The new hazardous jobs and worker reallocation*

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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 contracting a viral infection. 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 low infection risks. We label jobs that can be done from home or that present a low risk of infection as "safe jobs". We apply our classification to labour force survey data from 27 countries and find that, in most of them, the share of safe jobs is close to 50%. More variation across countries exists in the share of jobs that can be done from home. We also find that safe jobs are very unequally distributed across different types of workers, firms, and sectors. More vulnerable workers (younger, less educated, on fixed-term contracts, immigrants) are over-represented in unsafe occupations, and therefore more at risk of suffering from the economic consequences of a pandemic. We also consider the distribution of safe and unsafe jobs between essential and non-essential activities involved by the lockdown measures. We finally assess the process of reallocation of workers to jobs that is likely to take place should the pandemic reveal to be long-lasting as well as the policy actions that could ease this reallocation and make it more efficient. In particular, we provide suggestive evidence of the extent to which the wage setting increasingly values epidemiological risk.

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1. Introduction

Following the outbreak of the COVID-19 pandemic, epidemiological risk recently gained an enormous importance as a dimension of workers' safety. Such risk is not evenly distributed across jobs and workers. In this paper, we provide a method to classify occupations according to the risk of contagion by analysing several dimensions of workers safety. We expand on the previous literature that almost exclusively looks at the feasibility of working from home by analysing other dimensions of risk. Starting from O*NET data, which describe the characteristics of jobs at the current level of technology, we create four categories of jobs 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 contribution to the literature on the labour market consequences of the COVID-19 pandemic is threefold. First, we consider a broader definition of 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, comply with physical distancing protocols as they involve only infrequent contacts with other persons. Second, rather than examining a single country, our paper carries out a systematic analysis of labour markets in 27 countries. Third, we characterise the heterogeneity across a large number of jobs and firm characteristics and we discuss the potential implications in terms of workers' reallocation and workers-to-jobs matching along the epidemiological risk dimension.

Our classification is necessarily based on the characteristics of occupations that were prevailing 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 (such as the COVID-19 pandemic, for instance). 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.

The empirical analysis presented in the paper relies on data from the US Current Population Survey (CPS) and on harmonised labour force survey data for European countries (EU-LFS). We use these data to estimate the share of safe jobs in 27 countries. By using the information contained in the O*NET survey, and building on previous work by Dingel and Neiman (2020[1]) and Boeri, Caiumi and Paccagnella (2020[2]), we classify jobs in four categories, characterised by decreasing degree of safeness. To simplify the exposition, we label jobs belonging in the first three categories as "safe jobs", and those belonging in the last (residual) category as "unsafe jobs". We argue that the risks associated to jobs in *category 2* and *3*, although higher than those associated with jobs in *category 1* (which can be done from home), are still low enough to make them feasible even in a context where a virus is spreading at large scale. Each job falls into a category if the average response of workers to a set of O*NET item is above (or below, depending on how the question is formulated) a pre-determined threshold. Roughly 50% of jobs can be considered safe, although large cross-country variation exists, notably in the share of jobs that can be done from home (which we consider to be the safest possible form of work). This nuanced characterisation of job safety is one of the main contributions of this paper, and has clearly important policy implications.

We then examine in detail the characteristics of workers holding safe and unsafe jobs. We find that the most economically vulnerable workers, i.e. low-educated workers, immigrants, low-wage workers, workers on temporary contracts, and part-timers, are over-represented in unsafe jobs. Some of these results are in line with previous studies, but we offer an analysis on an unprecedented set of worker characteristics. 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.

Another element that we consider is the potential for workers' reallocation, which will be a crucial issue for labour markets in a scenario where the risk of a pandemic remains significant. In a world subject to the risk of recurrent pandemic waves, we envisage two broad forms of reallocation: the first is from unsafe to safe occupations, and the second is towards occupations that, despite being unsafe, are "essential", and thus not subject to restriction measures. A better match between workers and jobs along the infection risk dimension should be pursued, for instance, by ensuring that workers more prone to incur severe forms of the disease move away from unsafe jobs. For this reason, we also provide indications on the distribution of safe and unsafe jobs across sectors and occupations, and we pay special attention to those characteristics of workers, such as age, that are supposedly related to higher mortality risks from COVID-19. On top of this, changes in demand for certain goods or services are also likely to cause changes in the occupational structure, and a reallocation of workers across different sectors.

For this reason, we conclude the paper with some broad considerations on social protection and the need for policies that can ease such reallocation. In particular, we discuss how policies can help more disadvantaged workers, as they are also the ones more likely to work in unsafe jobs and thus be most affected, from both an economic and a health point of view, by the pandemic. We also investigate the extent to which market mechanisms can ease this reallocation by providing preliminary evidence about the extent to which wages incorporate a premium related to the fact of working in less safe jobs. Our results indicate that before the outset of the pandemic, information about risk of infections were not incorporated in wages, as safe jobs were actually rewarded with a positive wage premium. However, in recent US data covering the months between February and April 2020 we do find evidence of a decrease of such premium, which could signal the fact that infection risks is increasingly being taken into account in the process of wage setting. Finally, we try to assess future training needs in the field of ICT, which will likely be needed by the increased reliance on remote working.

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 apply our classification to 27 countries for which suitable data are available. After estimating the incidence of safe jobs, we analyse the heterogeneity according to a large number of jobs and workers characteristics. Section 5 discusses the implications of our results for the reallocation of workers that will have to take place in a world characterised by a significant pandemic risk. Section 6 concludes.

2. Literature Review

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. The earliest papers that attempted this exercise, and which have been developed simultaneously and independently, are Dingel and Neiman (2020[1]) and Boeri, Caiumi and Paccagnella (2020[2]). While the first focuses on the US and relies on the O*NET surveys to estimate the feasibility of working from home, the latter expands the perspective by taking into account also jobs entailing only sporadic or no personal interactions, and complements information derived from O*NET with personal judgements to classify jobs along the infection risk dimension in six European countries.

Relying on the American Time Use Survey (ATUS), Hensvik, Le Barbanchon and Rathelot (2020[3]) compute the share of hours actually worked at home by American workers 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. Mongey, Pilossoph and Weinberg (2020[4]) combine the two approaches by using ATUS data to empirically validate the information on the feasibility of working from home (derived from O*NET) with the actual habits of workers. 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 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 both occupations and types of workers predicted to be employed in low work-from-home jobs experienced greater declines in employment with respect to pre-pandemic months.

Similar exercises have been carried out for a larger set of countries. Saltiel (2020[5]) focuses on 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[6]) 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.

Barbieri, Basso and Scicchitano (2020[7]) use the Sample Survey of Professions, the Italian equivalent to O*NET, to study risk profiles for workers in the Italian labour market. They find that workers in occupations that are exposed to infection and disease risks tend to work in close physical proximity to other people, and that several other sectors, mainly related to personal services, leisure and recreation are not directly exposed to infections and diseases, but need physical proximity to operate. They also find that groups who are at risk of contagion and complications from COVID-19 (mainly male, and workers aged above 50) work in sectors that are either little exposed to physical proximity (such as agriculture), that were under lockdown or can potentially work remotely (such as public administration and some education subsectors). 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.

Adopting a different perspective, Adams-Prassl et al. (2020[8]) 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.

In an early attempt to associate workers' safety risk and actual contagion, Lewandowski (2020[9]) 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.

Other recent works analyse the heterogeneity in the impact of COVID-19. Yasenov (2020[10]) provides evidence of the distributional effects of stay-at-home orders caused by the pandemic in the United States. He links O*NET data to the American Community Survey (ACS) to understand the types of workers holding jobs that can be done from home, finding that workers with lower wages, lower levels of education, younger workers, ethnic minorities and immigrants are less likely to work in occupations for which working from home is feasible. Using data from the Survey of Business Uncertainty (SBU), Barrero, Bloom and Davis (2020[11]) 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.

Finally, a set of papers focused on the unequal effects of the pandemic on different groups of workers. Borjas and Cassidy (2020[12]) 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 (2020[13]) 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[14]) 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. For instance, 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.

Using real time survey data from the project REPEAT for a number of OECD countries, Foucault and Galasso (2020[15]) 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. Adjustments took place over the lockdown weeks, with higher shares of workers becoming active both from home and from their workplace, but such adjustments benefitted mostly highly educated workers and white collars.

3. Methodology

Within the context of the COVID-19 pandemic, safe jobs are those that can be carried out with a minimal risk of being infected and of spreading the virus. 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 involve 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.

We classify jobs in four categories: three are based on different definitions of safety and the last is built as a residual category, containing jobs that can be deemed “unsafe” (again, under normal circumstances).

The first category contains all occupations that can be potentially performed remotely (*category 1*). These jobs do not require workers to leave their home, 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.

The second category relaxes slightly these constraints by adding jobs that require at most a low level of physical proximity on the workplace and a limited number of interactions with external customers and the public. Arguably, these jobs do not pose significant risks to workers’ health under a pandemic.

The third category still requires a low level of physical proximity, but allows for the inclusion of jobs that involve a higher degree of 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.

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.

Our first three categories are constructed so that *category 1* is a subset of *category 2*, which is in turn a subset of *category 3*. *Category 3* therefore consists of all jobs that can be considered safe according to our least restrictive definition of safety (and it includes *category 1* and *category 2* jobs). The fourth and last category is instead residual as it contains all remaining jobs, which we label “unsafe” from now on as they entail a relatively high risk of being infected by COVID-19.

In order to assign occupations to these 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[1]), and on our previous classification of occupations (Boeri, Caiumi and Paccagnella, 2020[2]), 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[1]), 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. The questions considered as well as the conditions imposed are listed in Annex A.

If any such condition is true, we classify a job as not suitable for remote working. For instance, if for a given job the average answer to question 4 from the "Work context" section ("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, and we therefore exclude it from *category 1*.

This procedure generates a dummy value for each job, which we then aggregate 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. Next, using as weights the 2018 US employment shares of SOC occupations from the BLS Employment Projections program, we map values from SOC occupations into ISCO 3-digit codes that identify occupations in the EU LFS data through weighted averages.[1] Thus, for each ISCO 3-digit code, we obtain a coefficient, ranging from 0 to 1, proxying the share of jobs that can be carried out remotely according to our definition and to the description of occupations contained in O*NET. 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.[2] 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 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.

In order to identify the jobs belonging to *category 2* and *category 3* we use other questions from O*NET, in particular those on physical proximity and contacts with public and customers:

"Work context": Q21 – "How physically close to other people are you when you perform your current job?" (value 3.5/5.0)

"Work activities": Q32 – " How important is performing for or working directly with the public to the performance of your current job?" (value 3.0/5.0)

Category 2 includes, in addition to jobs that can be conducted remotely, those that entail low physical proximity and limited exposure to customers and to the public. In other words, *category 2* includes all jobs already present in *category 1*, plus those that feature low average answers to

[1] While the objective of the Employment Projections (EP) program by the U.S. Bureau of Labor Statistics is to provide estimates of occupational trends over a 10-year projection period, we use it as crosswalk as it is 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.

[2] 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. Similarly 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 a more aggregate version of the complete SOC2010 classification (which instead is used to crosswalk to ISCO). Consequently, we covert this classification into the granular version of SOC. This is a 1:m 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 m:m 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).

both Q21 and Q32.[3] *Category 3* further relaxes this criterion by allowing jobs reporting higher values for Q32 ("Performing for or working directly with public" can display values above 3.0), as such jobs may also require substantial exposure to external persons, while still maintaining low physical proximity. At the same time, we require all jobs in *category 2* and *3* to meet the same condition imposed for jobs belonging to *category 1* with respect to question Q29 of the "Work section": "Average respondent says they are exposed to diseases or infection at least once a month". Any job exposed to diseases or infection according to Q29 is classified as unsafe, regardless of whether the conditions on low physical proximity and few contacts are met. Finally, with a procedure analogous to the one described before, we map dummy values from O*NET occupations to SOC occupations and then to ISCO 3-digit codes for *category 2* and *category 3* as well.

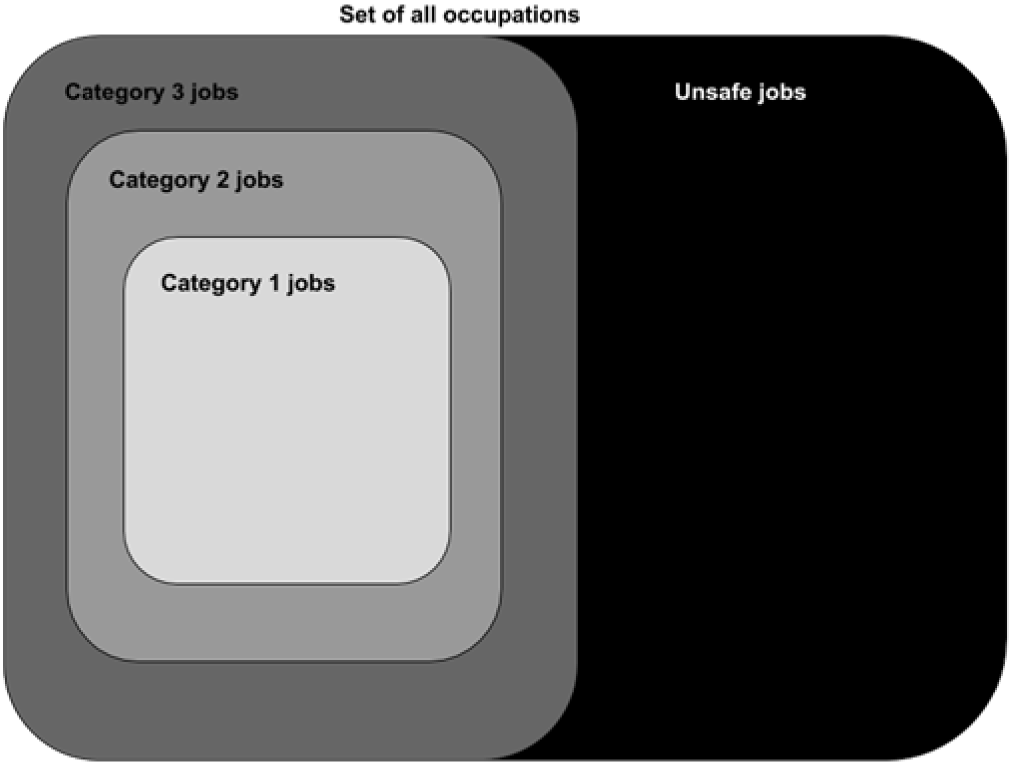
Having classified all occupations in one of these four categories, we can then compute the shares of *safe* jobs (where we consider a job safe if it belongs in one of the first three categories) in countries for which we have access to occupational identifiers from labour force surveys.

Some occupations well represent the categories that we identified.[4] For *category 1*, for instance, some ISCO codes report a coefficient equal to 1, the maximum value, indicating that these occupations have the highest number of workers who can *potentially* work remotely. Examples of such occupations are: information and communications technology service managers (ISCO 133), finance professionals (241), legal professionals (261), sales and purchasing agents and brokers (332), and secretaries (412). By construction, coefficients for these ISCO codes will also be equal to 1 for *category 2* and *category 3*.

For this reason, rather than looking at the highest coefficients for *category 2*, it is more informative to look at the ISCO codes that feature the largest increases in coefficients when moving from *category 1* to *category 2*. By doing this, we identify occupations where many workers cannot work from home but whose job entails low physical proximity and limited exposure to customers and the public.

[3] The 3.5 threshold for question Q21 corresponds to "Work more distant than arm's length", the 3.0 threshold for question Q32 corresponds to "Performing for or working directly with public is important".
[4] Detailed information on category coefficients for all ISCO 3-digit codes can be found in Annex A.

Figure 1. Occupation classification: safe and unsafe jobs



Note: The figure describes the relationship among the job categories identified according to different definition of safety. Remote working is the safest working arrangement so that *category 1* (light grey) is, by construction, a subset of *category 2* (grey), which in turn is a subset of *category 3* (dark grey), as the latter relies on the broadest definition of safety. Occupations not included in these three categories are classified as unsafe and belong to the residual category (black).

The five occupations for which the coefficient increases the most when moving from *category 1* to *category 2* are: mixed crop and animal producers (613), blacksmiths, toolmakers and related trades workers (722), wood processing and papermaking plant operators (817), other stationary plant and machine operators (818), and vehicle, window, laundry and other hand cleaning workers (912). Conversely, the occupations for which the coefficient increases the most when moving from *category 2* to *category 3* are social and religious professionals (263) and heavy truck and bus drivers (833). Wood treaters, cabinet-makers and related trade workers (752), subsistence crop farmers (631) and telecommunications and broadcasting technicians (352) also report lower but sizeable increases.

Finally, a few examples of “unsafe” occupations reporting a coefficient equal to 0 for *category 3* (i.e. ISCO codes with the highest number of workers in jobs belonging to the residual category) 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).

4. Data and Results

We apply our classification of occupations to labour force survey data for 2018 for EU countries (harmonised EU LFS data) and for the United States (CPS, averaging the 12 monthly waves), ending up with a sample of 27 countries: Austria, Belgium, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Luxembourg, the Netherlands, Norway, Portugal, Romania, the Slovak Republic, Spain, Sweden, Switzerland, the United Kingdom and the United States.[5]

For each country, Figure 2 reports the share of workers (either employees or self-employed persons) holding jobs that can be considered “safe” according to our taxonomy (*categories 1*, *2* and *3*). Workers in safe jobs make up more than 50% of overall employment in 22 countries out of 27. Overall, the average share of safe jobs, weighted by the number of employed individuals in each country, is 51.9%, with Luxembourg reporting the highest share (60.7%) and Spain the lowest (44.1%). The black portion of the bar represents the share of “unsafe” jobs for each country (residual category).

The figure also illustrates a breakdown according to the three categories defined above. The variation across countries in the incidence of the different categories is quite large.

The share of workers in *category 1* (i.e. jobs that can be performed from home), represented by the first light grey portion of the bars, ranges from 17.0% in Romania to 43.5% in Luxembourg, with a weighted average of 31.7% for the whole sample. As for *category 2*, given by the sum of the first two portions of the bars, Spain reports the lowest share (37.6%) and Luxembourg the highest (53.1%), with an overall weighted average of 44.9%. When we add also the jobs that require interaction with customers (*category 3*), the cross-country variation declines. This implies that countries in which fewer jobs can be done from home (*category 1*) have relatively more jobs that require infrequent personal contacts and that belong to *category 2* or *3*.[6]

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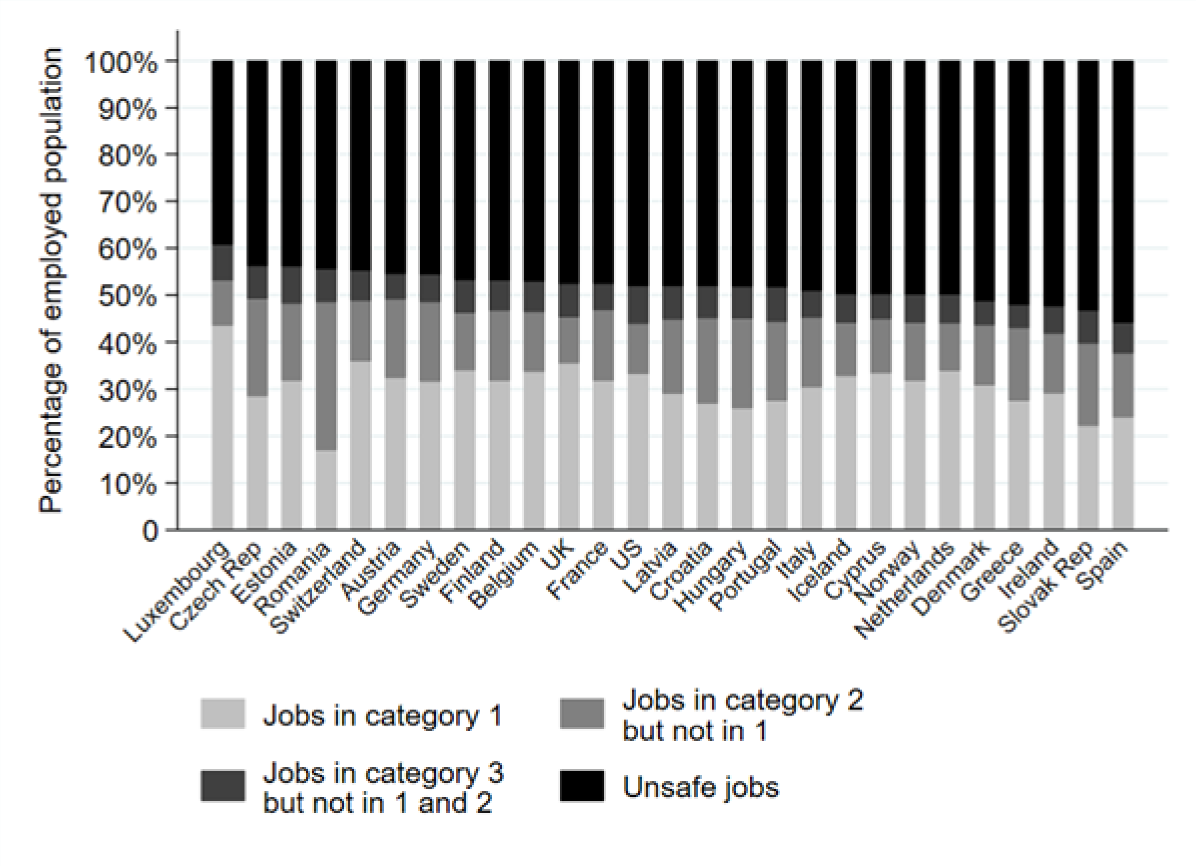
[5] We could not exploit data from Bulgaria, Lithuania, Malta, Poland and Slovenia due to missing information on many of the dimensions analysed.

[6] In the US the fraction of jobs that require contacts with customers in addition to co-workers and that are not suitable for remote arrangements, but are still considered safe according to our taxonomy, reaches 8%, the highest percentage of our sample.

Figure 2. Overall 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 27 countries of the sample. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

4.1. Heterogeneity across sectors, occupations and firms

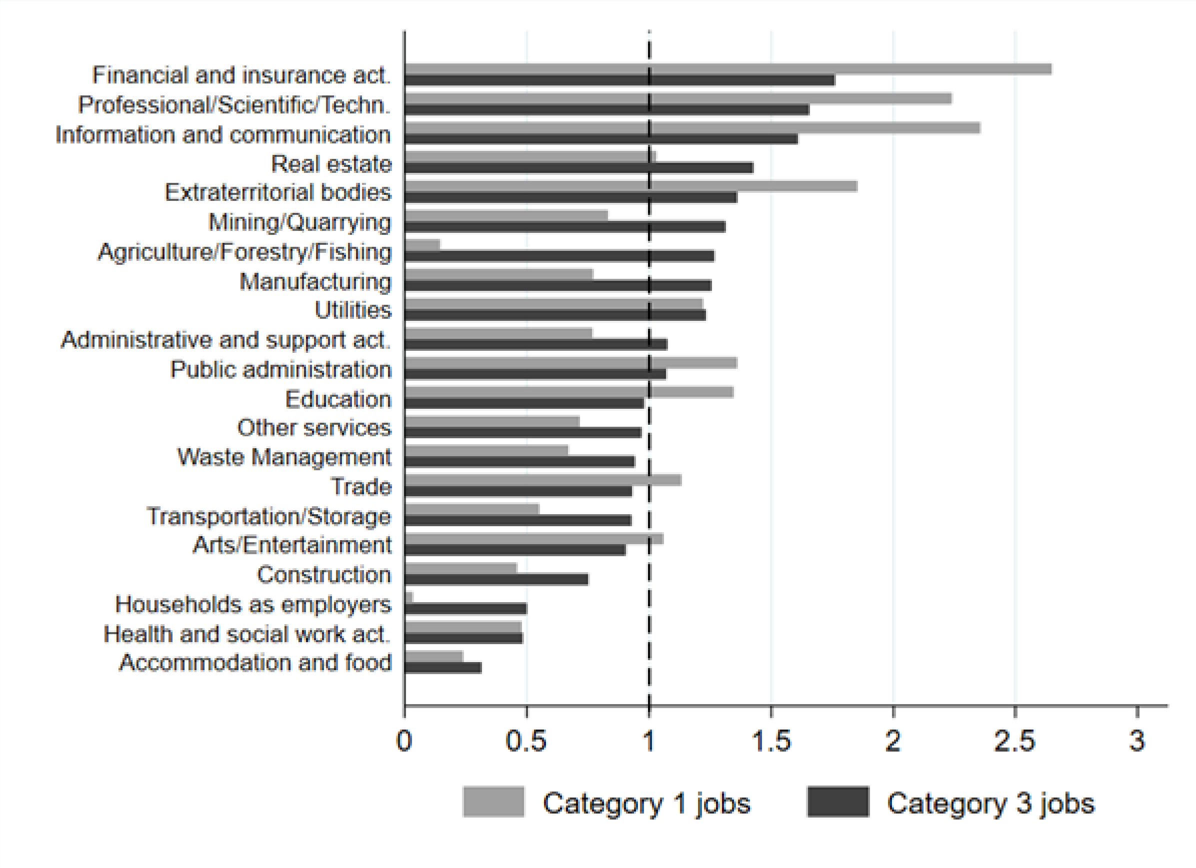
Figure 3 displays the distribution of jobs in *categories 1* and *3* across economic sectors, following the NACE Rev. 2 (2008) classification, pooling data from all countries in the sample.[7] Histograms display concentration indexes, computed as the ratio between the share of jobs of category i in sector j over the share of category i in total employment. A value greater (lower) than one of the index, denotes sectors over-represented (under-represented) in that specific category.

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 is twice as large as in the overall labour market. In these sectors, the share of jobs that can be considered safe according to our broader definition (*category 3* jobs) is close to 100%. At the other extreme of the distribution, sectors like “Human health and social work activities”, “Accommodation and food service activities” and “Households as employers” report the lowest concentration indices for *category 3* jobs. The agricultural sector represents a peculiar case: it has the second lowest share of jobs that can be conducted remotely, but when it comes to the share of safe jobs the concentration index is above 1. This can be explained by the fact that many activities

[7] We take a weighted average of the country-specific employment shares taking as weights the relative size of employment in each country and category. Information at the country level can be found in Annex A.

in agriculture can be carried out preserving physical distance among workers and only sporadic interactions are needed mostly with co-workers.

Figure 3. Concentration indexes of job categories by economic sector



Note: The figure shows concentration indexes for *category 1* and *category 3* jobs by economic sector (Nace rev 2). Concentration indexes are computed as the ratio between the share of jobs of category *i* in sector *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (vertical dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Focusing on occupations rather than on sectors, we find that the share of unsafe jobs is particularly large among health care professionals, personal care workers, food preparation assistants, and refuse workers (Annex Figure B.1 displays the five safest occupations and the five least safe occupations at the ISCO 2-digit level). Combined with Figure 3, the large cross-occupation dispersion in the incidence of safe jobs is an indicator of the likely extent of job and worker reallocation that will follow the pandemic. Indeed, given that job reallocation is the sum of employment-weighted firm-level employment growth rates, it is increasing in the heterogeneity of the impacts of the pandemic.

There is evidence that firms and workers are redirecting search away from these risky occupations (Hensvik, Le Barbanchon and Rathelot, 2020[3]), and surveys of employers indicate that firms implementing physical distancing may suffer marked declines in productivity and even in capacity and production levels. Thus, both labour demand and supply factors may induce substantial reallocation of jobs and workers away from these relatively unsafe occupations and sectors.

A significant downsizing can be expected in firms operating in sectors with lower productivity and in which labour supply will decline as a consequence of COVID-19. Before the pandemic, such firms were employing a significant portion of the overall workforce, but labour supply and labour demand are now self-reinforcing in reducing employment. Sectors like “Arts, entertainment and recreation” and “Accommodation and food service activities” jointly employ 29.1 million workers in our sample, corresponding to slightly less than 8% of total employment, a share comparable to half of that of the public sector.[8]

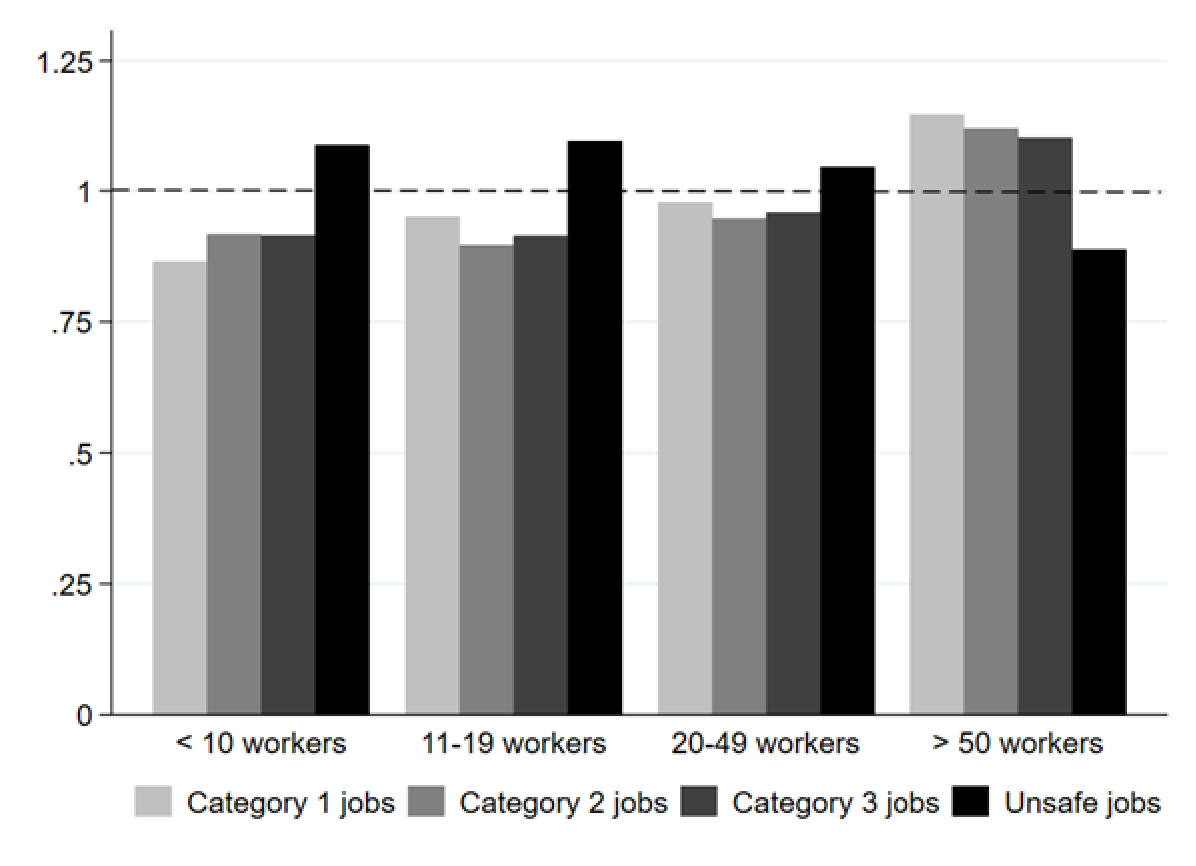
Job creation will likely be stronger in the health sector and in those industries that serve the health sector also as a result of stronger public expenditures in these strategic activities. Such industries revolve around two main poles: the pharmaceutical industry and healthcare services. The first 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.[9]

Unsafe jobs are also over-represented in small firms (Figure 4). This is consistent with the high risk of exposure that characterises jobs in the hospitality industry (e.g. the accommodation and food sectors), but may also have to do with the presence of fixed costs in organizing remote working. Early evidence from real-time privately-owned data in the United States also points to a concentration of job losses in small firms (Chetty et al., 2020[17]). 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[18]), although the take-up rate among SMEs has been relatively low (OECD, 2020[19]).

[8] Construction also features a large share of unsafe jobs. However, injury risk was particularly high in this sector even before the pandemic, and not all countries enforced the lockdown in construction. Thus, we consider it to be a rather special case.

[9] 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.

Figure 4. Concentration indexes of job categories by firm size



Note: The figure shows concentration indexes for job category by size of the firm. Concentration indexes are computed as the ratio between the share of jobs of category *i* in size group *j* over the share of category *i* in total employment, pooling data from 26 countries of the sample (data are not available for the US). Numbers greater (lower) than one (vertical dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: European Labour Force Survey (EU LFS).

4.2. Heterogeneity across rural vs. urban areas

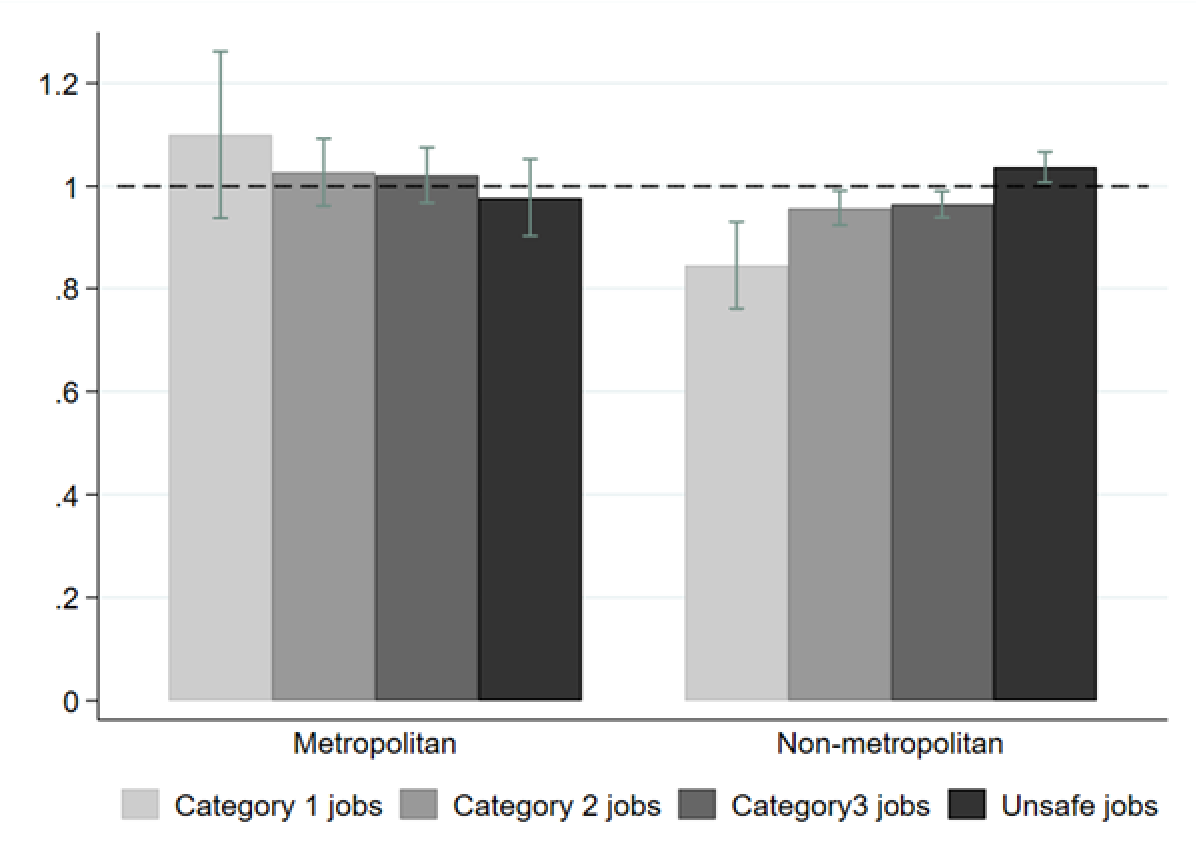
Another important dimension of potential reallocation relates to the place of residence of individuals. Higher population density is likely to increase the risk of infection, irrespective of the characteristics of jobs, as workers are for instance more likely to commute by public transportation. On the 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 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.[10]

Figure 5 documents that metropolitan areas feature a higher share of jobs that can be done from home (*category 1* jobs) compared to the whole economy, whereas safe jobs in general (including those in *category 3*) seem to be more evenly distributed across areas.[11] Vertical bars measure the

[10] 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.
[11] Metropolitan areas are defined as areas with more than 100,000 individuals. Annex Figure B.2 provides a more granular description of areas, relying on the EU LFS methodology to describe different degrees of urbanization (unfortunately, this breakdown is not available for the US). According to this breakdown, jobs that can be performed

cross-country variation in these concentration indexes. Additionally, non-metropolitan areas have, on average, a higher share of jobs belonging to *category 2* but not to *category 1* (i.e. jobs that entail low physical proximity and limited exposure to customers and public, but that cannot be conducted remotely). Likely, part of such jobs belongs to the agricultural sector, mostly present in rural and scarcely populated areas.

Figure 4. Concentration indexes of job categories by metropolitan and non- metropolitan area



Note: The figure shows concentration indexes of job categories by living area. Non-metropolitan areas are those with less than 100,000 inhabitants. For European countries, Towns and suburbs and Rural areas (as defined in EU LFS) are aggregated into Non-metropolitan. Concentration indexes are computed as the ratio between the share of jobs of category *i* in area *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

4.3. Heterogeneity across workers

The results presented so far suggest that a large fraction of workers (about one sixth of the total) may be at risk of dismissal, or are in any case likely to face significant changes in the way they

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remotely are over-represented in cities and under-represented in rural areas, whereas unsafe jobs are slightly over-represented in rural areas.

work, should the pandemic be long lasting. The high prevalence of unsafe jobs in small firms might also lead to the exit of business units and firms closures: job losses driven by firm exit, as opposed to downsizing of continuing units, would be less gradual. Traditional measures to smooth labour market adjustments over time – such as employment protection, and short-time work – or even the banning altogether of layoffs introduced in some countries, may prove rather ineffective in this context and are becoming unsustainable with the prolongation of the crisis.

It is therefore of uttermost importance to evaluate which categories of workers are likely to be most involved in the reallocation away from epidemiological hazard. In particular, a key issue is the extent to which this process will involve workers who were already in a vulnerable position at the outset of the crisis.

The analysis of the distribution of safe and unsafe jobs by worker characteristics can also shed light on the health complications potentially associated to a second wave of the pandemic. A key dimension to be considered in this context is age. A consensus seems to be emerging in the medical literature that males over the age of 60 are significantly more likely to develop serious or critical forms of COVID-19 infection (Poletti et al., 2020[20]). The evidence to date also points overwhelmingly to much higher mortality rates for elderly men.[12] The reallocation of older workers in safer occupations and/or of younger workers in riskier occupations can therefore potentially be an important mechanism through which mortality can be reduced while minimising the negative impacts on economic activity.[13]

The average age of workers in safe jobs is around 43, with little variation among the three different categories.[14] The average age of workers in jobs that we label unsafe is only slightly lower, at around 41. While the concentration index of safe occupations among older workers (55-65 years old) is slightly above 1, safe occupations are under-represented among the youngest workers (15-24 years old), a result that is consistent across all 27 countries (see Figure B.3 in Annex B). A similar pattern is detected if we consider specifically the relative presence of young workers in occupations that are suitable for remote working. 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 mortality during the pandemic.

This concentration of young workers in unsafe jobs may be related to selection effects: many occupations in *category 1* (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 occupation is steadily increasing with age up to the

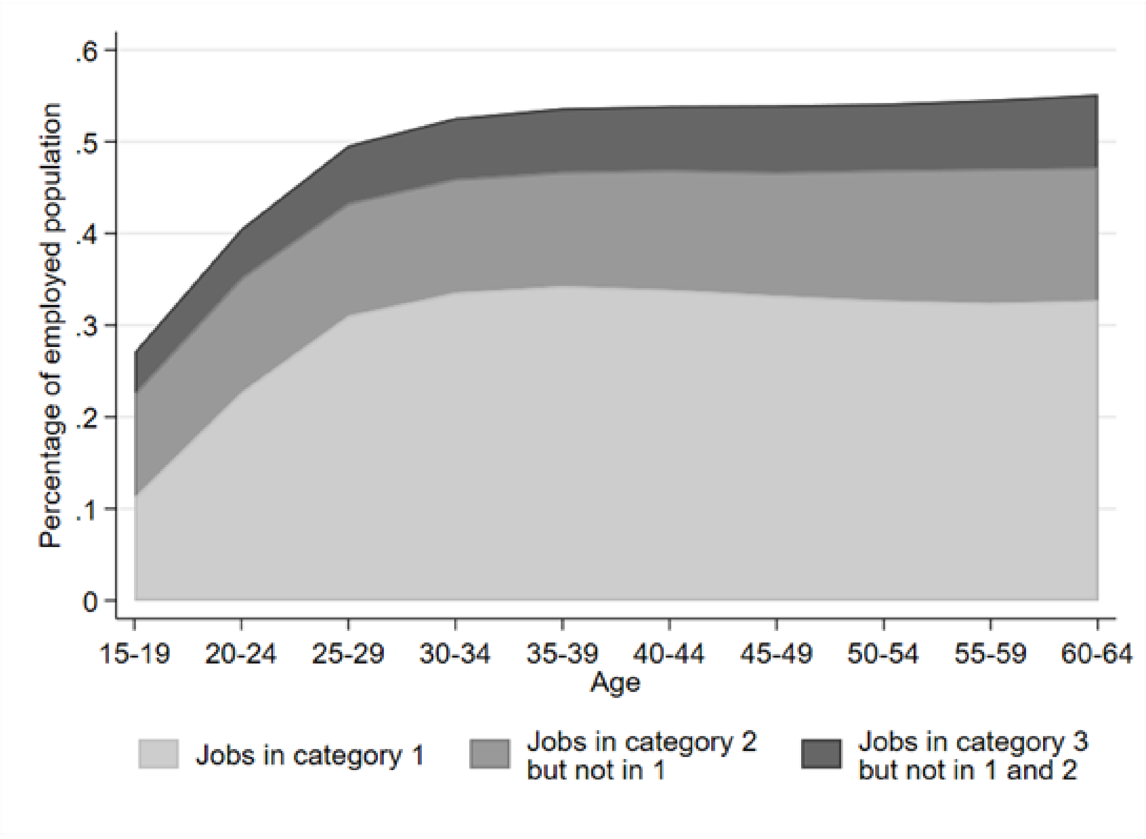
[12] It should be stressed here that age is of course not the only determinant of mortality risk from Covid-19, and that other pre-existing medical conditions probably play an important role. Unfortunately, we do not observe individual medical conditions in our data.

[13] Clearly being a young worker does not automatically makes the exposure to risky jobs worthwhile. However, an allocation of jobs where younger individuals are employed in riskier occupations is likely to drastically reduce mortality. Indeed, when riskier jobs are essential for the functioning of the economy and need to be performed, the best allocation is one where individuals performing them are those with lower probability of dealing with more aggressive forms of Covid-19. In this regard, the literature studying optimal lockdown policies often prescribes a differentiation in terms of age (see Acemoglu et al. (2020[28]) and Ichino, Favero and Rustichini (2020[29]). Moreover, it is worth stressing that here we are not considering spillover effects, notably the possibility of young workers transmitting the disease to more vulnerable members of their family or social network. This is of course an important issue to consider in the design of policies to contain the pandemic, but is something that we are not in a position to analyse with the available data.

[14] LFS data only report age as a categorical variable representing the midpoint of the 5-year age interval the individual belongs to. This clearly affects the precision of our estimates for the average age.

age of 39, and then stabilizes at about 54% (Figure 6). Moreover, people aged 25 to 34 years are over-represented in cities, whereas the age distribution is more skewed towards the oldest individuals in rural areas. 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 19 countries out of 27 (as depicted in Annex Figure B.4) 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).

Figure 6. Overall shares of jobs by category and age



Note: The figure shows the percentage of workers in the different job categories of our taxonomy, by age group. Pooled data from the 27 countries of the sample. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

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 (see Annex Figure B.5). 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 II. The over-representation of women in unsafe jobs involves all countries, with the exception of Cyprus, Greece and Romania (Figure B.6 in Annex B).[15]

[15] 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.

There is instead a monotonic relationship between the level of education of the workforce and exposure to epidemiological risk (see Annex Figure B.7), as low-educated workers are largely over-represented in unsafe jobs.

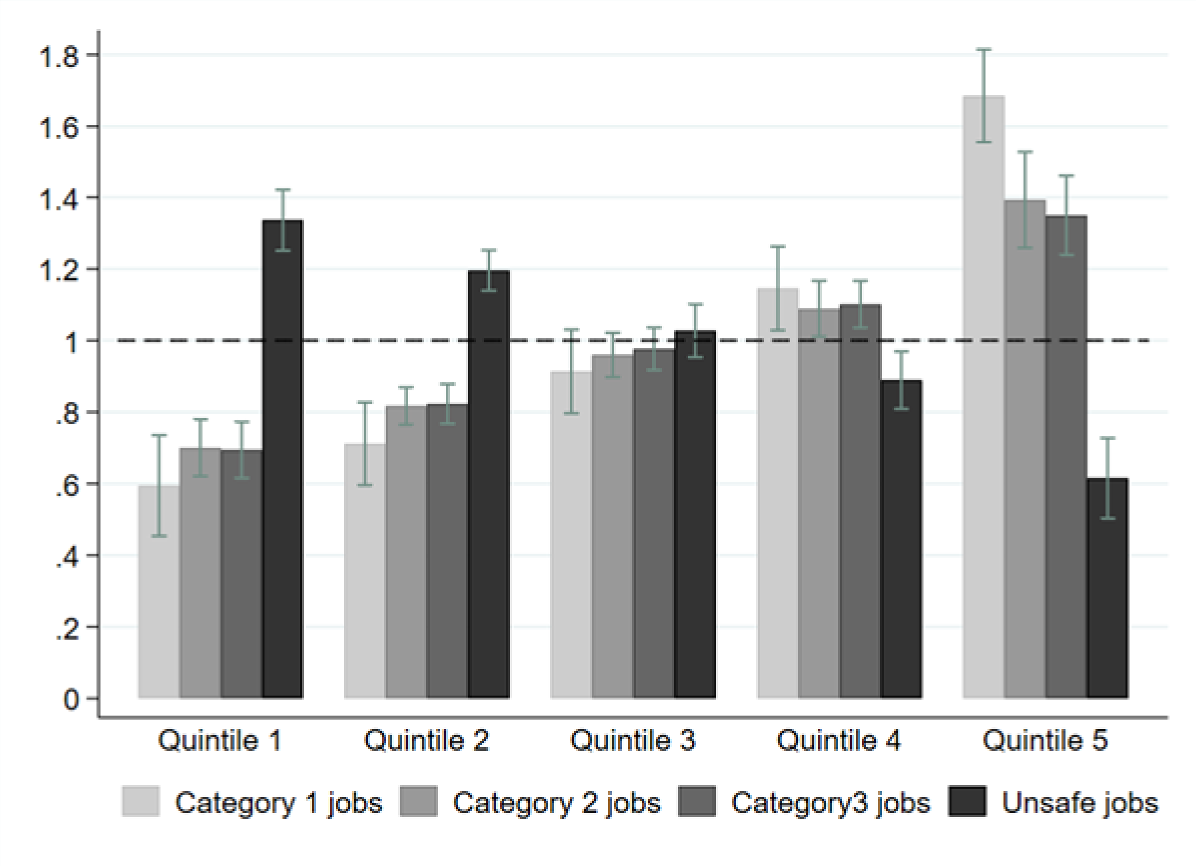
Finally, unsafe jobs are over-represented among migrants (see Annex Figure B.8). Indeed, as shown by Fasani and Mazza (2020[14]), unsafe occupations like cleaners and helpers, mining and construction, machine and food processing operators are often dominated by foreign-born workers.

4.4 Hazardous jobs and economic vulnerability

A better assessment of the economic vulnerability of the workers most likely to be made redundant in case of a long lasting epidemiological risk may come by analysing endogenous (to the labour market) characteristics such as incomes, job security, and under-employment.

Figure 7 reports concentration indices by quintile of the earning distribution. The focus here is on dependent employment. Workers holding safe jobs are seriously under-represented at the bottom of the distribution. This is especially true for jobs in *category 1*, whose prevalence markedly increases as we move toward the upper quintiles of the earnings distribution.

Figure 7. Concentration indexes of job categories by income quintiles



Note: The figure shows concentration indexes for job categories by income quintile. Concentration indexes are computed as the ratio between the share of jobs of category *i* for quintile of income *j* over the share of category *i* in total employment, pooling data from 20 countries of the sample. Data on income for Austria, the Czech Republic, Finland, Iceland, Norway, Spain and Sweden are not available. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of mean of the country-specific concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

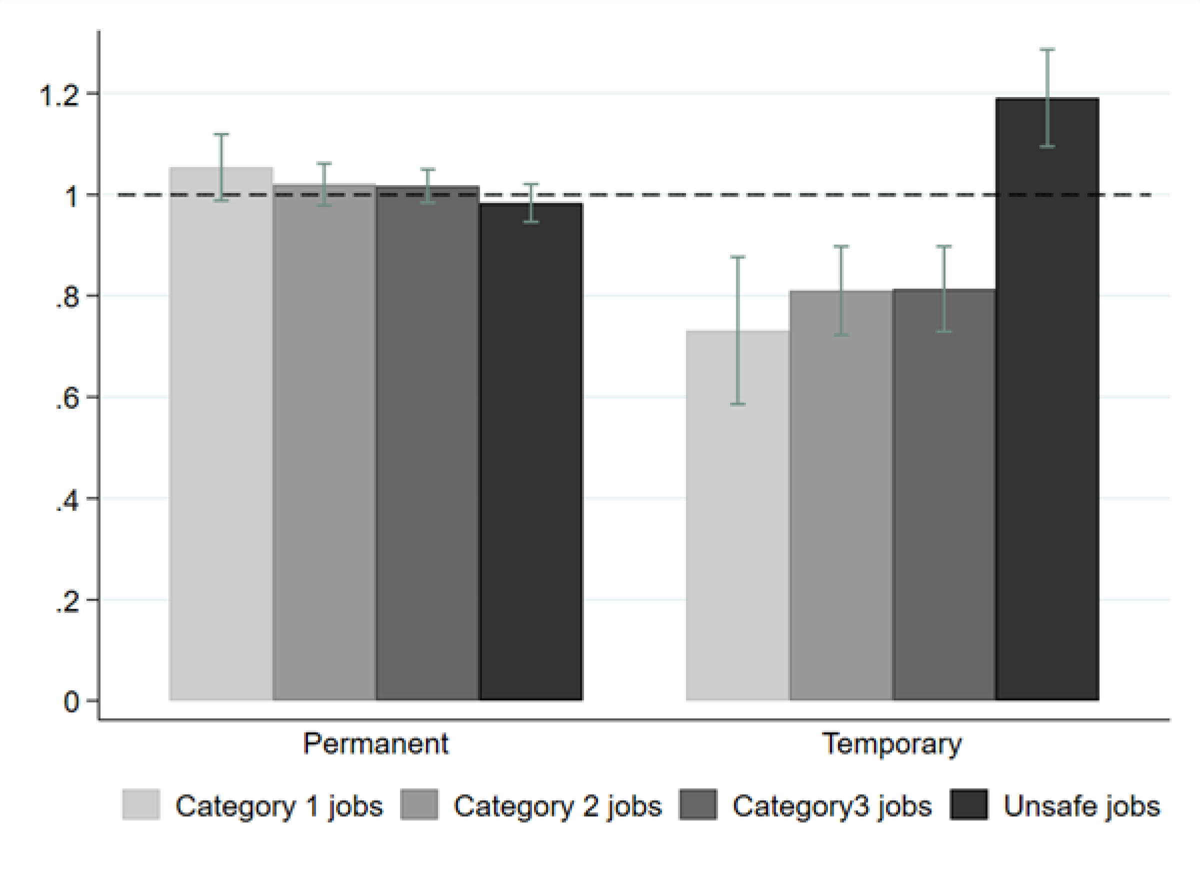
We also find a strong concentration of unsafe jobs in families of more than five members. Incidentally, large families may be at a serious disadvantage also when carrying out safe jobs: home is arguably a very poor substitute to the office if a large family lives in a small apartment, especially if children or other family members require assistance by those staying at home (e.g. because of school closures).

Finally, epidemiological risk appears to be positively correlated with unemployment risk. Job losses are typically concentrated on fixed-term contracts, especially in European countries with strong employment protection legislations. These contracts are over-represented in the pool of unsafe jobs (Figure 8), and such evidence is consistent across all the countries under investigation.[16] Part-timers are also disproportionally involved (Figure 9) and they are frequently under-employed (27.2% of part-time was involuntary in the EU27 even in the buoyant labour

[16] Concentration indexes for unsafe jobs among workers with a temporary contract are above 1 for all 26 countries analysed. Austria, Switzerland and Germany report the lowest figures (around 1.1), whereas Romania and Estonia the highest (around 1.5).

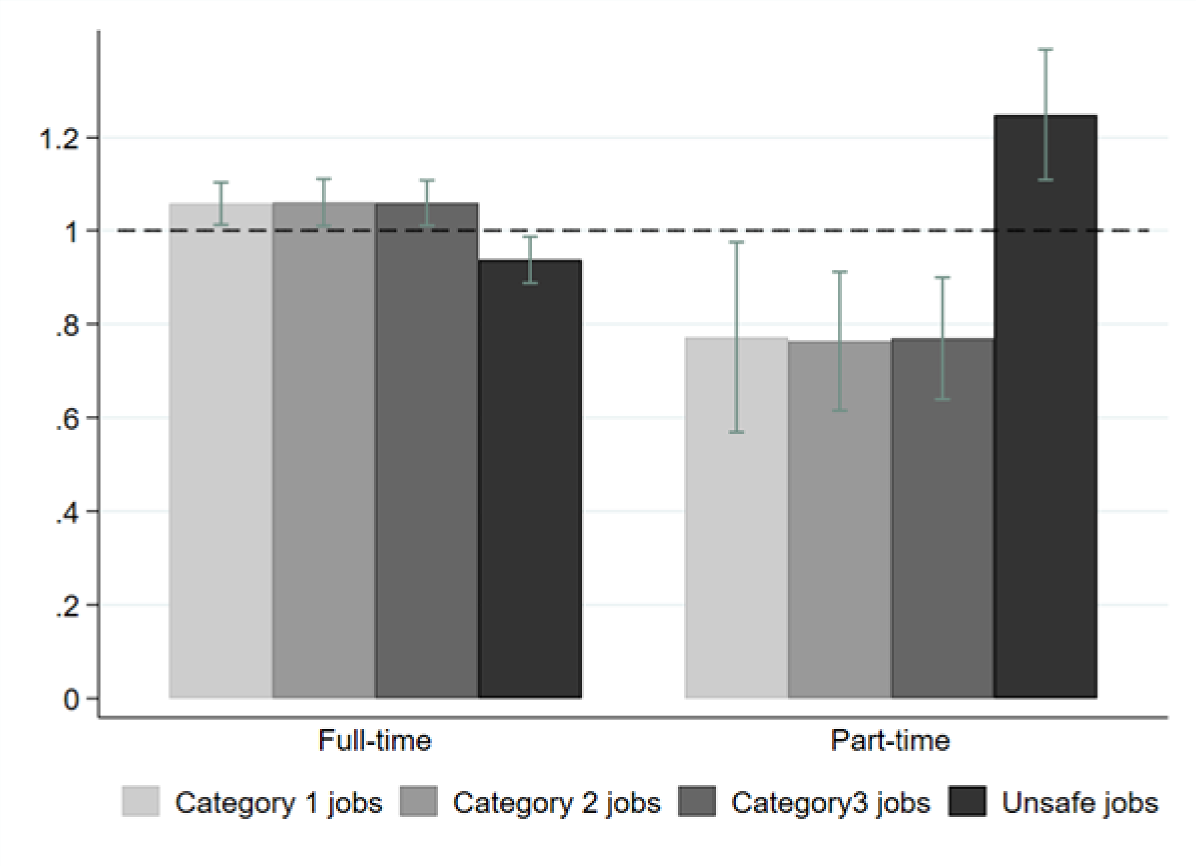
market conditions of 2018). In the United States solo self-employed are also over-represented in the pool of unsafe jobs. Overall, it should not come as a surprise that unsafe jobs are more prevalent among workers with relatively short tenures (i.e., having been for less than 6 months in the current job).

Figure 8. Concentration indexes of job categories by type of contract



Note: The figure shows concentration indexes for job categories by contract type. Concentration indexes are computed as the ratio between the share of jobs of category *i* for type *j* over the share of category *i* in total employment, pooling data from 26 countries of the sample (data are not available for the US). Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure 9. Concentration indexes of job categories by working time arrangement



Note: The figure shows concentration indexes for job categories by working-time arrangement. Concentration indexes are computed as the ratio between the share of jobs of category *i* for arrangement *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

5. Easing workers' reallocation in a pandemic

The previous Section presented a detailed snapshot of the distribution of workers in safe and unsafe jobs along several dimensions. This Section reflects on how such a distribution is likely to change, and how policies can accompany and ease job and workers reallocation and strike the best possible balance between preserving economic activity and avoiding as much as possible a further spread of the virus.

In doing so, we will touch upon four separate, but interrelated issues. First, we will discuss how the pandemic is having a very uneven impact, inflicting damages mostly to workers that were already vulnerable according to various dimensions. A priority for policy is clearly to increase the level of protection for these workers. Second, we will take a closer look at essential occupations, i.e. those jobs that, irrespective of how risky they are, need to be carried out even under the most restrictive measures that can be put in place to contain the propagation of a virus. Third, we will investigate how market mechanisms are operating to incorporate the new information about the risk of infection associated with some occupations. In particular, we will document that up until 2018 unsafe occupations were not enjoying a wage premium, indicating that epidemiological risk was likely not accounted for in the wage determination process. Preliminary evidence for the United States seems to suggest that this is changing, and the risk of infection is starting to be incorporated in wages. Finally, we draw on data on the ICT skills of workers in a number of OECD countries to reflect on the likely effects on training needs generated by the increased diffusion of remote working.

5.1. Targeting and reallocation

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[22])). 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. These workers are then at a double disadvantage, as they might have lower chances of finding a new job following a pandemic-induced layoff and they had already a weak labour market position before the crisis.

The fact that SMEs are hit particularly hard in this recession, compared for instance with the Great Recession, 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.

There is a core group of workers who are particularly exposed to long spells of joblessness and labour market related hardship. This group is mainly composed of individuals with low levels of education, currently employed in small units and performing unsafe occupations in the two sectors mentioned at the outset (arts, entertainment and recreation, and accommodation and food service activities). We estimate that in the countries covered by our analysis there are 2.0 million such individuals, representing 0.5% of the total workforce and 6.7% of the total employment in the two aforementioned sectors.[17]

These very vulnerable groups, as the other holders of unsafe jobs, are distributed rather uniformly over the age distribution above the prime age, and involve typically a higher share of very young people (below the age of 25).[18] Hence, 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 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.[19] These measures were necessary during the lockdown, but can only be temporary. If protracted over time, they would hinder worker reallocation.

Reallocation is even more important when account is made of the increasing number of people put at the margin of the labour market by the hiring freeze and the collapse of new business start-ups. STW is more costly than unemployment benefits because not only it typically offers higher replacement rates than unemployment benefits, but it also involves moral hazard problems that

[17] Since information on firm size are not available for the US, we assume that the EU share of workers in firms with less than 20 employees among low-educated workers in unsafe jobs in the two aforementioned sectors is equal to the US one for the same set of individuals.
[18] See Annex Figure B.9.
[19] See OECD (2020[18]) for a review of the economic initiatives undertaken so far by different countries.

can be particularly serious in the case where there is no experience-rating and small firms are involved that operate in sectors not directly exposed to the pandemic risk.

Serious consideration should therefore be given to: 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[20], 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.

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.

Most of the job creators – notably those related to the health value chain – could involve mainly skilled workers, hence may not offer employment opportunities to the twice vulnerable groups described above. 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, as discussed in the next section.

5.2. Essential and non-essential jobs: How risky? Who does them?

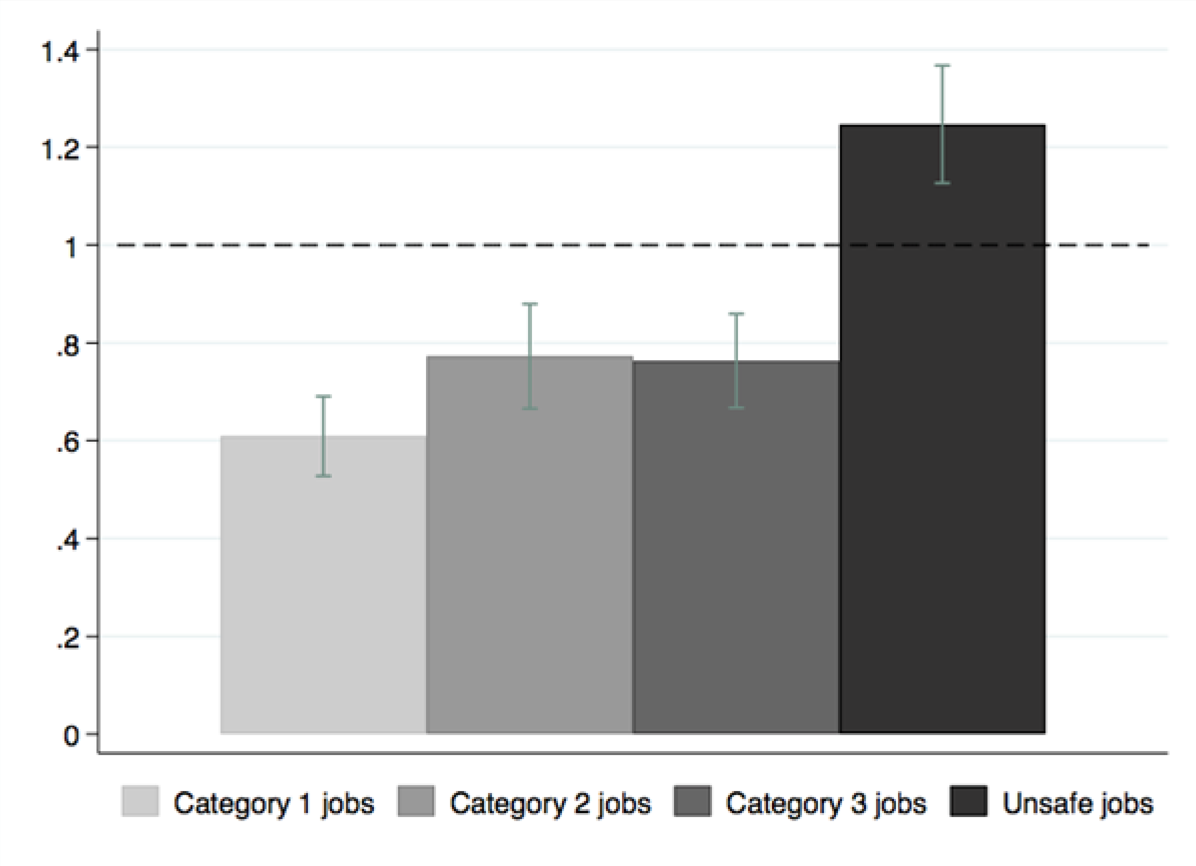
In order to identify those jobs that can be considered essential, we use the taxonomy provided in Fasani and Mazza (2020[14]), which identifies the occupations that need to be performed even during a pandemic in order to keep citizens healthy, safe and fed. The list of such "key" occupations can be found in Table A.19 in Annex A.

Essential occupations employ 119.5 million workers in our sample, representing 32.5% of the total employment.[21] About 60% of these essential workers (roughly 70 million people) hold a job that we classify as unsafe. Indeed, as shown by Figure 10, 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, safe jobs, notably 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.

[20] 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.

[21] Information at the country level can be found in Table A.20 in Annex A.

Figure 10. Concentration indexes of job categories in essential occupations



Note: The figure reports concentration indexes of job categories in essential occupations. Concentration indexes are computed as the ratio between the share of jobs of category *i* in occupations considered essential over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

These jobs often offer low wages, and employ disproportionally migrant workers who have typically lower reservation wages than natives.[22]

To attract more workers (and in particular young workers who are less exposed to the risk of severe forms of COVID-19), under conditions in which migration is restricted by tighter border controls, wages should compensate for the higher epidemiological risk involved by these jobs, a risk that was not perceived before the COVID-19 pandemic, as documented in the following section.

The notion of "essential" occupations also allows for the identification of an additional group of highly vulnerable workers, namely people holding unsafe jobs in non-essential occupations. These workers are in fact likely to face a particularly high risk of layoff, as their jobs are presumably among the first to be affected by lockdown measures and among the last to be authorised to

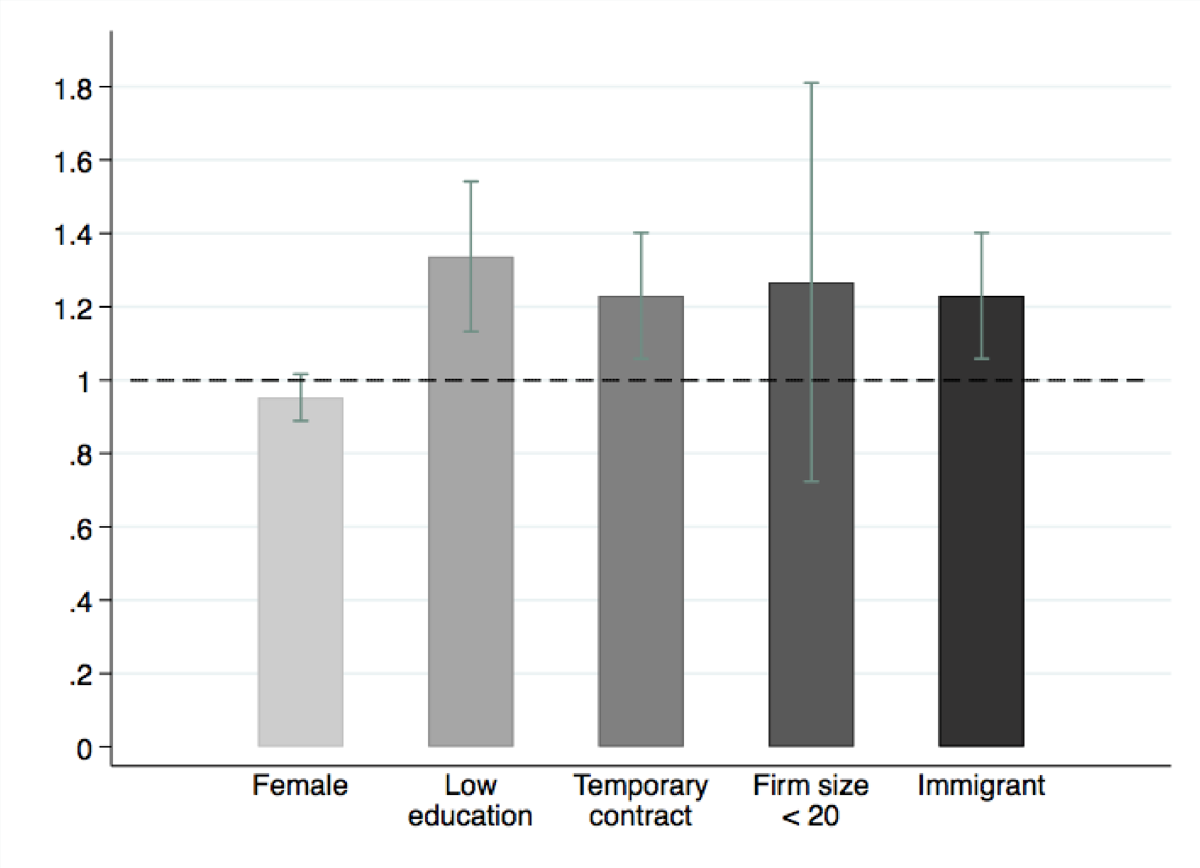
[22] In the US, the only country for which we have data on ethnicity, black and other minority ethnic groups tend to be over-represented in unsafe occupations. On the contrary, Asians tend to be over-represented in *category 1* jobs while white individuals perform mostly perform jobs in safe occupations, but in no specific category (see Figure B.10 in Annex B).

resume, or likely to face a substantial decline in demand. 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).

Similar to what we found for vulnerable workers considered in the previous section (i.e. individuals with low education levels, in small firms in arts, entertainment and recreation, and accommodation and food service activities), the traits associated with labour market hardship are over-represented among workers with unsafe jobs in non-essential activities. Figure 11 shows that being an immigrant, having a temporary contract and having a low level of education are predominant characteristics among these workers.[23] Not surprisingly, accommodation and food service activities, commercial and wholesale trade, construction, other services, and arts, entertainment and recreation sectors are over-represented among holders of unsafe jobs in non-essential occupations.[24]

[23] The age distribution of these workers, however, does not show relevant differences compared to the economy-wide distribution. See Figure B.11 in Annex B.
[24] See Figure B.12 in Annex B.

Figure 11. Concentration indexes of workers' characteristics in unsafe non-essential occupations



Note: The figure shows concentration indexes of individual characteristics for workers holding unsafe jobs in non-essential occupations (as defined by Fasani and Mazza, 2020). Concentration indexes are computed as the ratio between the share of workers with a specific trait among holders of unsafe jobs in non-essential occupations over the share of workers with that specific trait in total employment, pooling data from the 26 countries of the sample (data not available for the United States). Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) for that specific characteristic. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: European Labour Force Survey (EU LFS).

5.3. A risk-premium in unsafe jobs?

In a perfect labour market – where both workers and firms are price takers – in presence of a double heterogeneity (workers having different views as to their preferred income-risk combination and firms using different technologies) equilibrium wages compensate for differences in job-related health risk. More risk averse workers would accept lower wages only in exchange to a lower exposure to job related health risk. The opposite would happen for less risk-averse workers, as they would accept risky jobs insofar as they are paid more than the other jobs.

There is therefore a matching of workers and firms in either relatively low-pay and low-risk jobs or in high-pay and high-risk positions. These equilibrium *compensating wage differentials* involve wage premia allotted as a reward for workers facing higher job-related epidemiological risk.

The above holds insofar as both workers and firms are perfectly informed about risk. Absent the perception of risk among workers, they would all rank best paid jobs above all other jobs. In other words, there will not be the double heterogeneity (on the supply and demand side) required to have an equilibrium with compensating wage differentials. The equilibrium distribution of wages will be degenerate even if firms use different technologies.

We may think of the situation before the outbreak of the COVID-19 pandemic as one where the perception of epidemiological risk was absent among workers and employers. Under these conditions, we should not expect to observe a premium on unsafe jobs. Actually, some features that increase the epidemiological risk of jobs – such as frequent personal contacts with a heterogeneous and dynamic crowd – may actually be valued by some workers and preferred over jobs that are largely carried out in isolation.

The tables below show estimates of the risk premium (the coefficient associated to jobs involving epidemiological risk according to our definition) in 2018, i.e. well before COVID-19 when the epidemiological risk was likely not perceived by workers. We measure the riskiness of the job with the same index that we use to identify jobs belonging to *category 3*, i.e. our broadest definition of "safe" jobs. As LFS data allow for a limited breakdown of occupations and use ISCO codes, our index is not a binary variable, but it takes values between 0 and 1 depending on the share of safe jobs in any given occupation belonging to the 3-digit ISCO classification (in the EU LFS data) and to the more granular SOC classification of US data (for CPS regressions). Higher values of the index denote less exposure to risk in that occupation.

As the harmonised EU LFS do not contain information on wages, we first run our regression on CPS data for the United States (Table 1), and then we replicate the same exercise using data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC), covering 21 countries that participated in the survey in 2011-12 (Table 2). As in the EU LFS data, PIAAC classifies occupations using ISCO.

We find no wage premium for risky jobs, but rather a premium on safe jobs (or a discount on unsafe jobs). The premium narrows down as we add more covariates, i.e., as we make jobs more comparable along the epidemiological risk dimension. This can be seen by comparing in Table 1 the coefficient for safe job in the baseline specification (first column), to the specification with Mincer-type controls (education and tenure, second column) and to the specification with an extended number of controls (third column).

The additional covariates are generally statistically significant and with a sign in line with a priori expectations: for instance, being a woman, being an immigrant, having a part-time job are all traits connected to lower earnings. This suggests that we are improving our specification and that there may be other characteristics (not captured by our data) that could explain why unsafe jobs appear to be paid less than safe jobs even when we use extended controls. It should also be stressed that results for the US are consistent between the two datasets employed (CPS and PIAAC), with the coefficients on the main variables of interest that are always positive and statistically significant.

The main interest of using PIAAC data in this context lies in the fact that they include Asian countries like Japan and South Korea. As in the more recent past residents of these countries have already been exposed to epidemiological risks similar to those induced by COVID-19, they might have a higher awareness of the risks caused by jobs that require to have frequent personal contacts with a large and varying number of people. Despite these considerations, a wage premium on safe job is present also in these countries, and its size is larger than in many European countries.

A possible interpretation of these results is that, in addition to lack of information about epidemiological risk, unsafe jobs are more prevalent among workers with a relatively low bargaining position (and employers with monopsony power). This is consistent with our finding about the over-representation of migrants, temporary workers, solo self-employed, and low educated individuals in unsafe jobs. Moreover, the match between safe jobs and productivity-enhancing technologies could also contribute to explain these results.

Table 1. Wage premia on safe jobs – United States 2018

Variables	Baseline	Controls	Extended
	Log(weekly earnings)	Log(weekly earnings)	Log(weekly earnings)
	(1)	(2)	(3)
Safe job	0.514***	0.324***	0.148***
	(0.0903)	(0.0584)	(0.0360)
Age		0.0828***	0.0339***
		(0.00555)	(0.00450)
Age sq		-0.000838***	-0.000308***
		(5.78e-05)	(4.92e-05)
Education (middle level)		-0.172	-0.0109
		(0.118)	(0.0975)
Education (high level)		0.647***	0.0976
		(0.151)	(0.117)
Foreign-born			-0.0832***
			(0.0118)
Area 1			0.0529***
			(0.00710)
Area 2			0.139***
			(0.00957)
Female			-0.170***
			(0.0135)
Part-time			-0.927***
			(0.0244)
Constant	6.329***	4.142***	5.337***
	(0.0671)	(0.135)	(0.132)
Observations	157,286	157,286	157,286
R-squared	0.078	0.273	0.481
Age # education	NO	YES	YES
Age sq # education	NO	YES	YES
No. children dummies	NO	NO	YES
No. children # gender	NO	NO	YES
Sector dummies	NO	NO	YES

Note: Robust standard errors in parentheses, clustered at occupation level. *** p<0.01, ** p<0.05, * p<0.1.
Area 1: between 100k and 1 mln residents; area 2: more than 1 mln residents
Source: Current Population Survey (CPS, 2018).

Table 2. Wage premia on safe jobs – PIAAC data

Countries	Baseline	Controls	Extended controls	Observations for specifications (1) and (2)	Observations for specification (3)
	Safe job coeff	Safe job coeff	Safe job coeff		
	(1)	(2)	(3)	(4)	(5)
Austria	0.371***	0.247***	0.192***	2,823	1,721
	(0.0707)	(0.0518)	(0.0425)		
Flanders (Belgium)	0.222***	0.133***	0.102***	2,595	1,811
	(0.0578)	(0.0327)	(0.0299)		
Canada	0.381***	0.213***	0.106**	15,915	10,118
	(0.100)	(0.0699)	(0.0503)		
Czech Republic	0.273***	0.187***	0.128**	2,527	1,624
	(0.0771)	(0.0566)	(0.0563)		
Germany	0.458***	0.271***	0.137**	3,065	1,878
	(0.0934)	(0.0605)	(0.0550)		
Denmark	0.308***	0.175***	0.123***	4,316	3,155
	(0.0581)	(0.0316)	(0.0242)		
Spain	0.256***	0.118*	0.0230	2,338	1,464
	(0.0936)	(0.0614)	(0.0504)		
Estonia	0.397***	0.320***	0.231***	3,877	2,895
	(0.0905)	(0.0824)	(0.0569)		
Finland	0.319***	0.230***	0.140***	3,083	2,102
	(0.0637)	(0.0512)	(0.0417)		
France	0.324***	0.189***	0.153***	3,544	2,516
	(0.0748)	(0.0561)	(0.0453)		
England / N. Ireland (UK)	0.521***	0.406***	0.301***	4,639	2,880
	(0.0879)	(0.0635)	(0.0540)		
Ireland	0.319***	0.179**	0.148**	2,623	1,536
	(0.114)	(0.0760)	(0.0582)		
Italy	0.286***	0.147**	0.0782	1,673	901
	(0.0877)	(0.0632)	(0.0582)		
Japan	0.408***	0.293***	0.152***	3,146	1,909
	(0.110)	(0.0901)	(0.0509)		
Korea	0.458***	0.277***	0.184**	2,999	1,905
	(0.0965)	(0.0753)	(0.0804)		
Netherlands	0.444***	0.204***	0.157***	3,071	1,894
	(0.0869)	(0.0414)	(0.0295)		
Norway	0.309***	0.201***	0.100***	3,075	2,104
	(0.0668)	(0.0414)	(0.0303)		
Poland	0.337***	0.157**	0.0967	3,750	1,475
	(0.121)	(0.0651)	(0.0700)		
Slovak Rep.	0.346***	0.237***	0.143**	2,389	1,655

	(0.0797)	(0.0524)	(0.0549)		
Sweden	0.258***	0.219***	0.152***	2,765	1,891
	(0.0418)	(0.0387)	(0.0305)		
United States	0.550***	0.327***	0.182***	2,712	1,736
	(0.111)	(0.0782)	(0.0595)		

Note: Standard errors in parenthesis, clustered at the occupation level*** p<0.01, ** p<0.05, * p<0.1. The table reports three different specifications of a Mincer-type wage regressions run using PIAAC data. The dependent variable is log hourly wage. Only the coefficient on the main variable of interest "safe job", proxying for the share of safe jobs in each occupation, is reported. The specification reported in column (1) does not include any additional regressors other than the constant. In column (2) we add age, age squared, education dummies, age-education interactions, age squared-education interactions as controls. In column (3) we further add dummies for economic sector, gender, immigrant status, part-time job, number of children, and number of children-gender interactions.
Source: Survey of Adult Skills (2011/12)

To the extent that our inability to find a wage premium for risky jobs is due to the lack of awareness about infection risk prior to 2020 (or, rather, to the absence of that risk), we should expect the situation to change in recent months, at least for new hires. However, the information needed to observe this shift is rather limited. We resort to monthly CPS data for the United States, whose last wave at the time of writing cover April 2020. If we conventionally assume the pandemic to become common knowledge around February 2020, we can see whether between February and April 2020 we can detect a tendency for wages to rise in riskier occupations.[25] Unfortunately, we are not able to identify recent hires in the CPS, which makes it more difficult to detect the shift we would like to observe. Still, in spite of these difficulties, results in the first column of Table 3 do provide some suggestive evidence pointing to a reduction in the wage premium associated to safe jobs in the three months following the outbreak of the pandemic. Splitting the sample between essential and non-essential occupations, we see that this effect is more pronounced in essential jobs, where the premium associated to safe jobs was already smaller to begin with.

[25] Results change very little if we assume that the post-pandemic period started in March rather than in February. The estimated coefficient is less precisely estimated, but qualitatively similar.

Table 3. Wage premia on safe jobs – United States 2018-2020

	Log(weekly earnings) (1)	Log(weekly earnings) (2)	Log(weekly earnings) (3)	Log(weekly earnings) (4)	Log(weekly earnings) (5)
Safe job	0.146***	0.108***	0.112***	0.187***	0.339***
	(0.0036)	(0.0066)	(0.007)	(0.003)	(0.004)
Post	0.0606***		0.066***		0.064***
	(0.0066)		(0.010)		(0.009)
Post # Safe job	-0.021***		-0.043***		-0.023*
	(0.0086)		(0.015)		(0.012)
Obs.	356,048	129,251	129,251	265,039	265,039
R-sq.	0.478	0.467	0.467	0.488	0.283
Sample	Full sample	Essential jobs only	Essential jobs only	Non-Essential jobs only	Non-Essential jobs only

Note: Robust standard errors in parentheses, clustered at occupation level. *** p<0.01, ** p<0.05, * p<0.1. All specifications control for the extended set of regressors as in column 3 of Table 1.
Source: Current Population Survey (CPS, 2018, 2019, 2020).

Clearly, at this stage, we can only speculate on future developments, as the availability of data is still limited to analyse more deeply the changes in perceptions and wages produced by COVID-19. There is no doubt that workers (and employers) are informed about this risk by now. It seems reasonable to imagine that unsafe wages should increase relative to safe wages to induce workers to supply labour in unsafe occupations. To match workers requests, firms will be required to provide higher wages for these jobs and/or mitigate the health risks by adopting safety and distancing measures, although such actions could have a negative impact on productivity. On the other hand, workers in some unsafe jobs (for example hospitality and tourism) are among those hardest hit by the crisis. This might have worsened workers' relative bargaining position, and thus obstructed the upward adjustment of relative wages in (some) unsafe jobs. The distinction between essential and non-essential occupations is particularly important in this respect, as arguably workers in essential occupations have experienced an increase in their bargaining power. There is therefore the risk of a decline of employment and production capacity in essential goods and services through a reduction of the supply of labour. Such risk would be even stronger the more relatively elastic is final demand. 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. 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.

5.4. Workers training and reallocation

On-the-job training and retraining of unemployed adults will play a major role in mitigating the negative effects of the pandemic on employment and productivity. Not only workers will move away from 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[23]).

While it is too early to assess the extent of these changes, it is highly likely that training in digital skills should be required to ease this reallocation. Digitalization will be pervasive beyond *category 1* safe jobs, where remote working is already in place: it 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.

PIAAC provides a valuable source of information on the training needs of the population in working age in different countries. It included an assessment of Problem Solving in Technology-Rich Environment (PSTRE), aimed at evaluating the ability of adults to solve problems and perform a wide range of tasks using digital devices (PIAAC Expert Group in Problem Solving in Technology-Rich Environments, 2009[24]).

Adults taking the assessment are placed in 4 different proficiency levels, depending on their score: Below Level 1, Level 1, Level 2 and Level 3.[26] The conceptual framework allows to describe to some details what adults at different levels are actually able to do. For instance, adults scoring Below Level 1 are only able to perform tasks based on well-defined problems involving the use of only one function within a generic interface to meet one explicit criterion without any categorical, inferential reasoning or transforming of information.

Figure 12 shows that in all countries the share of workers scoring Below Level 1 is higher in unsafe than in safe jobs.[27] On average across countries, 37 percent of workers in unsafe jobs score Below Level 1, compared to 22 percent of workers holding safe jobs. A similar picture emerges if we focus on adults with very low ICT skills (those without previous computer experience, or who failed the ICT test, or who refused to take the computer assessment): on average across countries, 13 percent of workers employed in safe occupations have very low ICT skills, compared to 23 percent of workers in unsafe jobs.[28] This evidence confirms the prior that re-training policies will need to target workers in unsafe jobs.[29]

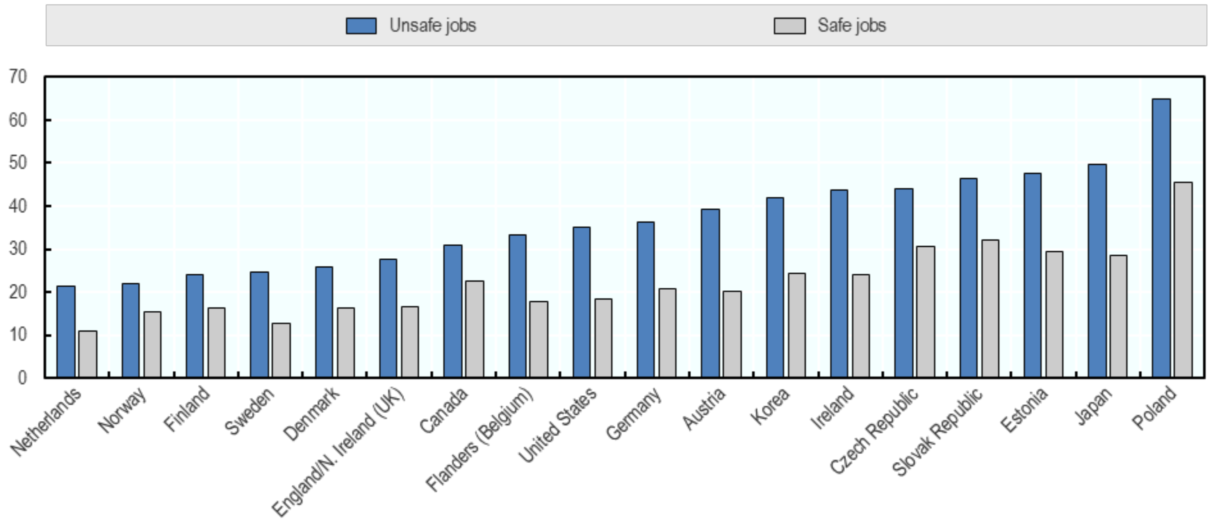
[26] Not all participants received a score in PSTRE. Adults who reported no previous experience with a computer, or who failed a very elementary assessment of ICT skills were not administered the PSTRE assessment, and took a test of literacy and numeracy (the two other domains assessed in PIAAC) using paper and pencil. Participants were also given the possibility to simply opt out of the computer-based assessment. We classify all these cases (about 18% of the overall sample across participating countries) at Below Level 1.

[27] We classify as safe jobs all the occupations for which the index for *category 3* is above 0.6. France, Italy and Spain are missing from the graph because they did not administer the PSTRE assessment.

[28] The shares are almost identical if we restrict the attention to essential occupations.

[29] Due to budget constraints and organizational feasibility it is hard to devise an active labour market policy offered to the universe of less-skilled workers. As long as there will be reallocation away from unsafe non-essential occupations towards new essential jobs, it will be preferable to target the workers involved in this reallocation.

Figure 12. Percentage of workers scoring below level 1 in PSTRE in safe and unsafe jobs



Note: The figure shows the share of workers in safe and unsafe occupations that score below Level 1 in the assessment of Problem Solving in Technology-Rich Environments (PSTRE). Adults who did not receive a score in PSTRE because they had no previous computer experience, or because they failed the ICT core assessment, or because they opted-out of the computer-based version of the assessment, are classified as being Below Level 1. Safe jobs are those whose *category 3* index is above 0.6.
Source: Survey of Adult Skills (2011/12)

6. Concluding Remarks

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.

The emergence of an epidemiological risk potentially poses an unprecedented problem of reallocation. First, relative price adjustments and a decrease in demand for goods and services that pose a higher epidemiological risk could cause a structural transformation, with a permanent shrinkage of certain occupations and a growth in labour demand in other jobs or sectors (such as health, pharmaceutical and digital technology industry). Additionally, under the current occupational structure, a new type of mismatch has materialised. At-risk workers – such as the elderly and people with co-morbidities known to increase the severity of the disease – would preferably hold jobs that can be carried out safely, while workers less at risk – the youngsters and those without co-morbidities – could increasingly take up unsafe jobs, especially in essential sectors. In order to encourage this latter group to take up essential but more unsafe jobs, wages should offer a premium for epidemiological risk. As shown in this paper, this was not the case before COVID-19, as this risk was not perceived, and workers had a very low bargaining position. This will be less the case in the future.

Labour supply will be impacted both because the risk of contagion is now well in the mind of potential jobseekers, but also because border restrictions enforced as a consequence of the pandemic naturally limit mobility and labour supply. Wage subsidies targeted to firms offering essential services could allow these compensating wage differentials to unfold without putting firms under serious strain.

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 at least until an effective vaccine is discovered and adopted.

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 reinstalled) while suffering hours (and salary) cuts, are a good way to preserve productive matches in the midst of an economic crisis (Boeri et al., 2011[25]; Cahuc, Kramarz and Nevoux, 2018[26]; Giupponi and Landais, 2020[27]). 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[18]). 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[30]

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)

[30] Data and other materials are available for download at http://www.frdb.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.1. Coefficients of job categories by ISCO 3-digit code

ISCO code	*ISCO name*	*Cat. 1*	*Cat. 2*	*Cat. 3*	*“Unsafe jobs”*
111	Legislators and Senior Officials	0.97	0.98	1.00	0.00
112	Managing Directors and Chief Executives	1.00	1.00	1.00	0.00
121	Business Services and Administration Managers	0.93	0.95	0.98	0.02
122	Sales, Marketing and Development Managers	0.88	1.00	1.00	0.00
131	Production Managers in Agriculture, Forestry and Fisheries	0.00	0.33	0.67	0.33
132	Manufacturing, Mining, Construction and Distribution Managers	0.29	0.64	1.00	0.00
133	Information and Communications Technology Services Managers	1.00	1.00	1.00	0.00
134	Professional Services Managers	0.75	0.76	0.96	0.04
141	Hotel and Restaurant Managers	0.00	0.00	0.13	0.87
142	Retail and Wholesale Trade Managers	1.00	1.00	1.00	0.00
143	Other Services Managers	0.76	0.87	0.98	0.02
211	Physical and Earth Science Professionals	0.50	1.00	1.00	0.00
212	Mathematicians, Actuaries and Statisticians	1.00	1.00	1.00	0.00
213	Life Science Professionals	0.71	0.82	0.94	0.06
214	Engineering Professionals (excluding Electrotechnology)	0.43	0.96	1.00	0.00
215	Electrotechnology Engineers	0.82	1.00	1.00	0.00
216	Architects, Planners, Surveyors and Designers	0.70	0.70	1.00	0.00
221	Medical Doctors	0.00	0.00	0.00	1.00

222	Nursing and Midwifery Professionals	0.00	0.00	0.00	1.00
223	Traditional and Complementary Medicine Professionals	0.00	0.00	0.00	1.00
224	Paramedical Practitioners	0.00	0.00	0.00	1.00
225	Veterinarians	0.00	0.00	0.00	1.00
226	Other Health Professionals	0.00	0.00	0.00	1.00
231	University and Higher Education Teachers	0.91	0.92	0.95	0.05
232	Vocational Education Teachers	0.06	0.06	0.06	0.94
233	Secondary Education Teachers	1.00	1.00	1.00	0.00
234	Primary School and Early Childhood Teachers	0.00	0.00	0.00	1.00
235	Other Teaching Professionals	0.48	0.48	0.48	0.52
241	Finance Professionals	1.00	1.00	1.00	0.00
242	Administration Professionals	0.76	0.76	0.93	0.07
243	Sales, Marketing and Public Relations Professionals	1.00	1.00	1.00	0.00
251	Software and Applications Developers and Analysts	1.00	1.00	1.00	0.00
252	Database and Network Professionals	1.00	1.00	1.00	0.00
261	Legal Professionals	1.00	1.00	1.00	0.00
262	Librarians, Archivists and Curators	0.87	0.87	1.00	0.00
263	Social and Religious Professionals	0.06	0.06	0.81	0.19
264	Authors, Journalists and Linguists	0.80	0.80	0.80	0.20
265	Creative and Performing Artists	0.57	0.57	0.57	0.43
311	Physical and Engineering Science Technicians	0.26	0.75	0.77	0.23
312	Mining, Manufacturing and Construction Supervisors	0.00	0.00	0.00	1.00
313	Process Control Technicians	0.00	0.12	0.29	0.71
314	Life Science Technicians and Related Associate Professionals	0.00	0.55	0.82	0.18
315	Ship and Aircraft Controllers and Technicians	0.00	0.10	0.10	0.90
321	Medical and Pharmaceutical Technicians	0.00	0.00	0.00	1.00
322	Nursing and Midwifery Associate Professionals	0.00	0.00	0.00	1.00
323	Traditional and Complementary Medicine Associate Professionals	0.00	0.00	0.00	1.00
324	Veterinary Technicians and Assistants	0.00	0.00	0.00	1.00
325	Other Health Associate Professionals	0.11	0.12	0.12	0.88
331	Financial and Mathematical Associate Professionals	0.95	0.97	1.00	0.00
332	Sales and Purchasing Agents and Brokers	1.00	1.00	1.00	0.00
333	Business Services Agents	0.46	0.57	0.87	0.13
334	Administrative and Specialized Secretaries	0.80	0.80	0.80	0.20
335	Government regulatory associate professionals	0.36	0.41	0.45	0.55
341	Legal, Social and Religious Associate Professionals	0.50	0.50	0.50	0.50
342	Sports and Fitness Workers	0.16	0.16	0.18	0.82

343	Artistic, Cultural and Culinary Associate Professionals	0.08	0.09	0.14	0.86
351	Information and Communications Technology Operations and User Support Technicians	1.00	1.00	1.00	0.00
352	Telecommunications and Broadcasting Technicians	0.08	0.41	0.86	0.14
411	General Office Clerks	1.00	1.00	1.00	0.00
412	Secretaries (general)	1.00	1.00	1.00	0.00
413	Keyboard Operators	1.00	1.00	1.00	0.00
421	Tellers, Money Collectors and Related Clerks	0.80	0.80	0.80	0.20
422	Client Information Workers	0.40	0.40	0.62	0.38
431	Numerical Clerks	1.00	1.00	1.00	0.00
432	Material recording and Transport Clerks	0.10	0.61	0.61	0.39
441	Other Clerical Support Workers	0.24	0.24	0.43	0.57
511	Travel Attendants, Conductors and Guides	0.05	0.05	0.05	0.95
512	Cooks	0.00	0.00	0.02	0.98
513	Waiters and Bartenders	0.00	0.00	0.00	1.00
514	Hairdressers, Beauticians and Related Workers	0.03	0.03	0.03	0.97
515	Building and Housekeeping Supervisors	0.00	0.77	1.00	0.00
516	Other Personal Services Workers	0.05	0.05	0.11	0.89
521	Street and Market Salespersons	0.20	0.20	0.20	0.80
522	Shop Salespersons	0.28	0.28	0.28	0.72
523	Cashiers and Ticket Clerks	0.00	0.00	0.00	1.00
524	Other Sales Workers	0.09	0.09	0.11	0.89
531	Child Care Workers and Teachers' Aides	0.01	0.01	0.01	0.99
532	Personal Care Workers in Health Services	0.00	0.00	0.00	1.00
541	Protective Services Workers	0.00	0.00	0.09	0.91
611	Market Gardeners and Crop Growers	0.00	0.52	0.52	0.48
612	Animal Producers	0.00	0.81	0.81	0.19
613	Mixed Crop and Animal Producers	0.00	0.94	0.94	0.06
621	Forestry and Related Workers	0.00	0.69	0.80	0.20
622	Fishery Workers, Hunters and Trappers	0.00	0.77	0.77	0.23
631	Subsistence Crop Farmers	0.00	0.50	1.00	0.00
632	Subsistence Livestock Farmers	0.00	0.00	0.00	1.00
633	Subsistence Mixed Crop and Livestock Farmers	0.00	0.34	0.68	0.32
711	Building Frame and Related Trades Workers	0.00	0.00	0.14	0.86
712	Building Finishers and Related Trades Workers	0.00	0.16	0.30	0.70
713	Painters, Building Structure Cleaners and Related Trades Workers	0.00	0.13	0.13	0.87
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers	0.00	0.59	0.59	0.41
722	Blacksmiths, Toolmakers and Related Trades Workers	0.00	0.96	0.98	0.02
723	Machinery Mechanics and Repairers	0.00	0.62	0.65	0.35
731	Handicraft Workers	0.05	0.51	0.63	0.37

732	Printing Trades Workers	0.16	1.00	1.00	0.00
741	Electrical Equipment Installers and Repairers	0.00	0.03	0.04	0.96
742	Electronics and Telecommunications Installers and Repairers	0.00	0.01	0.41	0.59
751	Food Processing and Related Trades Workers	0.00	0.41	0.41	0.59
752	Wood Treaters, Cabinet-makers and Related Trades Workers	0.00	0.48	0.98	0.02
753	Garment and Related Trades Workers	0.00	0.56	0.63	0.37
754	Other Craft and Related Workers	0.00	0.00	0.14	0.86
811	Mining and Mineral Processing Plant Operators	0.00	0.62	0.62	0.38
812	Metal Processing and Finishing Plant Operators	0.00	0.66	0.66	0.34
813	Chemical and Photographic Products Plant and Machine Operators	0.00	0.84	0.99	0.01
814	Rubber, Plastic and Paper Products Machine Operators	0.00	0.70	0.70	0.30
815	Textile, Fur and Leather Products Machine Operators	0.00	0.43	0.43	0.57
816	Food and Related Products Machine Operators	0.00	0.73	0.73	0.27
817	Wood Processing and Papermaking Plant Operators	0.00	1.00	1.00	0.00
818	Other Stationary Plant and Machine Operators	0.00	0.95	0.96	0.04
821	Assemblers	0.00	0.19	0.19	0.81
831	Locomotive Engine Drivers and Related Workers	0.00	0.36	0.36	0.64
832	Car, Van and Motorcycle Drivers	0.00	0.00	0.00	1.00
833	Heavy Truck and Bus Drivers	0.00	0.00	0.73	0.27
834	Mobile Plant Operators	0.00	0.80	0.84	0.16
835	Ships' Deck Crews and Related Workers	0.00	0.00	0.00	1.00
911	Domestic, Hotel and Office Cleaners and Helpers	0.00	0.40	0.40	0.60
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers	0.00	0.97	0.97	0.03
921	Agricultural, Forestry and Fishery Labourers	0.00	0.09	0.19	0.81
931	Mining and Construction Labourers	0.00	0.01	0.01	0.99
932	Manufacturing Labourers	0.00	0.29	0.29	0.71
933	Transport and Storage Labourers	0.00	0.13	0.13	0.87
941	Food Preparation Assistants	0.00	0.00	0.00	1.00
961	Refuse Workers	0.00	0.00	0.00	1.00
962	Other Elementary Workers	0.01	0.07	0.08	0.92

Note: The table reports job category coefficients assigned to each ISCO 3-digit occupation. Each coefficient is a proxy of the share of jobs that belong to the category under consideration within a given ISCO code. ISCO code 951 has been dropped due to inconsistencies between ICP INAPP and O*NET data.
Source: O*NET database.

Table A.2. Overall shares of job categories by country

Country	*Cat. 1*	*In Cat. 2 but not in 1*	*In Cat. 3 but not in 2*	*"Unsafe"*
Austria	.324	.167	.054	.455
Belgium	.337	.127	.065	.471
Croatia	.269	.182	.068	.481
Cyprus	.334	.115	.053	.498
Czech Rep	.285	.207	.07	.438
Denmark	.308	.128	.051	.513
Estonia	.318	.164	.079	.439
Finland	.318	.149	.064	.469
France	.318	.15	.056	.476
Germany	.316	.169	.059	.456
Greece	.275	.155	.049	.521
Hungary	.259	.191	.068	.482
Iceland	.328	.113	.061	.498
Ireland	.291	.127	.058	.524
Italy	.304	.148	.057	.491
Latvia	.29	.158	.071	.481
Luxembourg	.435	.096	.076	.393
Netherlands	.339	.101	.061	.499
Norway	.318	.123	.06	.499
Portugal	.275	.168	.074	.483
Romania	.17	.315	.07	.445
Slovak Rep	.222	.175	.07	.533
Spain	.24	.136	.065	.559
Sweden	.34	.122	.07	.468
Switzerland	.359	.129	.064	.448
UK	.355	.098	.071	.476
US	.332	.107	.08	.481

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 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.3. Concentration indexes of job categories for male workers by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Austria	.877	1.041	1.072	.914
Belgium	.961	1.052	1.074	.917
Croatia	.788	.987	1.033	.965
Cyprus	.784	.891	.948	1.052
Czech Rep	.825	1.024	1.064	.918
Denmark	.964	1.11	1.125	.881
Estonia	.843	1.004	1.068	.913
Finland	.962	1.12	1.139	.842
France	.881	1.013	1.046	.95
Germany	.902	1.054	1.077	.908
Greece	.836	.953	.994	1.006
Hungary	.753	.996	1.048	.948
Iceland	.933	1.075	1.09	.91
Ireland	.876	1.055	1.078	.929
Italy	.865	.996	1.031	.967
Latvia	.797	.987	1.05	.946
Luxembourg	.979	1.026	1.044	.931
Netherlands	1.029	1.118	1.118	.882
Norway	1.013	1.145	1.16	.84
Portugal	.88	1.025	1.068	.928
Romania	.788	.957	.993	1.009
Slovak Rep	.779	1.025	1.077	.932
Spain	.962	1.056	1.084	.934
Sweden	.985	1.119	1.124	.859
Switzerland	.958	1.039	1.053	.935
UK	.989	1.086	1.099	.891
US	.937	1.064	1.067	.927

Note: The table reports concentration indexes of job categories for male workers by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category i for male workers over the share of category i in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.4. Concentration indexes of job categories for female workers by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Austria	1.142	.955	.919	1.097
Belgium	1.042	.94	.915	1.096
Croatia	1.249	1.018	.961	1.042
Cyprus	1.24	1.12	1.054	.946
Czech Rep	1.218	.97	.92	1.103
Denmark	1.039	.876	.858	1.135
Estonia	1.167	.994	.929	1.091
Finland	1.038	.869	.847	1.173
France	1.129	.985	.952	1.053
Germany	1.114	.94	.91	1.107
Greece	1.229	1.063	1.01	.99
Hungary	1.297	1.004	.942	1.062
Iceland	1.076	.912	.894	1.106
Ireland	1.144	.935	.912	1.08
Italy	1.184	1.004	.959	1.043
Latvia	1.2	1.016	.952	1.052
Luxembourg	1.023	.97	.949	1.079
Netherlands	.968	.866	.866	1.134
Norway	.984	.839	.818	1.182
Portugal	1.124	.975	.928	1.077
Romania	1.282	1.056	1.011	.987
Slovak Rep	1.279	.967	.904	1.084
Spain	1.042	.931	.9	1.079
Sweden	1.012	.87	.861	1.158
Switzerland	1.047	.953	.938	1.076
UK	1.014	.905	.889	1.122
US	1.071	.928	.924	1.082

Note: The table reports concentration indexes of job categories for female workers by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* for female workers over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.5. Concentration indexes of job categories for young workers (15-24) by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Austria	.799	.868	.859	1.169
Belgium	.635	.769	.764	1.265
Croatia	.483	.741	.736	1.285
Cyprus	.554	.63	.62	1.384
Czech Rep	.667	.896	.879	1.155
Denmark	.487	.544	.538	1.439
Estonia	.774	.813	.781	1.28
Finland	.475	.645	.652	1.394
France	.714	.846	.832	1.185
Germany	.763	.835	.818	1.217
Greece	.607	.672	.666	1.307
Hungary	.68	.851	.815	1.199
Iceland	.442	.499	.496	1.508
Ireland	.67	.672	.653	1.315
Italy	.579	.748	.737	1.273
Latvia	.814	.973	.919	1.087
Luxembourg	.609	.672	.689	1.481
Netherlands	.475	.568	.557	1.445
Norway	.487	.608	.599	1.403
Portugal	.705	.84	.799	1.215
Romania	.659	.998	.944	1.07
Slovak Rep	.694	.839	.824	1.154
Spain	.671	.729	.707	1.231
Sweden	.521	.613	.617	1.436
Switzerland	.808	.844	.839	1.199
UK	.682	.717	.702	1.328
US	.548	.651	.671	1.356

Note: The table reports concentration indexes of job categories for young workers (15-24) by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* for young workers over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.6. Concentration indexes of job categories for older workers (55-65) by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC “unsafe”*
Austria	.994	1.051	1.057	.932
Belgium	1.05	1.03	1.036	.96
Croatia	.974	1.064	1.062	.933
Cyprus	.955	1.007	1.028	.972
Czech Rep	.916	.99	1.004	.995
Denmark	.987	1.055	1.068	.936
Estonia	.818	.909	.952	1.062
Finland	.994	1.028	1.034	.962
France	1.016	1.032	1.031	.966
Germany	.959	1.002	1.015	.982
Greece	.884	1.088	1.084	.923
Hungary	.811	.969	.983	1.019
Iceland	1	1.063	1.068	.932
Ireland	.99	1.086	1.103	.906
Italy	1.112	1.06	1.061	.937
Latvia	.817	.915	.944	1.06
Luxembourg	1.103	1.092	1.071	.891
Netherlands	1.021	1.05	1.056	.944
Norway	1.148	1.134	1.16	.84
Portugal	.924	.971	.975	1.027
Romania	.735	1.118	1.09	.888
Slovak Rep	.919	1	1.015	.987
Spain	.925	.995	1.011	.991
Sweden	.974	1.009	1.019	.979
Switzerland	.958	1.01	1.013	.984
UK	.949	.998	1.021	.977
US	1.084	1.087	1.091	.902

Note: The table reports concentration indexes of job categories for older workers (55-65) by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* for older workers over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.7. Concentration indexes by quintile of income (sample weighted average)

Quintile	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Quintile 1	.488	.576	.603	1.428
Quintile 2	.642	.804	.823	1.191
Quintile 3	.964	1.016	1.017	.981
Quintile 4	1.229	1.164	1.146	.842
Quintile 5	1.666	1.444	1.356	.615

Note: The table reports concentration indexes of job categories by quintile of income, pooling data from 20 countries of the sample. Data on income for Austria, the Czech Republic, Finland, Iceland, Norway, Spain and Sweden are not available. For each country concentration indexes are computed as the ratio between the share of jobs of category *i* in quintile of income *j* over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.8. Concentration indexes for *category 3* jobs by quintile of income and country

Country	*Quintile 1*	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Belgium	.679	.809	.964	1.127	1.42
Croatia	.732	.861	.946	.96	1.212
Cyprus	.741	.871	1.102	1.124	1.448
Denmark	.63	.747	.982	1.133	1.515
Estonia	.724	.765	.939	1.144	1.257
France	.74	.834	.956	1.088	1.464
Germany	.75	.835	.976	1.11	1.32
Greece	.758	.858	1.008	1.027	1.228
Hungary	.801	.873	.965	1.06	1.344
Ireland	.624	.725	.901	1.107	1.361
Italy	.684	.835	.996	1.059	1.279
Latvia	.769	.8	.975	1.119	1.362
Luxembourg	.654	.916	1.132	1.176	1.275
Netherlands	.583	.798	.944	1.136	1.503
Portugal	.671	.716	1	1.164	1.327
Romania	.78	.814	.877	.926	1.041
Slovak Rep	.557	.792	.949	1.131	1.368
Switzerland	.822	.855	.929	1.04	1.293
United Kingdom	.586	.721	.943	1.122	1.408
United States	.603	.823	1.017	1.146	1.356

Note: The table reports concentration indexes of *category 3* jobs by quintile of income for 20 countries of the sample. Data on income for Austria, the Czech Republic, Finland, Iceland, Norway, Spain and Sweden are not available. For any of the 20 countries for which data are available, concentration indexes are computed as the ratio between the share of jobs of *category 3* in quintile of income *j* over the share of *category 3* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.9. Concentration indexes by job category and economic sector (sample weighted average)

Economic sector	*IC Cat.1*	*IC Cat.2*	*IC Cat.3*	*IC "unsafe"*
Agriculture/Forestry/Fishing	0.144	1.252	1.266	0.698
Mining/Quarrying	0.831	1.368	1.312	0.665
Manufacturing	0.771	1.344	1.254	0.727
Utilities	1.219	1.215	1.232	0.752
Waste Management	0.670	0.797	0.941	1.065
Construction	0.458	0.617	0.752	1.268
Trade	1.131	1.011	0.931	1.077
Transportation/Storage	0.550	0.650	0.928	1.079
Accommodation and food	0.238	0.254	0.314	1.728
Information and communication	2.355	1.740	1.608	0.350
Financial and insurance act.	2.649	1.946	1.759	0.181
Real estate	1.029	0.971	1.426	0.543
Professional/Scientific/Techn.	2.239	1.792	1.655	0.296
Administrative and support act.	0.768	1.023	1.074	0.920
Public administration	1.360	1.080	1.070	0.922
Education	1.345	1.039	0.979	1.024
Health and social work act.	0.479	0.415	0.482	1.562
Arts/Entertainment	1.058	0.888	0.904	1.105
Other services	0.716	0.870	0.968	1.034
Households as employers	0.033	0.540	0.499	1.532
Extraterritorial bodies	1.851	1.416	1.360	0.582

Note: The table reports concentration indexes of job categories by economic sector (Nace rev 2), pooling data from the 27 countries of the sample. For any country concentration indexes are computed as the ratio between the share of jobs of category *i* in economic sector *j* over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.10. Concentration indexes of *category 3* jobs by economic sector and country

Economic sector	*Austria*	*Belgium*	*Cyprus*	*Czech Rep*	*Denmark*	*Estonia*	*Germany*	*Spain*	*Switz*
Accommodation and food	0.39	0.29	0.41	0.52	0.25	0.33	0.39	0.25	
Administrative and support act.	1.02	1.06	0.97	0.96	1.15	0.88	1.07	1.02	
Agriculture/Forestry/ Fishing	1.34	1.19	0.98	1.28	1.37	1.22	1.28	1.03	
Arts/Entertainment	0.94	1.12	1.14	1.05	1.02	1.06	0.91	1	
Construction	0.83	0.72	0.62	0.74	0.73	0.75	0.84	0.70	
Education	1.02	0.96	1.07	0.89	0.87	0.86	1.07	1.12	
Extraterritorial bodies	1.55	1.62	0.94	1.51	1.72	0.73	1.37	2.27	
Financial and insurance act.	1.70	1.79	1.86	1.71	1.89	1.69	1.60	1.91	
Health and social work act.	0.43	0.47	0.48	0.33	0.36	0.33	0.45	0.36	
Households as employers	0.89	0.42	n/a	0.07	0.44	n/a	0.78	0.85	
Information and communication	1.60	1.71	1.70	1.65	1.75	1.63	1.52	1.94	
Manufacturing	1.23	1.24	1.24	1.09	1.42	1.13	1.21	1.34	
Mining/Quarrying	1.22	1.01	1.34	1.1	1.75	1.08	1.29	1.38	
Other services	0.74	0.92	0.50	0.59	1.01	0.72	0.81	0.70	
Professional/Scientific/ Techn.	1.49	1.64	1.83	1.54	1.70	1.58	1.55	1.80	
Public administration	1.03	1.06	0.75	1.05	1.43	1.03	1.13	0.96	
Real estate	1.54	1.48	1.82	1.53	1.63	1.19	1.46	1.87	
Trade	0.91	0.95	0.95	0.88	0.91	1.02	0.87	0.95	
Transportation/Storage	1	1.06	1.14	1.08	1.04	1.08	0.99	1.01	
Utilities	1.19	1.31	1.24	1.25	1.74	1.12	1.22	1.51	
Waste Management	0.98	1.04	0.58	1.14	1	1.08	0.98	1.01	

Note: The table reports concentration indexes of *category 3* jobs by economic sector a set of 9 countries belonging to our sample. For any country concentration indexes are computed as the ratio between the share of jobs of *category 3* in economic sector *j* over the share of *category 3* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: European Labour Force Survey (EU LFS).

Table A.11. Concentration indexes of job *category 3* jobs by economic sector and country

Economic sector	*Croatia*	*Finland*	*France*	*Greece*	*Hungary*	*Iceland*	*Ireland*	*Italy*	*Latvia*	*Luxemb.*
Accommodation and food	0.33	0.23	0.38	0.29	0.36	0.50	0.33	0.27	0.41	0.31
Administrative and	0.83	1.19	1.02	1	1	1.16	1.07	0.91	0.86	0.89

support act.										
Agriculture/Forestry/ Fishing	1.36	1.37	1.30	1.21	1.24	1.28	1.61	0.93	1.08	1.41
Arts/Entertainment	1.13	1.01	0.99	1.02	1.15	0.95	1.14	1.02	1.10	0.97
Construction	0.77	0.76	0.77	0.76	0.65	0.76	0.73	0.66	0.82	0.73
Education	0.81	0.94	1.01	1.10	0.77	0.72	1.08	1.08	0.74	0.60
Extraterritorial bodies	1.25	1.53	1.22	1.20	1.65	1.91	1.49	1.45	1.89	1.44
Financial and insurance act.	1.72	1.76	1.73	1.87	1.77	1.89	1.72	1.86	1.81	1.53
Health and social work act.	0.29	0.34	0.52	0.42	0.51	0.40	0.42	0.42	0.40	0.54
Households as employers	0.54	0.15	0.62	0.69	0.60	n/a	0.27	0.45	0.01	0.63
Information and communication	1.73	1.74	1.65	1.74	1.68	1.65	1.15	1.79	1.64	1.43
Manufacturing	1.28	1.32	1.22	1.30	1.15	1.17	1.26	1.24	1.25	1.15
Mining/Quarrying	1.34	1.36	1.33	1.20	1.32	1.37	1.29	1.30	1.16	1.26
Other services	0.62	0.92	0.78	0.72	0.54	1.13	0.79	0.67	0.50	0.86
Professional/Scientific/Techn.	1.61	1.59	1.57	1.91	1.72	1.65	1.72	1.73	1.64	1.46
Public administration	1.13	1.20	0.99	1	0.93	1.31	1.07	1.04	1.23	1.02
Real estate	1.50	1.63	1.60	1.91	1.59	1.61	1.63	1.53	0.73	1.36
Trade	0.92	0.89	0.96	0.86	0.95	0.93	0.98	0.98	1.02	0.92
Transportation/Storage	1	0.91	1.11	0.92	1.19	0.92	0.86	1.10	1.09	0.91
Utilities	0.93	1.51	1.27	1.32	1.35	1.34	1.30	1.29	1.06	1.19
Waste Management	0.83	1.40	1.05	0.76	1.18	1.03	1.14	0.78	0.90	1.11

Note: The table reports concentration indexes of *category 3* jobs by economic sector a set of 10 countries belonging to our sample. For any country concentration indexes are computed as the ratio between the share of jobs of *category 3* in economic sector *j* over the share of *category 3* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: European Labour Force Survey (EU LFS).

Table A.12. Concentration indexes of job *category 3* jobs by economic sector and country

Economic sector	*Netherlands*	*Norway*	*Portugal*	*Romania*	*Slovak Rep*	*Sweden*	*UK*	*US*
Accommodation and food	0.33	0.41	0.33	0.30	0.33	0.30	0.36	0.30
Administrative and support act.	1.00	1.15	0.93	0.53	0.84	1.09	1.11	1.15
Agriculture/Forestry/Fishing	1.26	1.47	1.47	1.46	1.41	1.42	1.19	1.26
Arts/Entertainment	1.05	0.95	1.02	0.97	1.25	1.02	1.05	0.78
Construction	0.79	0.83	0.69	0.57	0.78	0.78	0.89	0.73
Education	1.10	0.82	1.02	1.05	0.72	0.63	0.87	0.98
Extraterritorial bodies	1.95	1.49	0.92	n/a	1.36	1.70	1.04	n/a
Financial and insurance act.	1.74	1.92	1.81	1.62	1.95	1.82	1.66	1.79
Health and social work act.	0.58	0.28	0.43	0.25	0.27	0.32	0.52	0.52
Households as employers	0.59	n/a	0.74	0.60	0.17	0.01	0.85	0.05
Information and communication	1.73	1.76	1.75	1.57	1.85	1.74	1.68	1.47
Manufacturing	1.18	1.40	1.21	1.059	1.18	1.31	1.31	1.31
Mining/Quarrying	1.53	1.39	1.25	1.12	1.32	1.30	1.32	1.33
Other services	0.82	0.97	0.71	0.72	0.71	0.93	0.81	1.12
Professional/Scientific/Techn.	1.61	1.75	1.73	1.50	1.80	1.61	1.58	1.69
Public administration	1.26	1.38	0.97	0.95	0.96	1.30	1.10	1.08
Real estate	1.49	1.68	1.61	1.52	1.81	1.54	1.45	1.36
Trade	0.86	1.10	0.92	0.82	0.96	1.06	0.90	0.95
Transportation/Storage	1	1.06	1.09	0.83	1.19	1	0.86	0.80
Utilities	1.45	1.45	1.27	0.90	1.11	1.31	1.27	1.21
Waste Management	1.15	1.03	1.06	0.65	1.04	1.09	0.98	0.88

Note: The table reports concentration indexes of *category 3* jobs by economic sector a set of 8 countries belonging to our sample. For any country concentration indexes are computed as the ratio between the share of jobs of *category 3* in economic sector *j* over the share of *category 3* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.13. Concentration indexes of job categories by living area (sample weighted avg.)

Area	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Metropolitan	1.1	1.027	1.021	.977
Non-metropolitan	.845	.957	.965	1.037

Note: The table reports concentration indexes of job categories by living area, pooling data from the 27 countries of the sample. For any country concentration indexes are computed as the ratio between the share of jobs of category *i* in area *j* over the share of category *i* in total employment. Metropolitan areas are defined as areas with more than 100,000 individuals. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018. Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.14. Concentration indexes of job categories for metropolitan areas by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Austria	1.167	1	1.007	.991
Belgium	1.095	1.037	1.036	.96
Croatia	1.476	1.124	1.125	.865
Cyprus	1.147	1.085	1.072	.928
Czech Rep	1.389	1.104	1.084	.893
Denmark	1.24	1.067	1.064	.94
Estonia	1.248	1.089	1.062	.92
Finland	1.305	1.094	1.073	.917
France	1.226	1.083	1.076	.916
Germany	1.146	1.021	1.024	.971
Greece	1.262	1.026	1.033	.969
Hungary	1.479	1.131	1.124	.867
Iceland	1.171	1.057	1.046	.954
Ireland	1.237	1.045	1.036	.968
Italy	1.22	1.073	1.057	.941
Latvia	1.169	1.054	1.029	.969
Luxembourg	1.469	1.298	1.254	.608
Netherlands	1.094	1.034	1.034	.966
Norway	1.28	1.122	1.106	.894
Portugal	1.255	1.072	1.044	.952
Romania	1.729	.942	.987	1.016
Slovak Rep	1.536	1.166	1.139	.878
Spain	1.188	1.059	1.043	.966
Sweden	1.229	1.097	1.083	.906
Switzerland	1.153	1.043	1.049	.94
United Kingdom	1.028	1.004	1.002	.998
United States	1.042	1.016	1.01	.99

Note: The table reports concentration indexes of job categories for metropolitan areas by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* in metropolitan areas over the share of category *i* in total employment. Metropolitan areas are defined as areas with more than 100,000 individuals. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018. Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.15. Concentration indexes of job categories for non-metropolitan areas by country

Country	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*	*IC "unsafe"*
Austria	.932	1	.998	1.003
Belgium	.964	.987	.987	1.015
Croatia	.758	.936	.935	1.07
Cyprus	.821	.896	.912	1.088
Czech Rep	.825	.955	.963	1.047
Denmark	.87	.964	.967	1.032
Estonia	.783	.921	.946	1.069
Finland	.782	.933	.947	1.06
France	.825	.933	.941	1.065
Germany	.919	.988	.987	1.016
Greece	.83	.982	.98	1.019
Hungary	.765	.935	.939	1.065
Iceland	.682	.896	.914	1.087
Ireland	.857	.972	.981	1.017
Italy	.872	.957	.967	1.034
Latvia	.862	.957	.976	1.025
Luxembourg	.866	.915	.928	1.112
Netherlands	.876	.957	.956	1.044
Norway	.881	.948	.956	1.044
Portugal	.796	.946	.964	1.039
Romania	.601	1.031	1.007	.992
Slovak Rep	.859	.955	.962	1.033
Spain	.771	.93	.947	1.042
Sweden	.864	.943	.951	1.056
Switzerland	.938	.981	.979	1.026
United Kingdom	.963	.998	.997	1.003
United States	.717	.884	.923	1.083

Note: The table reports concentration indexes of job categories for non-metropolitan areas by country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* in non-metropolitan areas over the share of category *i* in total employment. Non-metropolitan areas are defined as areas with less than 100,000 individuals. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.16. Concentration indexes of *category 3* jobs by level of education and country

Country	*Low*	*Middle*	*High*
Austria	0.77	0.91	1.22
Belgium	0.75	0.84	1.23
Croatia	0.91	0.88	1.27
Cyprus	0.68	0.83	1.25
Czech Rep	0.68	0.92	1.28
Denmark	0.71	0.99	1.17
Estonia	0.79	0.88	1.19
Finland	0.82	0.85	1.19
France	0.79	0.84	1.24
Germany	0.74	0.93	1.24
Greece	0.9	0.87	1.21
Hungary	0.69	0.91	1.33
Iceland	0.76	0.87	1.27
Ireland	0.93	0.85	1.15
Italy	0.78	1.02	1.26
Latvia	0.75	0.87	1.24
Luxembourg	0.7	0.86	1.26
Netherlands	0.69	0.88	1.3
Norway	0.86	0.89	1.15
Portugal	0.84	0.97	1.3
Romania	1.13	0.84	1.37
Slovak Rep	0.55	0.93	1.27
Spain	0.8	0.83	1.24
Sweden	0.72	0.93	1.15
Switzerland	0.79	0.92	1.15
United Kingdom	0.83	0.89	1.18
United States	0.7	0.85	1.18

Note: The table reports concentration indexes of job categories by level of education and country. We rely on LFS threefold classification of education derived from ISCED2011 (low: lower secondary, middle: upper secondary, high: higher education attainment). For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category i in education level j over the share of category i in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.17. Concentration indexes of *category 1* and *3* jobs by nativity status and country

Country	*Native - IC Cat.1*	*Native - IC Cat.3*	*Foreign - IC Cat.1*	*Foreign - IC Cat.3*
Austria	1.09	1.04	0.68	0.84
Belgium	1.04	1.01	0.81	0.94
Croatia	1	1	0.97	1
Cyprus	1.07	1.03	0.78	0.89
Czech Rep	1	1.01	0.89	0.88
Denmark	1.03	1.02	0.79	0.89
Estonia	1.03	1.01	0.73	0.89
Finland	1.02	1.01	0.7	0.84
France	1.03	1.01	0.81	0.91
Germany	1.08	1.03	0.66	0.88
Greece	1.05	1.02	0.4	0.75
Hungary	1	1	1.17	1
Iceland	1.03	1.02	0.68	0.84
Ireland	1.04	1.04	0.86	0.88
Italy	1.1	1.05	0.39	0.71
Latvia	1.02	1.01	0.82	0.92
Luxembourg	0.87	0.91	1.09	1.07
Netherlands	1.02	1.01	0.87	0.94
Norway	1.05	1.03	0.75	0.87
Portugal	0.99	1	1.07	0.97
Romania	1	1	1.92	1.09
Slovak Rep	1	1	1.41	1.15
Spain	1.07	1.04	0.62	0.8
Sweden	1.06	1.04	0.77	0.84
Switzerland	1.06	1.03	0.86	0.94
UK	1.02	1.01	0.92	0.94
US	1.05	1.02	0.81	0.91

Note: The table reports concentration indexes of job categories by nativity status (foreign-born vs. native-born) and country. For any of the 27 countries of the sample, concentration indexes are computed as the ratio between the share of jobs of category *i* in status *j* over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.18. Concentration indexes of job categories by ISCO 2-digit code

ISCO code	*ISCO name*	*IC Cat. 1*	*IC Cat. 2*	*IC Cat. 3*
11	Chief Executives, Senior Officials and Legislators	2.99	2.16	1.90
12	Administrative and Commercial Managers	2.82	2.12	1.89
13	Production and Specialized Services Managers	1.65	1.50	1.77
14	Hospitality, Retail and Other Services Managers	1.52	1.17	1.18
21	Science and Engineering Professionals	1.81	1.95	1.87
22	Health Professionals	0.00	0.00	0.00
23	Teaching Professionals	1.51	1.08	0.95
24	Business and Administration Professionals	2.87	2.02	1.85
25	Information and Communications Technology Professionals	3.11	2.20	1.90
26	Legal, Social and Cultural Professionals	1.58	1.12	1.53
31	Science and Engineering Associate Professionals	0.39	0.90	0.86
32	Health Associate Professionals	0.14	0.11	0.10
33	Business and Administration Associate Professionals	2.35	1.71	1.64
34	Legal, Social, Cultural and Related Associate Professionals	0.98	0.70	0.67
35	Information and Communications Technicians	2.58	1.96	1.85
41	General and Keyboard Clerks	3.05	2.16	1.86
42	Customer Services Clerks	1.40	0.99	1.24
43	Numerical and Material Recording Clerks	1.51	1.70	1.49
44	Other Clerical Support Workers	0.74	0.53	0.83
51	Personal Services Workers	0.06	0.25	0.33
52	Sales Workers	0.87	0.61	0.54
53	Personal Care Workers	0.01	0.01	0.01
54	Protective Services Workers	0.04	0.03	0.18
61	Market-oriented Skilled Agricultural Workers	0.00	1.50	1.35
62	Market-oriented Skilled Forestry, Fishery and Hunting Workers	0.00	1.45	1.44
63	Subsistence Farmers, Fishers, Hunters and Gatherers	0.00	1.01	1.39
71	Building and Related Trades Workers (excluding Electricians)	0.00	0.25	0.46
72	Metal, Machinery and Related Trades Workers	0.00	1.58	1.42
73	Handicraft and Printing Workers	0.32	1.61	1.53

74	Electrical and Electronic Trades Workers	0.00	0.05	0.20
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	0.04	0.75	0.92
81	Stationary Plant and Machine Operators	0.00	1.61	1.42
82	Assemblers	0.00	0.60	0.52
83	Drivers and Mobile Plant Operators	0.00	0.40	0.88
91	Cleaners and Helpers	0.00	1.01	0.88
92	Agricultural, Forestry and Fishery Labourers	0.00	0.44	0.67
93	Labourers in Mining, Construction, Manufacturing and Transport	0.00	0.41	0.36
94	Food Preparation Assistants	0.00	0.00	0.06
96	Refuse Workers and Other Elementary Workers	0.04	0.13	0.13

Note: The table reports concentration indexes of job categories by ISCO 2-digit code using data from the 27 countries of the sample. For any given occupation, concentration indexes are computed as the ratio between the share of jobs of category *i* in occupation *j* over the share of category *i* in total employment. Numbers greater (lower) than one denote over-representation (under-representation) in that specific category. ISCO code 95 has been dropped due to inconsistencies between ICP INAPP and O*NET data. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Table A.19. Essential occupations as identified by Fasani and Mazza (2020)

ISCO code	*ISCO name*
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).

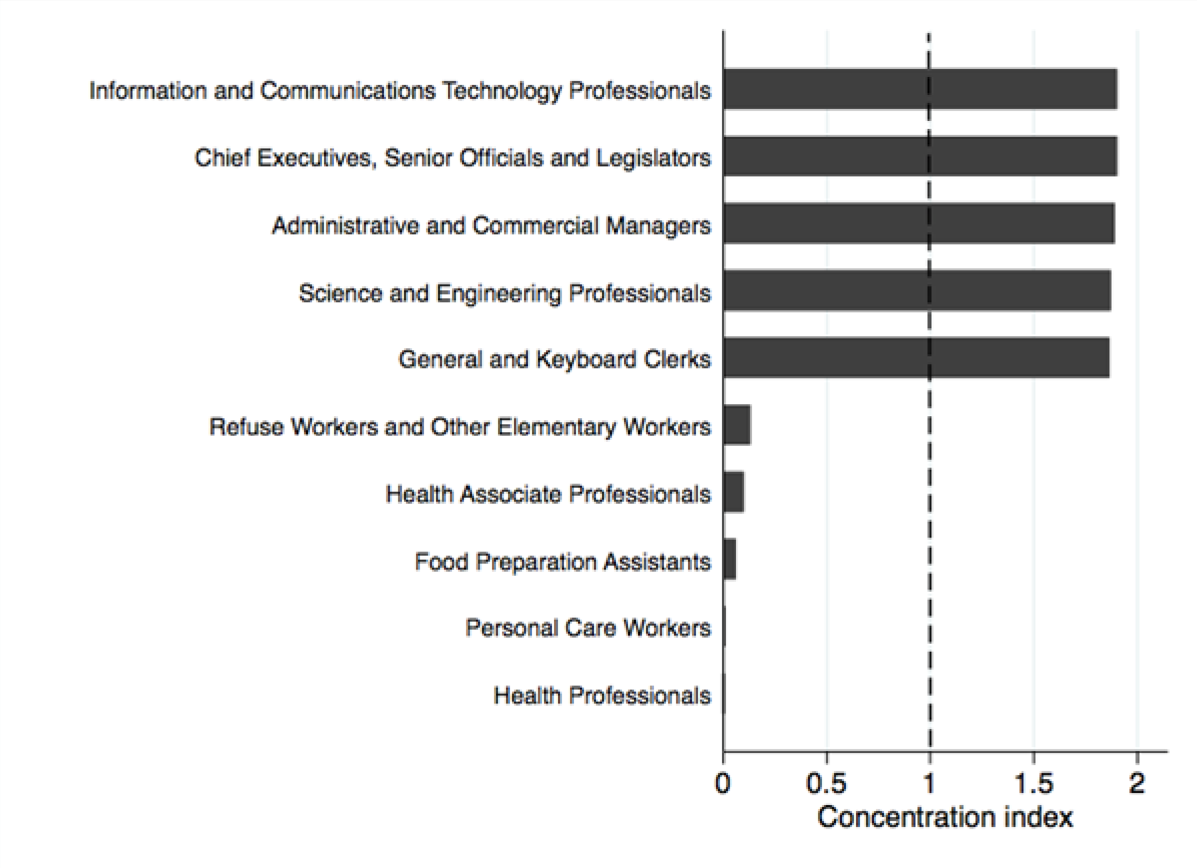
Table A.20. Essential workers by job category in European countries and in the US

Country	Essential workers	Essential workers (% of total)	Cat. 1 (% of essential)	Cat. 2 (% of essential)	Cat. 3 (% of essential)	Unsafe (% of essential)
Austria	1,503,010	0.35	0.21	0.42	0.47	0.53
Belgium	1,790,841	0.38	0.19	0.34	0.39	0.61
Croatia	543,614	0.33	0.16	0.39	0.45	0.55
Cyprus	120,257	0.31	0.19	0.38	0.43	0.57
Czech Republic	1,557,736	0.29	0.22	0.39	0.47	0.53
Denmark	1,222,528	0.43	0.20	0.35	0.38	0.62
Estonia	195,221	0.30	0.24	0.37	0.45	0.55
Finland	1,009,995	0.40	0.22	0.37	0.42	0.58
France	10,978,456	0.41	0.15	0.34	0.39	0.61
Germany	12,956,722	0.31	0.21	0.38	0.43	0.57
Greece	1,433,295	0.38	0.15	0.41	0.46	0.54
Hungary	1,326,309	0.30	0.17	0.37	0.46	0.54
Iceland	69,299	0.35	0.21	0.32	0.36	0.64
Ireland	727,134	0.33	0.16	0.37	0.41	0.59
Italy	7,494,234	0.33	0.18	0.36	0.42	0.58
Latvia	272,169	0.30	0.13	0.30	0.39	0.61
Luxembourg	85,329	0.32	0.21	0.39	0.45	0.55
Netherlands	2,989,351	0.35	0.22	0.36	0.40	0.60
Norway	1,082,006	0.41	0.18	0.31	0.34	0.66
Portugal	1,539,085	0.32	0.20	0.37	0.43	0.57
Romania	3,559,995	0.41	0.11	0.59	0.65	0.35
Slovak Rep.	760,054	0.30	0.15	0.27	0.35	0.65
Spain	6,766,205	0.36	0.17	0.34	0.39	0.61
Sweden	2,059,073	0.40	0.21	0.34	0.38	0.62
Switzerland	1,483,723	0.34	0.23	0.41	0.45	0.55
UK	10,616,055	0.33	0.22	0.34	0.38	0.62
US	45,366,814	0.29	0.20	0.31	0.35	0.65

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).

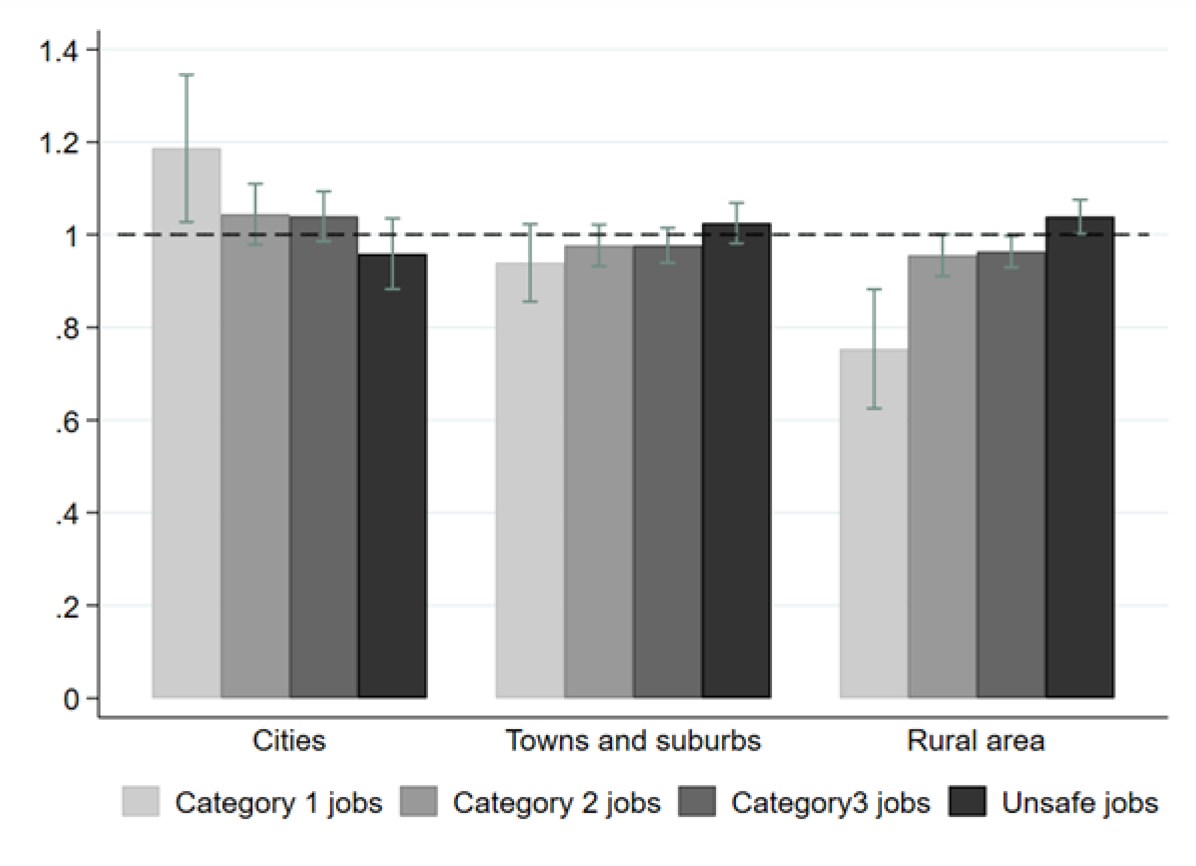
Annex B. Additional Figures

Figure B.1. Concentration indexes of *category 3* jobs by ISCO-2d occupation



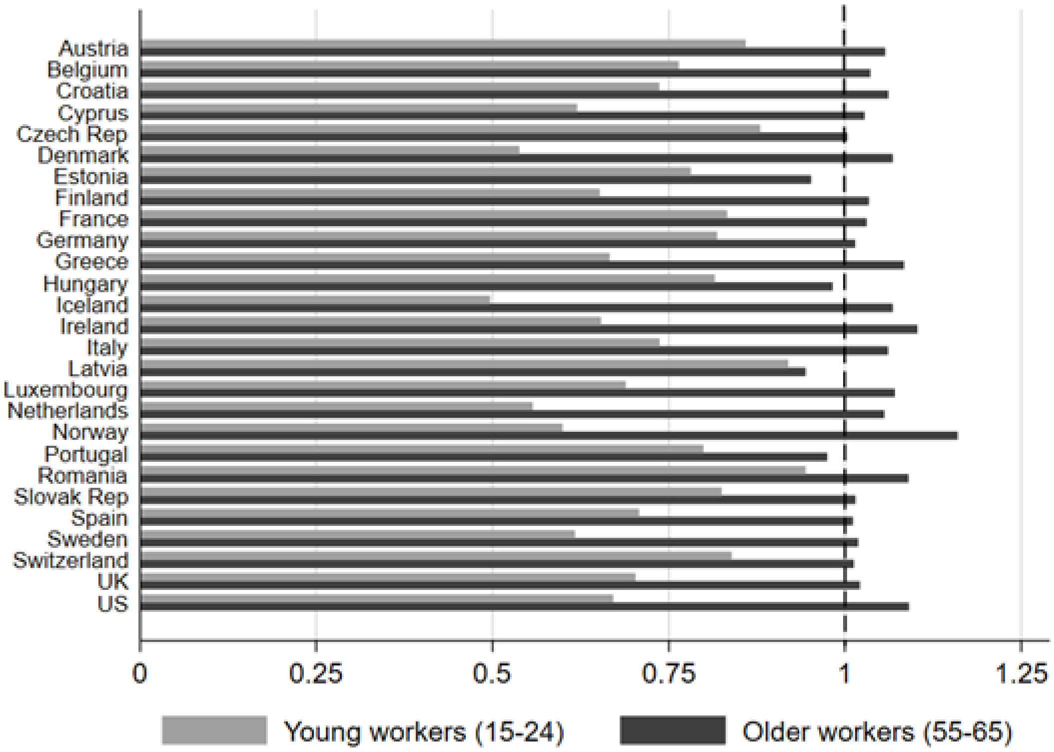
Note: The figure reports the 5 occupations at the ISCO 2-digit level at the top and at the bottom of the distribution of concentration indexes for *category 3*. Concentration indexes are computed as the ratio between the share of jobs of *category 3* in occupation j over the share of *category 3* in total employment, pooling data from the 27 countries of the sample. ISCO code 95 has been dropped due to inconsistencies between ONET and ICP INAPP data. Numbers greater (lower) than one (vertical dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.2. Concentration indexes of job categories by city, town and rural areas



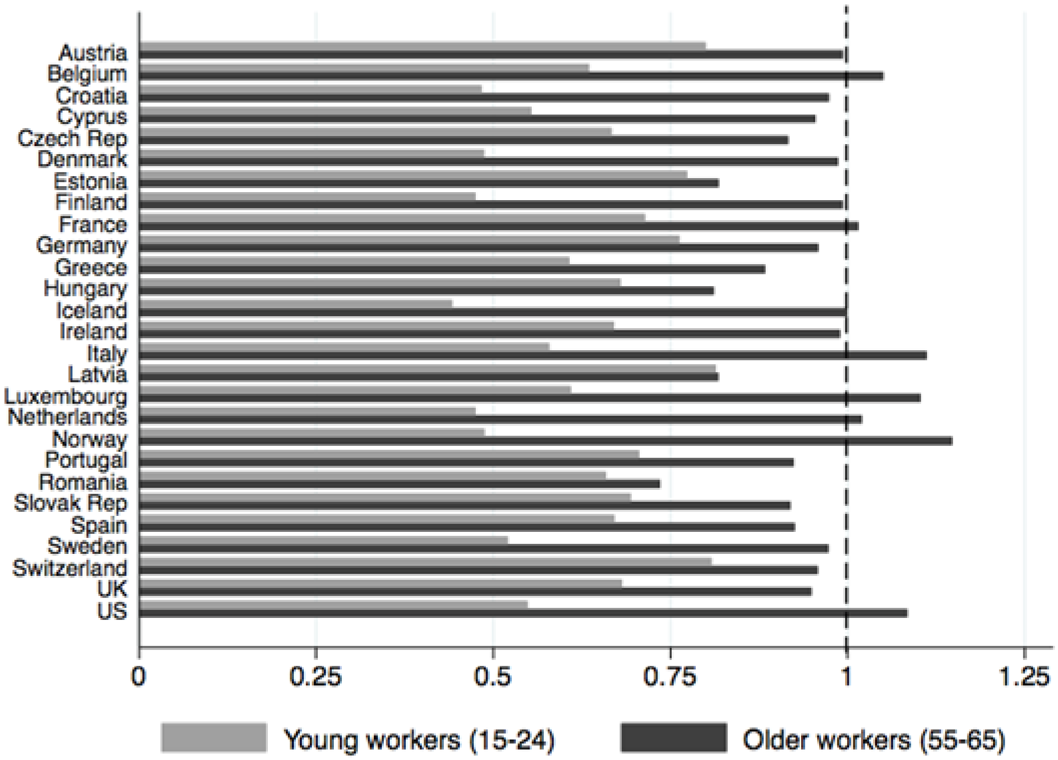
Note: The figure shows concentration indexes of job categories by area of residence. Definition of areas follows the methodology adopted by Eurostat. In cities, at least 50% lives in high-density clusters, defined as contiguous grid cells of 1 km2 with a density of at least 1,500 inhabitants per km2 and a minimum population of 50,000. In rural areas: more than 50% of the population lives in rural grid cells, defined as grid cell outside high-density clusters and urban clusters (cluster of contiguous grid cells of 1 km2 with a density of at least 300 inhabitants per km2 and a minimum population of 5,000). In towns, less than 50% of the population lives in rural grid cells and less than 50% live in high-density clusters. Concentration indexes are computed as the ratio between the share of jobs of category *i* in living area *j* over the share of category *i* in total employment, pooling data from the 26 countries of the sample (no data available for the United States). Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: European Labour Force Survey (EU LFS).

Figure B.3 Concentration indexes of *category 3* jobs by age group and country



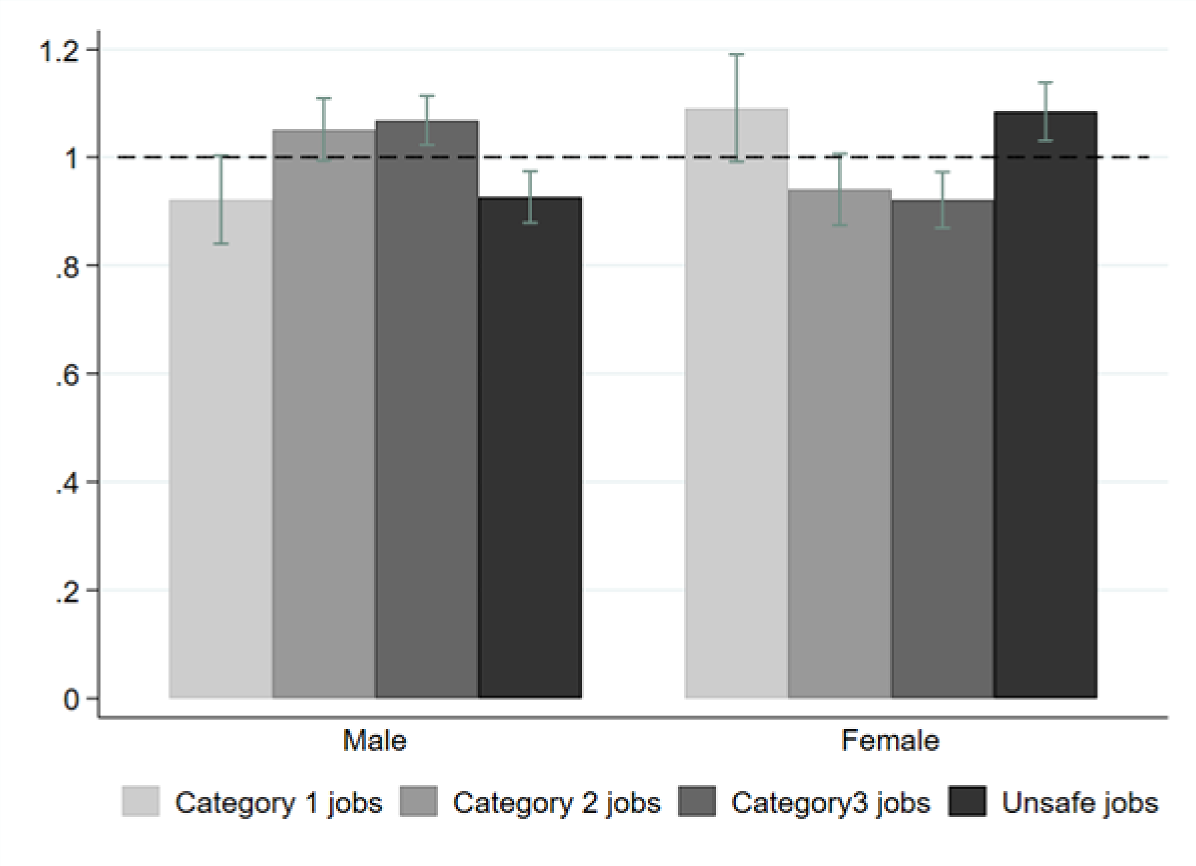
Note: The figure above shows concentration indexes for job *category 3* by age group across the 27 countries of the sample. Concentration indexes are computed as the ratio between the share of jobs of *category 3* for group *j* over the share of *category 3* in total employment. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.4. Concentration indexes of *category 1* jobs by age group and country



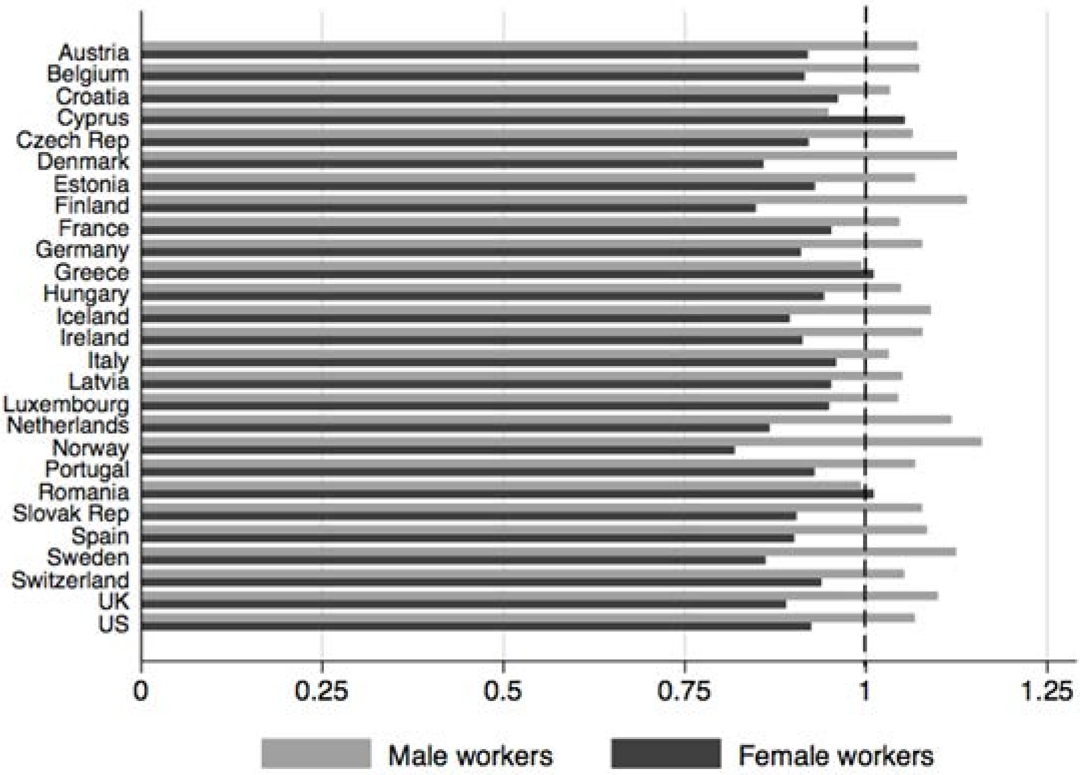
Note: The figure above shows concentration indexes for job *category 1* by age group across the 27 countries of the sample. Concentration indexes are computed as the ratio between the share of jobs of *category 1* for group *j* over the share of *category 1* in total employment. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.5. Concentration indexes of job categories by gender



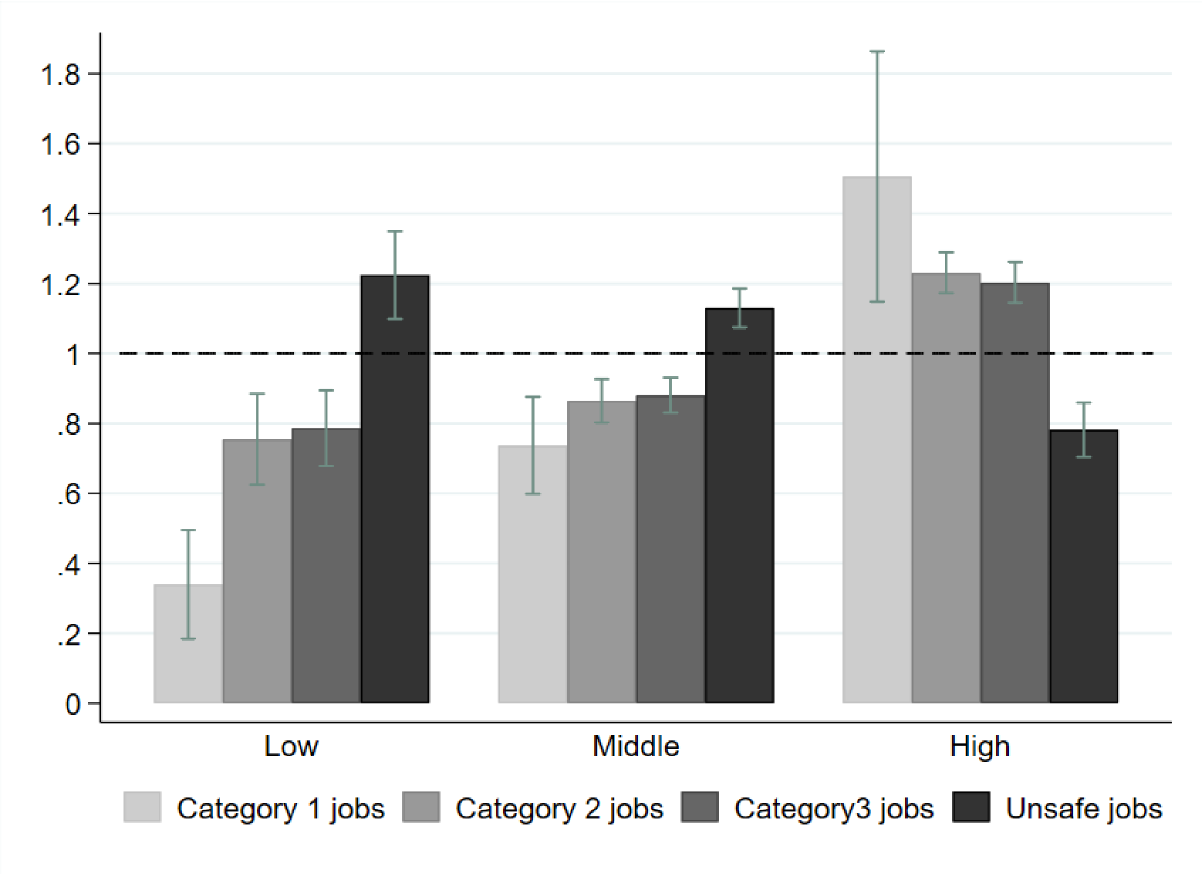
Note: The figure shows concentration indexes for job categories by gender. Concentration indexes are computed as the ratio between the share of jobs of category *i* for gender *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.6. Concentration indexes of *category 3* jobs by gender and country



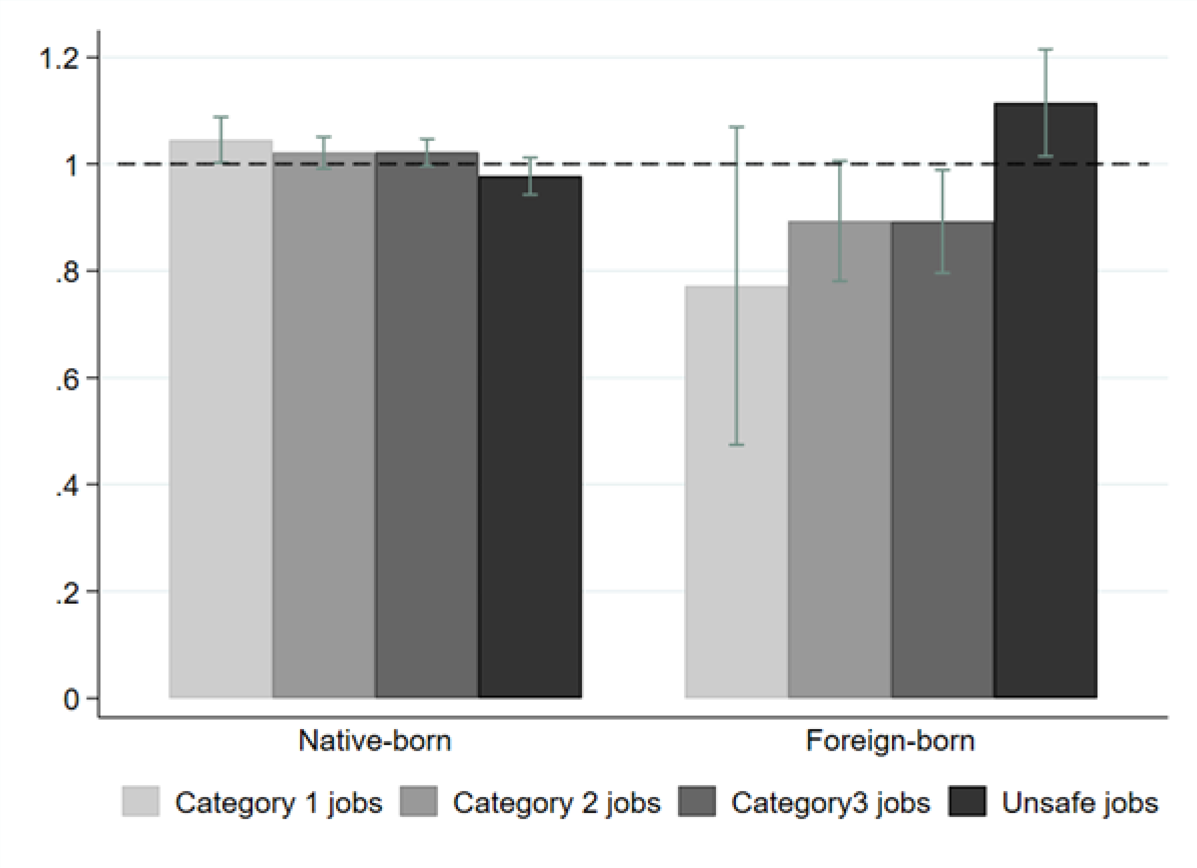
Note: The figure shows concentration indexes for job *category 3* by gender across the 27 countries of the sample. Concentration indexes are computed as the ratio between the share of jobs of *category 3* for gender *j* over the share of *category 3* in total employment. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.7. Concentration indexes of job categories by education



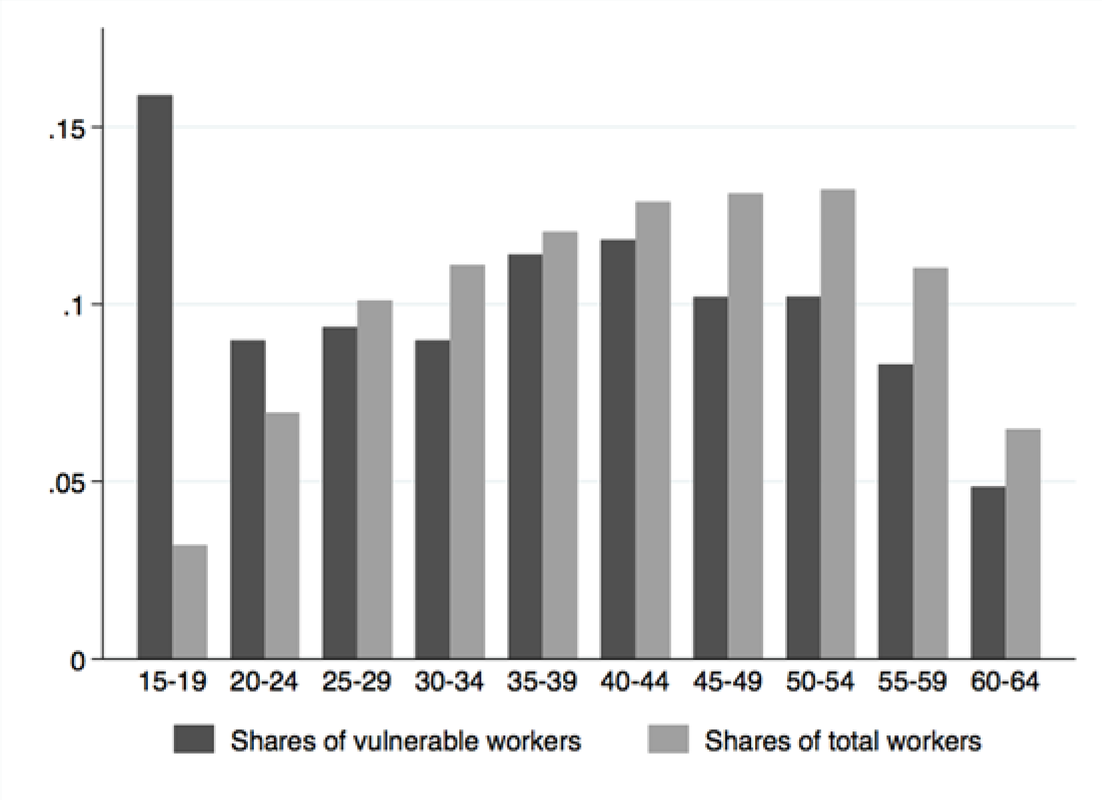
Note: The figure shows concentration indexes for job categories by education level. We rely on LFS threefold categorization derived from ISCED2011 (low: lower secondary, middle: upper secondary, high: higher education attainment). Concentration indexes are computed as the ratio between the share of jobs of category *i* for education level *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.8. Concentration indexes of job categories by nativity status



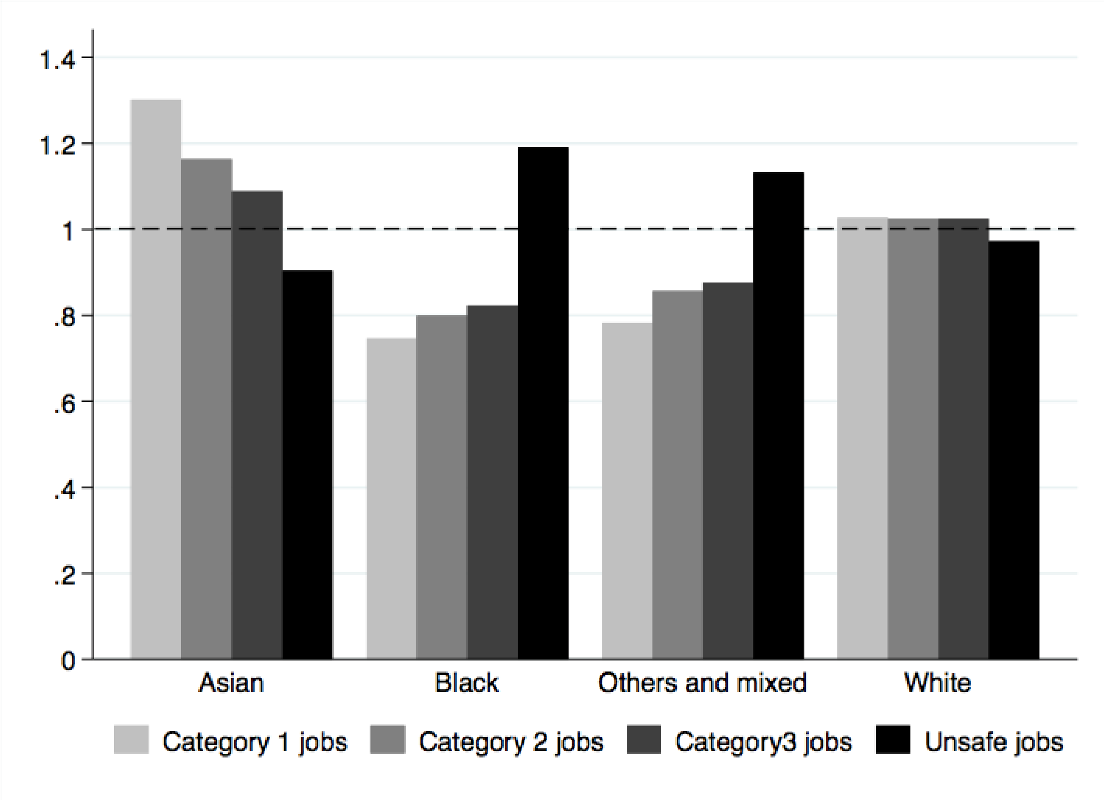
Note: The figure shows concentration indexes for job categories by country of origin. Concentration indexes are computed as the ratio between the share of jobs of category *i* for status *j* over the share of category *i* in total employment, pooling data from the 27 countries of the sample. Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category. Vertical bars measure one standard deviation above and below the cross-country average of concentration indexes. Data refer to 2018.
Source: Current Population Survey (CPS) and European Labour Force Survey (EU LFS).

Figure B.9. Age distribution of vulnerable and total workers



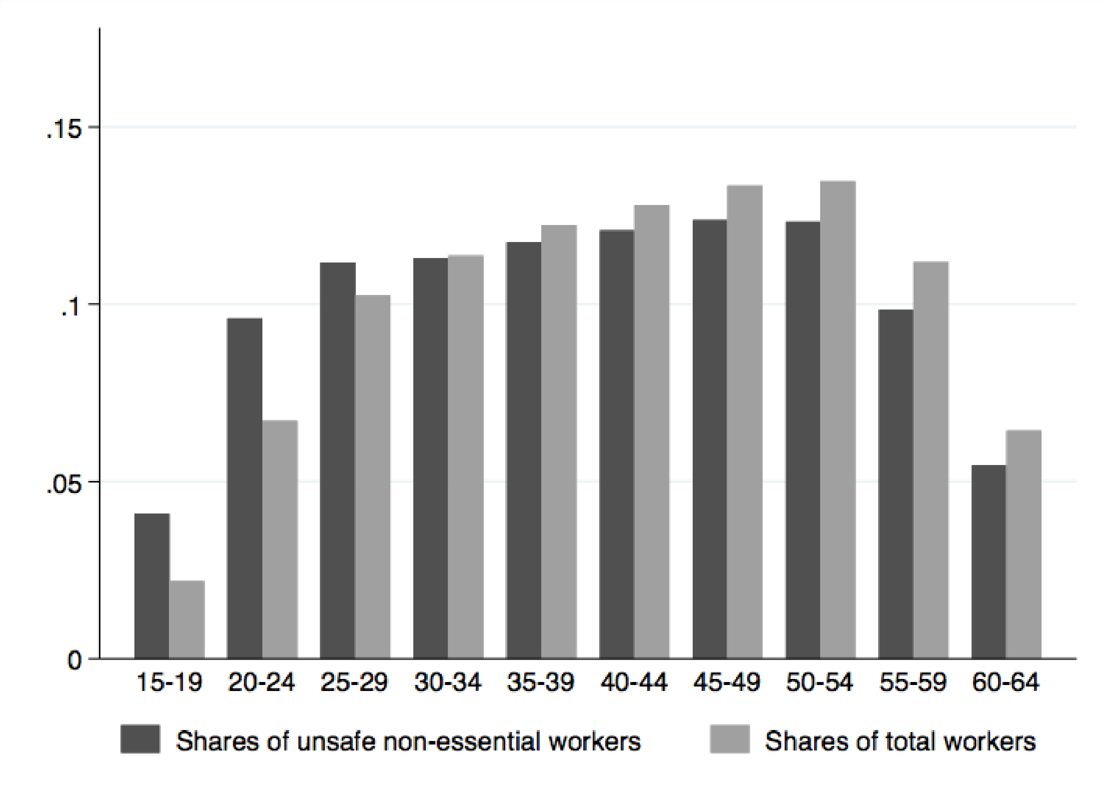
Note: The figure shows the age distribution for total workers and vulnerable workers (low educated individuals with an unsafe job in a firm with less than 20 employees in the "Accommodation and food service activities" or "Arts, entertainment and recreation" sectors). Shares are computed as the number of vulnerable (total) workers in a given age bracket over the total number of vulnerable (total) workers, pooling data from 25 countries (data are not available for Latvia and the United States). Data refers to 2018.
Source: European Labour Force Survey (EU LFS).

Figure B.10. Concentration indexes of job categories by ethnicity



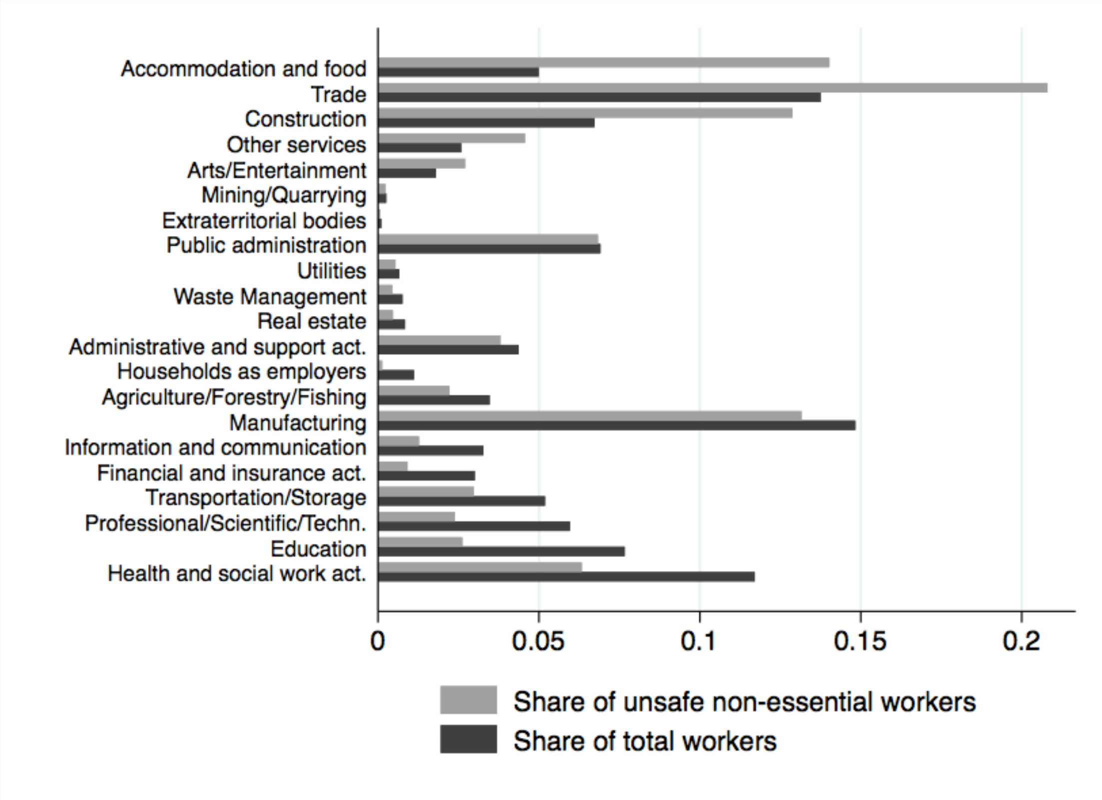
Note: The figure shows concentration indexes of job categories by ethnicity. Concentration indexes are computed as the ratio between the share of jobs of category *i* for ethnic group *j* over the share of category *i* in total employment. Data refer to US in 2018 (data are not available for EU countries). Numbers greater (lower) than one (horizontal dashed bar) denote over-representation (under-representation) in that specific category.
Source: Current Population Survey (CPS).

Figure B.11. Age distribution of unsafe non-essential and total workers



Note: The figure shows the age distribution for total workers and unsafe non-essential workers (as defined in Fasani and Mazza, 2020). Shares are computed as the number of unsafe non-essential (total) workers in a given age bracket over the total number of unsafe non-essential (total) workers, pooling data from 25 countries (data are not available for Latvia and the United States). Data refers to 2018.
Source: European Labour Force Survey (EU LFS).

Figure B.12. Distribution of unsafe non-essential workers over economic sectors



Note: The figure shows the distribution for unsafe non-essential workers over economic sectors (Nace rev 2). Shares are computed as the number of unsafe non-essential (total) workers in a given sector over the total number of unsafe non-essential (total) workers, pooling data from 26 countries (data are not available for the United States). Data refers to 2018.
Source: European Labour Force Survey (EU LFS).