on attendance to training courses aimed at increasing digital proficiency, which we have shown to be significantly lower for workers more vulnerable to the consequences of the COVID-19 pandemic.

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Annex A. Statistical Annex (for online publication)²⁶

Table A.1 Taxonomy of occupations - List of questions and conditions

1. From the “Work context” section:

-
- Q4 – "Average respondent says they use email less than once per week" (value < 3.0/5.0)
 - Q14 – "Average respondent says they deal with violent people at least once a week" (value > 4.0/5.0)
 - Q16 – "Average respondent says they work indoors, in an environment not controlled, almost every day" (value > 4.5/5.0)
 - Q17 – "Average respondent says they work outdoors, exposed to all conditions, almost once per week at least" (value > 3.5/5.0)
 - Q18 – "Average respondent says they work outdoors, under cover, almost every day" (value > 4.5/5.0)
 - Q19 – "Average respondent says they work in an open vehicle or operating equipment almost every day" (value > 4.5/5.0)
 - Q20 – "Average respondent says they work in a closed vehicle or operate enclosed equipment almost every day" (value 4.5/5.0)
 - Q23 – "Average respondent says they are exposed to extreme temperatures almost every day" (value > 4.5/5.0)
 - Q29 – "Average respondent says they are exposed to diseases or infection at least once a month" (value > 3.0/5.0)
 - Q30 – "Average respondent says they are exposed to high places at least once a week" (value > 4.0/5.0)
 - Q31 – "Average respondent says they are exposed to hazardous conditions at least once a week" (value > 4.0/5.0)
 - Q32 – "Average respondent says they are exposed to hazardous equipment at least once a week" (value > 4.0/5.0)
 - Q33 – "Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week" (value > 4.0/5.0)
 - Q34 – "Average respondent says they are sitting less than half the time" (value < 2.0/5.0)
 - Q36 – "Average respondent says they spend more than about half the time climbing ladders, scaffolds, or poles" (value 3.5/5.0)
 - Q37 – "Average respondent says they spend more than about half the time walking or running" (value 3.5/5.0)
 - Q43 – "Average respondent says they wear common protective or safety equipment more than once per month" (value 3.5 > 5.0)
 - Q44 – "Average respondent says they wear specialized protective or safety equipment more than once per month" (value 3.5 > 5.0)
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²⁶ Data and other materials are available for download at <http://www.frd.org/page/data>.

2. From the “Work activities” section:

- Q4 – "Inspecting equipment, structures or materials is important/very important" (value > 3.5/5.0)
- Q16 – "Performing general physical activities is important/very important" (value > 3.5/5.0)
- Q17 – "Handling and moving objects is important/very important" (value > 3.5/5.0)
- Q18 – "Controlling machines and processes is very important" (value > 4.0/5.0)
- Q19 – "Working with computers is not important" (value < 1.5/5.0)
- Q20 – "Operating vehicles, mechanized devices or equipment is important/very important" (value 3.5/5.0)
- Q22 – "Repairing and maintaining mechanical equipment is important/very important" (value > 3.5/5.0)
- Q23 – "Repairing and maintaining electronic equipment is very important" (value 4.0/5.0)
- Q29 – "Assisting and Caring for others is important/very important" (value 3.5/5.0)

Table A.2. Coefficients of job categories by ISCO 3-digit code

ISCO - 3 digits	ISCO name	Work from Home	Low physical proximity	Interactions with customers	Unsafe jobs
111	Legislators and Senior Officials	X			
112	Managing Directors and Chief Executives	X			
121	Business Services and Administration Managers	X			
122	Sales, Marketing and Development Managers	X			
131	Production Managers in Agriculture, Forestry and Fisheries				X
132	Manufacturing, Mining, Construction and Distribution Managers	X			
133	Information and Communications Technology Services Managers	X			
134	Professional Services Managers	X			
141	Hotel and Restaurant Managers				X
142	Retail and Wholesale Trade Managers	X			
143	Other Services Managers	X			
211	Physical and Earth Science Professionals	X			
212	Mathematicians, Actuaries and Statisticians	X			
213	Life Science Professionals	X			
214	Engineering Professionals (excluding Electrotechnology)		X		
215	Electrotechnology Engineers	X			
216	Architects, Planners, Surveyors and Designers	X			
221	Medical Doctors				X
222	Nursing and Midwifery Professionals				X
223	Traditional and Complementary Medicine Professionals				X
224	Paramedical Practitioners				X

225	Veterinarians				X
226	Other Health Professionals				X
231	University and Higher Education Teachers	X			
232	Vocational Education Teachers				X
233	Secondary Education Teachers	X			
234	Primary School and Early Childhood Teachers				X
235	Other Teaching Professionals	X			
241	Finance Professionals	X			
242	Administration Professionals	X			
243	Sales, Marketing and Public Relations Professionals	X			
251	Software and Applications Developers and Analysts	X			
252	Database and Network Professionals	X			
261	Legal Professionals	X			
262	Librarians, Archivists and Curators	X			
263	Social and Religious Professionals			X	
264	Authors, Journalists and Linguists	X			
265	Creative and Performing Artists	X			
311	Physical and Engineering Science Technicians		X		
312	Mining, Manufacturing and Construction Supervisors				X
313	Process Control Technicians				X
314	Life Science Technicians and Related Associate Professionals		X		
315	Ship and Aircraft Controllers and Technicians				X
321	Medical and Pharmaceutical Technicians				X
322	Nursing and Midwifery Associate Professionals				X
323	Traditional and Complementary Medicine Associate Professionals				X
324	Veterinary Technicians and Assistants				X
325	Other Health Associate Professionals				X
331	Financial and Mathematical Associate Professionals	X			
332	Sales and Purchasing Agents and Brokers	X			
333	Business Services Agents	X			
334	Administrative and Specialized Secretaries	X			
335	Government regulatory associate professionals				X
341	Legal, Social and Religious Associate Professionals	X			
342	Sports and Fitness Workers				X
343	Artistic, Cultural and Culinary Associate Professionals				X
351	Information and Communications Technology Operations and User Support Technicians	X			
352	Telecommunications and Broadcasting Technicians			X	
411	General Office Clerks	X			
412	Secretaries (general)	X			
413	Keyboard Operators	X			
421	Tellers, Money Collectors and Related Clerks	X			
422	Client Information Workers	X			
431	Numerical Clerks	X			

432	Material recording and Transport Clerks		X		
441	Other Clerical Support Workers				X
511	Travel Attendants, Conductors and Guides				X
512	Cooks				X
513	Waiters and Bartenders				X
514	Hairdressers, Beauticians and Related Workers				X
515	Building and Housekeeping Supervisors		X		
516	Other Personal Services Workers				X
521	Street and Market Salespersons	X			
522	Shop Salespersons				X
523	Cashiers and Ticket Clerks				X
524	Other Sales Workers				X
531	Child Care Workers and Teachers' Aides				X
532	Personal Care Workers in Health Services				X
541	Protective Services Workers				X
611	Market Gardeners and Crop Growers				X
612	Animal Producers		X		
613	Mixed Crop and Animal Producers		X		
621	Forestry and Related Workers		X		
622	Fishery Workers, Hunters and Trappers				X
631	Subsistence Crop Farmers			X	
632	Subsistence Livestock Farmers				X
633	Subsistence Mixed Crop and Livestock Farmers			X	
634	Subsistence Fishers Hunters Trappers And Gatherers				X
711	Building Frame and Related Trades Workers				X
712	Building Finishers and Related Trades Workers				X
713	Painters, Building Structure Cleaners and Related Trades Workers				X
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers		X		
722	Blacksmiths, Toolmakers and Related Trades Workers		X		
723	Machinery Mechanics and Repairers		X		
731	Handicraft Workers		X		
732	Printing Trades Workers		X		
741	Electrical Equipment Installers and Repairers				X
742	Electronics and Telecommunications Installers and Repairers				X
751	Food Processing and Related Trades Workers				X
752	Wood Treaters, Cabinet-makers and Related Trades Workers			X	
753	Garment and Related Trades Workers		X		
754	Other Craft and Related Workers				X
811	Mining and Mineral Processing Plant Operators		X		
812	Metal Processing and Finishing Plant Operators		X		
813	Chemical and Photographic Products Plant and Machine Operators		X		
814	Rubber, Plastic and Paper Products Machine Operators		X		
815	Textile, Fur and Leather Products Machine Operators				X

816	Food and Related Products Machine Operators		X		
817	Wood Processing and Papermaking Plant Operators		X		
818	Other Stationary Plant and Machine Operators		X		
821	Assemblers				X
831	Locomotive Engine Drivers and Related Workers		X		
832	Car, Van and Motorcycle Drivers				X
833	Heavy Truck and Bus Drivers			X	
834	Mobile Plant Operators		X		
835	Ships' Deck Crews and Related Workers				X
911	Domestic, Hotel and Office Cleaners and Helpers		X		
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers		X		
921	Agricultural, Forestry and Fishery Labourers				X
931	Mining and Construction Labourers				X
932	Manufacturing Labourers				X
933	Transport and Storage Labourers				X
941	Food Preparation Assistants				X
952	Street Vendors Excluding Food	X			
961	Refuse Workers				X
962	Other Elementary Workers				X

Note: The table reports our classification of ISCO 3-digit occupation. ISCO code 951 has been dropped due to inconsistencies between ICP INAPP and O*NET data.

Source: O*NET database.

Table A.3. Overall shares of job categories by country

Country	% Work from Home	% Low physical proximity	% Interactions with customers	% Unsafe jobs
Austria	33,2	21,5	3,5	41,9
Belgium	36,4	17,5	3,7	42,5
Croatia	27,1	22,2	5,4	45,3
Cyprus	34,0	16,1	2,6	47,3
Czech Republic	28,8	25,0	4,7	41,5
Denmark	33,6	17,0	3,1	46,2
Estonia	35,8	18,4	4,8	41,0
Finland	33,5	18,9	4,5	43,1
France	33,8	19,7	3,4	43,1
Germany	32,5	23,0	3,8	40,7
Greece	28,0	14,0	4,0	54,1
Hungary	25,6	22,2	4,9	47,2
Iceland	35,9	11,8	2,8	49,5
Ireland	31,4	14,1	2,3	52,2
Italy	31,6	18,7	3,3	46,5
Latvia	32,2	19,2	4,9	43,7
Lithuania	34,1	19,8	5,4	40,7
Luxembourg	51,1	13,6	5,8	29,5
Netherlands	38,9	12,4	3,6	45,2
Norway	33,0	17,0	3,1	47,0
Portugal	30,2	18,4	5,9	45,5
Romania	17,4	31,8	5,9	44,9
Slovakia	23,8	22,6	5,1	48,5
Spain	27,1	17,4	3,9	51,6
Sweden	37,1	16,0	4,1	42,7
Switzerland	39,5	18,6	2,8	39,1
United Kingdom	40,8	11,1	2,8	45,3
United States	33,1	10,0	8,1	48,8

Note: The table reports the share of workers holding a job in any of the job categories of our taxonomy for the 27 countries of the sample. Data refer to 2019.

Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.4. Essential occupations as identified by Fasani and Mazza (2020)

<i>ISCO code</i>	<i>ISCO name</i>
213	Life Science Professionals
214	Engineering Professionals (excluding Electrotechnology)
221	Medical Doctors
222	Nursing and Midwifery Professionals
223	Traditional and Complementary Medicine Professionals
224	Paramedical Practitioners
226	Other Health Professionals
231	University and Higher Education Teachers
232	Vocational Education Teachers
233	Secondary Education Teachers
234	Primary School and Early Childhood Teachers
235	Other Teaching Professionals
251	Software and Applications Developers and Analysts
252	Database and Network Professionals
314	Life Science Technicians and Related Associate Professionals
311	Physical and Engineering Science Technicians
312	Mining, Manufacturing and Construction Supervisors
313	Process Control Technicians
315	Ship and Aircraft Controllers and Technicians
321	Medical and Pharmaceutical Technicians
322	Nursing and Midwifery Associate Professionals
351	ICT Operations and User Support Technicians
352	Telecommunications and Broadcasting Technicians
511	Travel Attendants, Conductors and Guides
516	Other Personal Services Workers
531	Child Care Workers and Teachers' Aides
532	Personal Care Workers in Health Services
612	Animal Producers
613	Mixed Crop and Animal Producers
611	Market Gardeners and Crop Growers
751	Food Processing and Related Trades Workers
816	Food and Related Products Machine Operators
831	Locomotive Engine Drivers and Related Workers
832	Car, Van and Motorcycle Drivers
833	Heavy Truck and Bus Drivers
835	Ships' Deck Crews and Related Workers
911	Domestic, Hotel and Office Cleaners and Helpers
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers
933	Transport and Storage Labourers
961	Refuse Workers

Note: The table lists the ISCO 3-digit occupations identified as “key” in the work by Fasani and Mazza (2020), i.e. occupations that need to be performed even during a pandemic in order to keep citizens healthy, safe and fed. Source: Fasani and Mazza (2020).

Table A.5. Essential workers by job category in European countries and in the US

Country	Essential workers	Essential workers (% of total)	Work from Home (% of essential)	Low Physical Proximity (% of essential)	Interactions with customers (% of essential)	Unsafe Jobs (% of essential)
<i>Austria</i>	1 505 561	34,7%	18,6%	53,2%	51,1%	36,4%
<i>Belgium</i>	1 779 757	37,0%	18,4%	53,4%	53,5%	44,9%
<i>Croatia</i>	563 275	33,9%	17,1%	47,2%	50,1%	35,6%
<i>Cyprus</i>	125 705	30,8%	16,3%	62,8%	69,7%	28,3%
<i>Czech Republic</i>	1 609 648	30,5%	20,8%	32,8%	69,4%	31,5%
<i>Denmark</i>	1 224 919	43,3%	24,7%	60,9%	60,6%	49,3%
<i>Estonia</i>	205 739	30,9%	20,2%	32,1%	75,3%	34,6%
<i>Finland</i>	1 048 619	41,1%	24,2%	50,5%	60,2%	48,2%
<i>France</i>	11 076 785	41,2%	14,4%	62,3%	58,5%	51,4%
<i>Germany</i>	13 059 880	31,0%	16,1%	38,3%	50,2%	37,0%
<i>Greece</i>	1 435 878	37,3%	20,5%	56,1%	63,5%	39,3%
<i>Hungary</i>	1 366 084	30,4%	19,2%	36,0%	69,8%	29,9%
<i>Iceland</i>	70 820	35,3%	20,4%	47,7%	59,4%	41,8%
<i>Ireland</i>	733 533	32,7%	14,1%	58,0%	64,8%	35,9%
<i>Italy</i>	7 581 093	32,8%	17,9%	45,5%	64,5%	35,6%
<i>Latvia</i>	271 518	30,1%	15,0%	40,8%	66,6%	32,8%
<i>Luxembourg</i>	88 771	31,9%	15,1%	67,3%	37,3%	43,7%
<i>Netherlands</i>	3 063 543	35,0%	19,7%	50,5%	42,7%	43,3%
<i>Norway</i>	1 097 125	40,7%	17,6%	53,2%	55,6%	51,5%
<i>Portugal</i>	1 607 527	32,9%	20,1%	46,3%	39,9%	35,7%
<i>Romania</i>	3 189 108	37,0%	21,5%	59,6%	52,7%	29,0%
<i>Slovak Rep.</i>	777 508	30,6%	18,5%	28,8%	60,3%	34,5%
<i>Spain</i>	6 984 011	36,5%	21,8%	53,9%	66,2%	36,1%
<i>Sweden</i>	2 077 773	40,7%	21,8%	50,6%	50,5%	52,4%
<i>Switzerland</i>	1 521 963	33,6%	18,1%	51,8%	43,6%	39,8%
<i>United Kingdom</i>	11 011 663	33,7%	17,9%	54,8%	54,0%	41,6%
<i>United States</i>	44 062 644	29,97%	17,95%	36,80%	32,11%	36,63%

Note: The table reports details on the number and the distribution across the four job categories of our taxonomy of essential workers, i.e. individuals holding a job in any of the occupations defined as “key” by Fasani and Mazza (2020).

Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A6. Ex-ante risk and ex-post labour market outcomes, third quarter

	Work from Home (1)	Short-time work (2)	Sick leave (3)	Log Wages (4)
Italy				
Post	0.191** (0.005)	0.012** (0.001)	0.003* (0.001)	-0.002 (0.005)
Post*Low proximity	-0.186** (0.006)	0.007** (0.003)	-0.000 (0.002)	-0.010 (0.007)
Post*Unsafe Jobs	-0.187** (0.006)	0.006** (0.002)	0.001 (0.002)	-0.001 (0.006)
Essential	-0.020** (0.003)	0.007** (0.002)	0.001 (0.001)	0.055** (0.005)
Post*Essential	0.044** (0.004)	-0.012** (0.002)	-0.000 (0.002)	0.010+ (0.006)
R2	0.189	0.012	0.003	0.328
N	95885	95885	95885	72669
United Kingdom				
Post	0.071** (0.004)	0.198** (0.006)	-0.032** (0.004)	0.033* (0.013)
Post*Low proximity	-0.041** (0.007)	0.104** (0.013)	-0.009 (0.010)	0.028 (0.024)
Post*Unsafe Jobs	-0.064** (0.005)	0.074** (0.009)	-0.010 (0.006)	0.012 (0.017)
Essential	-0.008** (0.003)	0.029** (0.003)	-0.009+ (0.005)	0.031** (0.011)
Post*Essential	0.002 (0.004)	-0.072** (0.008)	0.011+ (0.006)	-0.004 (0.016)
R2	0.101	0.153	0.034	0.359
N	75008	26957	26957	18551
United States				
Post		0.008** (0.001)	0.003** (0.001)	0.049** (0.009)
Post*Low proximity	-0.151** (0.004)	0.000 (0.001)	0.002* (0.001)	0.024 (0.015)
Post*Unsafe Jobs	-0.205** (0.003)	0.003** (0.001)	0.004** (0.001)	0.021+ (0.012)
Essential	0.006* (0.003)	0.004** (0.001)	0.001+ (0.001)	0.052** (0.009)
Post*Essential		-0.004** (0.001)	-0.002* (0.001)	-0.008 (0.012)
R2	0.231	0.012	0.004	0.265
N	135121	303396	303396	64447

Notes: The table reports the estimated coefficients of equation (1) calculated on the Italian and the UK Labour Force Survey and on the US CPS. The sample period is the third quarter of 2019 and of 2020: the dummy post stands for the third quarter of 2020. Data on Work from Home for the US are only available in 2020: the coefficients shown in the table are therefore not interacted with a post-Covid dummy. The occupation categories are those described in the text: the omitted category is remote working. We control for age and age square, the level of education also interacted with age and its square, immigrant status, gender, the number of children (also interacted with gender), sector and working time arrangement (part-time or full time; the coefficients are not reported, but available). The table does not report also the estimated effects on the risk groups not interacted with the post dummy because of space constraints. The mean of the dependent variable is computed as the baseline level in the 2nd quarter of 2019. All the regressions are weighted by sample weights and standard errors are robust to heteroskedasticity. * and ** denote significance at 5 and 10 percent level, respectively.

Table A7. Ex-ante risk and ex-post labour market outcomes for essential and non-essential jobs, third quarter

	Work from Home		Short-time work		Sick leave		Log Wages	
	Non-essentials	Essentials	Non-essentials	Essentials	Non-essentials	Essentials	Non-essentials	Essentials
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Italy								
Post	0.176**	0.308**	0.013**	-0.007	0.003*	0.001	-0.001	0.004
	(0.006)	(0.013)	(0.001)	(0.006)	(0.001)	(0.002)	(0.005)	(0.012)
Post*Low proximity	-0.159**	-0.272**	0.003	0.015*	-0.001	0.001	-0.016+	-0.001
	(0.007)	(0.015)	(0.003)	(0.006)	(0.003)	(0.003)	(0.008)	(0.015)
Post*Unsafe Jobs	-0.163**	-0.277**	0.004+	0.013*	0.000	0.003	-0.000	0.001
	(0.006)	(0.014)	(0.002)	(0.006)	(0.002)	(0.003)	(0.007)	(0.013)
R2	0.177	0.230	0.011	0.023	0.003	0.006	0.286	0.385
N	64015	31870	64015	31870	64015	31870	46555	26114
United Kingdom								
Post	0.069**	0.086**	0.196**	0.134**	-0.030**	-0.029**	0.033*	0.043+
	(0.004)	(0.009)	(0.006)	(0.011)	(0.005)	(0.008)	(0.014)	(0.025)
Post*Low proximity	-0.039**	-0.053**	0.075**	0.128**	0.004	-0.013	0.026	0.009
	(0.009)	(0.011)	(0.018)	(0.019)	(0.013)	(0.014)	(0.034)	(0.036)
Post*Unsafe Jobs	-0.057**	-0.081**	0.084**	0.050**	-0.016*	0.004	0.018	-0.005
			(0.011)	(0.014)	(0.008)	(0.011)	(0.020)	(0.030)
R2	0.083	0.129	0.142	0.118	0.013	0.021	0.342	0.357
N	49583	25425	17193	9764	17193	9764	12005	6546
United States								
Post			0.008**	0.002	0.003**	0.001	0.055**	0.022
			(0.001)	(0.002)	(0.001)	(0.001)	(0.010)	(0.022)
Post*Low proximity	-0.124**	-0.268**	-0.001	0.004	0.002	0.003+	0.009	0.045
	(0.005)	(0.009)	(0.001)	(0.002)	(0.001)	(0.002)	(0.017)	(0.033)
Post*Unsafe Jobs	-0.170**	-0.295**	0.002+	0.006*	0.004**	0.003*	0.013	0.038
	(0.004)	(0.009)	(0.001)	(0.002)	(0.001)	(0.001)	(0.013)	(0.026)
R2	0.218	0.278	0.010	0.016	0.003	0.004	0.278	0.240
N	95149	39972	214022	89374	214022	89374	44393	20054

Notes: The table reports the estimated coefficients of equation (1) calculated on the Italian and the UK Labour Force Survey and on the US CPS. The sample period is the third quarter of 2019 and of 2020: the dummy post stands for the third quarter of 2020. Data on Work from Home for the US are only available for 2020: the coefficients shown in the table are therefore not interacted with a post-Covid dummy. The occupation categories are those described in the text: the omitted category is remote working. We control for age and age square, the level of education also interacted with age and its square, immigrant status, gender, the number of children (also interacted with gender), sector and working time arrangement (part-time or full time; the coefficients are not reported, but available). The table does not report also the estimated effects on the risk groups not interacted with the post dummy because of space constraints. All the regressions are weighted by sample weights and standard errors are robust to heteroskedasticity. * and ** denote significance at 5 and 10 percent level, respectively