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JOB LOSS AND COVID-19: DO REMOTE WORK, AUTOMATION AND TASKS AT WORK MATTER?

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CEDEFOP

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The COVID-19 pandemic struck the world both unexpectedly and fiercely. In mid-2021, one year after the first surge in cases, restrictions are still in place in many countries across the globe, including the EU. The adverse impacts on many aspects of the economy are already visible. Yet, both the current and future effects of COVID-19 on employment prospects in the EU are not expected to be uniform across different job positions.

This paper explores two possible determinants of the variation in future (short- and long-term) employment loss due to the pandemic: the potential of a job to be carried out remotely (i.e. 'from home') and the extent to which a job is at risk of being substituted by automation in the near future. We rely on a unique data set of employment forecasts provided by a dedicated Cedefop skills forecast scenario that incorporates COVID-19, and we relate the expected loss of employment by 2030 due to the emergence of COVID-19 for different occupations, industries and countries, with indices of work from home (WFH) potential and automation risk. Expected employment loss due to the pandemic is also analysed though the lens of the different tasks performed at work, which is a major driver of both the remote working potential and the automation risk.

Our findings suggest that, for different occupations and EU Member States, more remote working potential and less automation risk are related to smaller expected losses in employment due to COVID-19 by 2030. In other words, work from home and low risk of replacement by technology both provide a shield against job loss due to COVID. However, no such relationship emerges at the sectoral level. At the country level, these links are stronger in the short term where the effects of the pandemic are still intense, and fade away as countries are expected to gradually recover from the crisis. At the occupation level, these relations are instead strengthened in the medium-term future. This might indicate that, as protective measures taken by EU governments (such as furlough schemes for workers and rescue packages for firms) are gradually lifted, workers in certain occupations – most notably those related to lower levels of skill and qualifications – will experience intense difficulties in returning to work or finding a new job. This may have severe consequences for social cohesion in (as well as between) different EU countries, and stresses the need for a strong safety net to protect the most vulnerable parts of the EU workforce.

When we relate employment loss to tasks performed most frequently in different countries or occupations, we find that, wherever social, intellectual and information and communication technology (ICT) skills are important for a larger proportion of jobs, employment loss is expected to be relatively less. This stresses the

importance of social and digital skills for the future of (post-pandemic) work in the EU. It also highlights that, to strengthen resilience against similar future shocks, countries should exploit to the fullest extent possible the set of policies and measures to be implemented under the umbrella of the Commission's newly announced *Pact For Skills*, which is a massive initiative towards skills upgrading to facilitate the shift to an era of digitisation, automation and green technologies in the EU.

CHAPTER 1.
Introduction

The emergence of the COVID-19 pandemic and the associated health and economic shocks that have been unfolding during the past and present year have had a profound impact on the lives and the livelihoods of millions of people across the globe. In the European Union (EU), millions of jobs have been either temporarily or permanently lost as a result of confinement measures, lockdowns and restrictions implemented by all the EU-27 Member State authorities. However, the COVID-19 effect on employment has not been uniform across countries, industries and occupations. It is also expected to persist, even after the vaccination of the general population, varying in persistence across countries and economic sectors, and acting as an accelerator for past EU employment trends towards job automation (Cedefop and Eurofound, 2018; Pouliakas, 2018), job polarisation (Cedefop, 2018; 2021) and remote working (Eurofound, 2020).

Since the emergence of COVID-19, many attempts have been made to identify the parts of the economy where the effect of lockdowns and related measures (in terms of job loss) is expected to be harsher; that is, the countries, industries and occupations where employment is at a higher risk of pandemic impact. The ability of a particular job to be carried out from home or through social distancing has been identified as a major driver of the risk of job loss due to COVID-19. Many recent studies have constructed indices reflecting the relative ability to work from home (WFH) (e.g. Dingel and Neiman, 2020; Gottlieb et al., 2020; Boeri et al., 2020) or exercise social distancing (e.g. Avdiu and Nayyar, 2020; Pouliakas and Branka, 2020) for countrywide economies, economic sectors and occupations within a particular country or intra-country organisations such as the EU. These indices draw on data from labour force surveys related to the skills requirements and tasks that are usually performed in different jobs (e.g. physical tasks, working with machines or computers, performing routine tasks). They provide valuable information for policy-makers shaping government response measures at a national or supranational level.

To better identify the differential impact of the pandemic on employment, the above-mentioned indices were subsequently related to the various demographic, socioeconomic and job characteristics of individual workers (e.g. gender, age, salary, skills requirements, tasks performed at work) and countries (e.g. gross domestic product). In certain cases (Adams-Prassl et al., 2020; Kören and Peto, 2020), the authors related such indices to actual data on job losses or unemployment levels, measured during the initial stages of the pandemic. Nevertheless, as the pandemic effects unfold and new and updated data on job losses become available, a valuable addition to the above research would be to investigate the relation between the ability for remote operation as well as other job characteristics and the effects of COVID-19 on employment trends in the near or medium-term future. An important such characteristic is the risk that different job positions face of being substituted with machines or computers in the near future, as the pandemic is expected to accelerate the ongoing trend of job automation in the EU. This could provide valuable insights to policy-makers in charge of designing long-term government responses (such as upskilling and reskilling of workers) to restore employment to its pre-COVID track.

The aim of this paper is twofold. First, we assess the relation between remote work potential and automation risk, and the expected future effects of COVID-19 on employment in the EU. More specifically, we employ data from the recent release of Cedefop's skills forecast COVID-19 scenario (Cedefop, 2021) on the expected decrease in employment due to the emergence of the pandemic for different EU countries, occupations and industries, and WFH and automation risk estimates provided, respectively, by Dingel and Neiman (2020), Gottlieb et al. (2020) and Pouliakas (2018). We distinguish between three time periods: a COVID shock period (2020-21), a short-term recovery period (2022-23) and a medium-term period (2024-30). Second, we use data from Eurofound (2016) related to the relative intensity of performing different tasks at work (e.g. tasks requiring physical strength, social or intellectual skills, routine ones or tasks carried out through the use of computers) – which is a major driver of both WFH potential and automation risk in different jobs – to identify in more detail these job characteristics which will allow individuals to better buffer the shock of the crisis (Adams-Prassl et al., 2020) in the short and medium term.

We find that countries in which jobs are less prone to remote work and face high automation risks are expected to face larger employment loss in the short term due to the pandemic. The same appears to hold for occupational employment, but in the medium rather than short term, and to be more intense for low-skilled occupations. On the other hand, remote work potential and automation risk are not significantly related to future sectoral employment loss due to COVID-19. Also, the pandemic is expected to take a smaller future toll on jobs in which the tasks performed require mainly intellectual, ICT and social skills, compared to jobs requiring physical skills and operating with machine tools. These findings suggest that COVID-19 indeed acts as an accelerator for the job automation and polarisation trends already present in the EU labour market.

The rest of this paper unfolds as follows: Chapter 2 presents a review of the rapidly developing literature on the construction of indices capturing the potential to work remotely, practise social distancing and the risk of automation. It also discusses briefly the main assumptions regarding Cedefop's skills forecast COVID-19 scenario. In Chapter 3 we present the paper's main results, while Chapter 4 concludes.

CHAPTER 2.
Literature review

The emergence of the COVID-19 crisis has given rise to a constantly expanding literature which uses various sources of data in order to understand the adverse consequences of the pandemic in the overall economy, trade, economic sectors and labour markets, with the aim of informing future policy decisions. For example, Coibon et al. (2020) use a large-scale US household survey conducted after the first protective measures against COVID-19 were issued. They record a drop in labour force participation caused by a wave of earlier-than-planned retirement as well as by newly unemployed workers not actively seeking new jobs. Also, Baert et al. (2020) study the expected impact of COVID-19 on employees' future career outcomes and aspirations. They find that about one in four workers experiences job insecurity and/or concern about their promotion prospects, while 14% fear immediate job loss in the near future. In a similar fashion, Adams-Prassl et al. (2020), using data on real-time surveys from Germany, the UK and the US, show that the likely impacts of the pandemic tend to concentrate more on the vulnerable parts of the workforce in the US and UK, compared to Germany. They also highlight the importance of differences in remote working potential, which they argue to be a major driver of the variation in job loss across both industries and occupations in all three countries.

Further, Barrot et al. (2020) study the effects of exercising social distancing on sectoral output and GDP for 16 European countries. Using a model accounting for sectoral interrelationships, they estimate that six weeks of social distancing rules could result in a decrease in GDP ranging from 4.3% (Denmark) to 9.2% (Bulgaria), which is partly explained by sectoral composition and the workforce propensity to telework in each country. In addition, a recent study by the European Joint Research Centre (JRC, Fana et al., 2020) highlights that the impact of the COVID-19 crisis is more likely to concentrate on the most vulnerable segments of the working population such as migrant, low-skilled, low-wage and young workers. The report also argues that economic sectors involving a higher degree of social interaction and closer to final demand will most likely face downturn until the pandemic is under full control.

The relative ability to operate remotely appears to be a major driver of the likely impacts of COVID-19 on individual jobs, as well as different sectors and occupations. Several scholars have developed quantitative measures of remote working potential. Dingel and Neiman (2020) rely on the US O*NET database to construct a WFH index for different occupations. They use a subset of 15 questions, stemming from the Work Context and the Generalised Work Activities Questionnaires, that capture the ability of a particular job to be performed remotely. These questions are related to the use of machine and information and communication technology (ICT) equipment, exposure to diseases or injuries, the use of protective equipment at work, and working outdoors. Higher WFH index values indicate greater potential for remote operation, suggesting that COVID-19 is less likely to affect employment adversely. Also, WFH varies significantly across occupations, while it is positively related to average occupation wage. Repeating the analysis using International Labour Organization data, the authors construct country-level WFH indices for over 85 countries. These are positively related to country per capita income ([1]). Gottlieb et al. (2020) use worker-level data for 10 developing countries to construct a WFH index following the suggestions of Dingel and Neiman (2020), at the country as well as the International standard for classification of occupations (ISCO) two-digit occupational level. Their index is also positively related to a country's per capita income, occupational skills requirements (high skills are associated with greater remote work potential) and average wage. The authors also constructed ISCO two-digit occupational WFH indices based on data from the O*NET database. A comparison between the occupational WFH from the two databases revealed that a given occupation is generally less amenable to work from home in a developing country compared to a developed one. This was attributed to differences in the tasks performed in the same occupation in developed and developing countries.

Arguing that physical proximity to work is a factor that will become increasingly important for occupational employment as confinement measures ease in the near future, Avdiu and Nayyar (2020) rely on US O*NET data to construct a face-to-face interactions index. Higher values in this index indicate that a given occupation requires more intense face-to-face interactions and that it is more difficult for workers to exercise social distancing. Thus, the index actually captures whether employment in an occupation is at higher risk due to the exercise of social distancing ([2]). Comparing their index with the WFH one by Dingel and Neiman (2020), the authors note that, in sectors where remote work is not an option but social distancing is easier to exercise (e.g. manufacturing and construction), employment is more likely to recover faster than in sectors where neither remote work nor social distancing are easy to perform (e.g. retail and accommodation services). Kören and Peto (2020) use US O*NET data to

([1]) David and Dienknagura (2020) use the WFH index produced by Dingel and Neiman (2020) to explain ineffectiveness in countries' COVID-19 containment policies. Their findings suggest that containment policies were more effective in countries with a higher WFH index, which experienced gradual declines in reported cases as opposed to countries in which WFH was lower. The latter did not see the reported cases decline, while some even experienced case increases.

([2]) The index captures the extent to which an occupation involves maintaining personal relations, assistance and caring for others, performing for or working directly with the public and selling to or influencing others.

construct three indices that indicate the level of sectoral employment risk due to limiting face-to-face interactions. These reflect the intensity of required interactions with customers and co-workers, and physical presence to work, respectively. Only the former index was found to be significantly related to actual job losses in different US sectors during the early stages of the pandemic.

Similarly, Pouliakas and Branka (2020) use data from the first wave of Cedefop's European skills and jobs survey to construct a social distancing risk index for employment in the 27 EU Member States. Their index takes into account the extent to which physical contact and proximity to others are essential for carrying out a particular job, as well as the extent of digital skills required for it. The latter serves as a proxy for the ability of a job to be carried out safely from home. The authors report noticeable differences in employment risk due to social distancing across countries, occupations, economic sectors and population groups. Employing data reported by Eurofound (2016) on the intensity of performing different tasks at work, they also find that jobs with a high intensity of social tasks are associated with higher risk due to social distancing, while the reverse occurs for jobs requiring intense use of ICT tools.

In addition, Barbieri et al. (2020) and Beland et al. (2020) rely on Italian and US data, respectively, to construct three indices for different occupations and sectors: a WFH index, an index of physical proximity to others at work, and an index of relative exposure to infectious diseases. The former find that disease exposure is positively related to proximity to others, while the latter estimate a positive (negative) relation of physical proximity (WFH) and occupational unemployment estimates during the initial stages of the pandemic in the US. Crowley and Doran (2020) and Mongey et al. (2020) estimate two indices: one for WFH potential and another for the risk of social distancing, for Ireland and the US respectively. According to the former, the two indices go hand-in-hand at the occupational level but differences between them are observed at the sectoral level. The latter relate the two indices to actual job losses in the US and estimate that the most affected occupations are associated with lower potential for WFH and higher intensity for physical proximity. Also, in a multi-country study, Hatayama et al. (2020) use data on skills surveys from 53 countries regarding the intensity of performing physical, manual and face-to-face tasks, using ICT-related tools at work as well as the availability of internet connections at workers' homes, to construct a WFH index. They find that occupational differences in WFH potential explain more than half of the variability of WFH across countries.

In research parallel to the development of the above literature, Cedefop studied the potential impact of the pandemic on future employment forecasts. Estimates of trends in future employment in EU countries are released every two years in the Cedefop skills forecast, a project providing comprehensive information about the current structure of Europe's labour market and potential future trends (see e.g. Cedefop, 2018). Skills forecast uses harmonised data and a single methodology to make results comparable across countries, involving also individual country experts in the peer review and validation of results (Cedefop and Eurofound, 2018) ([3]) ([4]).

Estimations for the latest Cedefop skills forecast update, which include employment forecasts up to the year 2030 (released in March 2020; see Cedefop, 2021), were finalised before the spread of COVID-19 around the world and thus they do not incorporate any potential repercussions of the pandemic. These estimates will be hereafter referred to as the skills forecast baseline scenario. An additional analysis was later conducted in order to provide quantitative estimates of the likely impact of COVID-19 on future employment trends in the EU. This quantitative analysis, termed skills forecast COVID-19 scenario, relied on a series of assumptions, which were used in assessing the macroeconomic and sectoral employment implications of COVID-19.

The assumptions, most of which were made at Member State level, were drawn using the most recent statistical data available at the time of the modelling exercise, as well as comments and insights about national policies obtained from individual country experts ([5]). They concern the following:

(a) the lockdowns, including the nature of the lockdown restrictions, duration and travel restrictions;
(b) labour market participation, leveraging EU labour force survey data for the latest quarter available at the time and including the effects of short-time work schemes, absences, and temporary lay-offs on the 2020 average hours worked per week;
(c) changes in aggregate demand, including impacts on consumer expenditure, investment and trade;
(d) government response measures, including working arrangements, fiscal support and any additional final expenditure measures implemented or announced by the time of the modelling exercise ([6]).

For more details, see Cedefop (2021).

Regarding the COVID-19 impact on employment through time, it was assumed that the greater impacts would fade by the end of 2021, followed by a short-term period

([3]) The data used draw primarily on Eurostat sources, including demographic data, national accounts and the European labour force survey.

([4]) The skills forecast methodology uses a modular approach that incorporates the demand and supply sides of labour and estimates future potential labour market imbalances. For a more detailed description of the forecasting methodology, assumptions and the process of incorporating the comments and suggestions of experts, see Cedefop, 2012.

([5]) The data used to inform the assumptions include mostly data releases for the second quarter of 2020 from Eurostat and EU national statistics sources. Other sources used include IMF (2020a, 2020b), Bruegel (2020), European Commission (2020b, 2020c) and the OECD (2020).

([6]) A preliminary version of the results of the COVID-19 skills forecast scenario based on the above assumptions was reviewed by country experts; the feedback received led to regional and sectoral adjustment of the assumptions.

of recovery of EU economies during the next two years. Nevertheless, certain longer-term consequences, such as degradation of skills, loss of investment capital and permanent closure of businesses, were assumed to persist in the medium term following the recovery, until the end of the projection period (2030).

The extent to which workers are in jobs with high risk of substitutability by machines, robots or other algorithmic processes (hereafter automation risk) has also attracted the interest of researchers, albeit not yet in relation to the COVID-19 pandemic. This interest is driven by concerns that technological change and the substitution of labour by machines or, currently, artificial intelligence, leads to unemployment. This concerns particularly occupations that rely heavily on routine and non-complex tasks (Autor et al., 2003; 2006). Identifying the occupations and job positions most prone to the risk of automation can provide valuable insights to policy-makers seeking to alleviate possible adverse effects of technological advancements on employment. Many studies have so far pursued this goal, mainly relying on the task characteristics of different job positions. As estimated by these studies, the share of jobs or occupational categories that are at risk of automation ranges from around 9% to as high as 47% (see Pouliakas, 2018 for a review). Occupations requiring low or medium skills are in general more susceptible to future automation. Jobs relying heavily on intellectual and social skills (e.g. problem-solving, situational adaptability, transversal skills, selling skills, interaction with customers, caring) are safer, as these skills constitute ‘engineering bottlenecks’ to automation (Pouliakas, 2018).

The first detailed categorisation of occupations based on their relative automation risk was provided by Autor and Dorn (2013). They classify 323 three-digit US occupational titles as automatable or non-automatable, using US census data from 1950 to 2000 and the American Community Survey for 2005. For each occupation, the authors constructed a measure of ‘routine employment share’; that is, an index capturing the intensity of routine, manual and abstract task activities performed at work. The occupations in the top third of this measure’s distribution in 1980 were termed as automatable and the rest as non-automatable. Lordan (2018) and Josten and Lordan (2020) argue that this classification captures the jobs that were automatable during the past three decades but does not account for newer technological advancements that may replace workers in the near future. They rely on data about filed patents related to different three-digit occupations to reclassify some of Autor and Dorn’s (2013) non-automatable occupations as ‘recently automatable’. For these, there are many recently filed patents for machine, robot or AI substitutes, indicating intense research activity that is likely to result in partial replacement of workers by automation in the next decade.

In contrast to the above binary classifications of occupations as automatable or not, Pouliakas (2018) employs data from the first European skills and jobs survey (see Cedefop, 2015) to estimate the relative automation risk of different job positions in the

EU. Drawing on information on jobs' skills requirements and using a logistic regression methodology, he estimates the mean probability of automation for different ISCO occupations. This ranges from 42% for personal care workers to 57% for assemblers. For each occupation, the author also provides an estimate of the share of employment which is at high risk of being automated. This corresponds to the share of workers in each occupation for which the probability of automation is more than 70%. This share is minimum for chief executives, senior officials and legislators (2%) and maximum for food processing, wood working, garment and other craft and related trades workers, handicraft and printing workers, and subsistence farmers, fishers, hunters and gatherers (18%). Automation was found to be a greater threat for employment in occupations that have high routinisation frequency, require low skills and are more related to the primary and, to some extent, the secondary economic sectors. On the other hand, occupations requiring rich transversal and selling skills, most of which are related to the service sector, are in general safer in the sense that they have low automation risk.

Although the potential relation between the pandemic ramifications on employment and automation has not yet been examined, the skills associated with more automation risk are also the ones associated with less amenability to remote operation. Thus, we may expect that COVID-19 will have a greater impact on job positions with greater automation risk. Also, as the pandemic is expected to affect future investment decisions, it is likely that (to a certain extent) firms across the EU will accelerate the adoption of automation. An example is online retailing. Certain firms might choose to go fully online, with adverse effects for workers in their physical stores.

CHAPTER 3.
Main results

3.1. Variables and modelling choices

In this section, we relate the expected decrease in future employment due to the impact of COVID-19 for different EU countries, industries and occupations to amenability to working from home, automation risk, and the intensity of performing various tasks at work. The expected impact of COVID-19 on employment is obtained through employment forecasts from the skills forecast baseline and COVID-19 scenarios. From these we construct the percentage difference of employment in the COVID-19 scenario compared to the baseline one, for different EU countries and EU-wide occupational (ISCO two-digit occupation classification) and industry employment (17 NACE industries) as follows:

$$D_{it} = \left[\frac{employment_{it}^{covid-19}}{employment_{it}^{baseline}} - 1\right] \times 100$$

where i stands for a country, occupation or industry and t ranges from 1 to 11, corresponding to the years from 2020 to 2030. D_{it} takes negative (positive) values if employment is expected to reduce (increase) as an impact of COVID-19 in year t for country/occupation/industry i. For example, a value of D_{it} equal to -7.5 highlights that employment is expected to decrease by 7.5% compared to what it would have been if the pandemic had not occurred.

In accordance with the assumptions made to inform the skills forecast COVID-19 scenario, we concentrate on three distinct time periods: 2020-21, which reflects the initial shock on employment due to the pandemic (hereafter shock period); 2022-23, which is the period in which EU economies are expected to gradually recover (hereafter short-term recovery period), and 2024-30, in which economic activity is expected to return to pre-pandemic levels (hereafter medium-term period). For each period, we average D_{it} values over t, resulting in three such estimates for each different country and EU-wide occupation and industry. These averages allow us to investigate which countries, occupations and industries are the hardest hit by the pandemic (those suffering greater loss during the shock-period) and also which are those that recover faster than others (i.e. those suffering a small loss in the recovery and long-term period).

Further, data on the estimated remote working potential of different EU countries and occupations are obtained from Dingel and Neiman (2020) and Gottlieb et al. (2020) respectively (reproduced in Tables A1 and A2 in Annex 1). We note here that these estimates are based on the O*NET database and therefore refer to the US. We are fully aware that using US data to describe occupational employment in the EU might be prone to some bias (Barbieri et al., 2020) but, in the absence of readily available figures for the EU, we postulate that US data are a good approximation. The WFH indicators are real dimensionless numbers ranging from zero to 100, where a higher value indicates that employment is more amenable to remote operation. We also construct a crude estimate of remote work potential for each of the 17 NACE industries across the EU as a weighted average of the occupational WFH estimates provided by Gottlieb et al. (2020). The weights correspond to the employment shares of occupations within each sector across all 27 EU Member States for the year 2018 ([7]) ([8]). The NACE classification of industries and the corresponding industry codes are presented in Table A3 in Annex 2.

Regarding automation risk, we employ the estimates of mean probability of automation and the share of high automation risk constructed by Pouliakas (2018) for different ISCO two-digit occupational categories. These are also reproduced in Table A2 in the Appendix. Note that these estimates are based on data collected in, and therefore refer to, the year 2014. As the author did not provide estimates on automation risk at the country or the NACE industry level, we construct crude estimates of the mean probability of automation and the share of high risk for each of the 27 EU Member States and the 17 NACE industries ([9]). In a similar fashion to WFH, these are weighted averages of the occupational automation risk, in which the weights correspond to the 2014 employment shares of occupations in each sector across all 27 EU Member States and in each country, respectively.

Lastly, we use Eurofound (2016) data on the relative intensity of performing different tasks at work. Eurofound (2016) uses an approach in which the production of goods and services is seen as a mechanical process of transforming inputs into outputs, so as to study the different tasks that Europeans do at work. The work is thus split into discreet units, called tasks, which differ along with the complexity of the production process in each job. These tasks are categorised with respect to (a) their content ('what is done') and (b) the methods and tools used for carrying them out ('how it is

([7]) We selected the year 2018, since Dingel and Nieman (2020) use that year's data on employment from the US Bureau of Labor Statistics to aggregate WFH estimates from the six-digit to the two-digit occupations for the US Standard Occupational Classification.

([8]) To assess the accuracy of the crude WFH estimates at the industry level, we used the occupational WFH data to also re-estimate WFH for the 27 EU countries, using as weights the occupational shares within each country for 2018. When comparing the constructed country WFH with the one provided by Dingel and Niemann (2020), their correlation was 0.976 and statistically significant at the 1% significance level.

([9]) Pouliakas (2018) provides industry estimates for automation risk, but the industry classification used is different from the classification into the 17 NACE industries which is used by Cedefop's skills forecast.

done'). The former include physical and intellectual tasks aimed at manipulating materials and information respectively, and social tasks aimed at interaction with other people. The latter include autonomous, teamwork and routine tasks as well as tasks involving the use of machines (excluding ICT) and ICT tools ([10]). The intensity of performing each type of task for different countries and occupations is estimated using 2014 EU labour force survey data as dimensionless numbers ranging from zero to 100. Higher values indicate that a particular type of task is more frequently performed by workers in a particular occupation or country. Data availability restricted us to considering only six types of tasks for both countries and occupations: physical, intellectual and social tasks from the context category and routine, and machine and ICT-related tasks from the methods and tools category. Industry estimates for the intensity of the six types of tasks were constructed as weighted averages of the corresponding occupational data, using 2014 EU-wide occupational employment shares within each of the 17 NACE industries.

Descriptive statistics of the study's variables are presented in Table 1, while Table 2 presents average values over the four major occupational groups: high-skilled non-manual, skilled non-manual, skilled-manual, and elementary occupations.

3.2. Empirical results

This section presents the empirical results relating expected employment loss due to the emergence of the COVID-19 pandemic with remote work potential, automation risk, and the intensity of performing different tasks at work. Pearson correlation coefficients are depicted in Table 3 while Tables 4, 5 and 6 present various specifications of OLS regression estimations in which the dependent variable is the average percentage difference in employment in 2020-21, 2022-23 and 2024-30 ([11]). From Table 1 we see that the maximum difference values are negative across all three time periods for all countries and occupations, while there is only one industry with a positive difference in employment between the baseline and the COVID-19 scenarios (Human Health and Social Work Activities for 2020-21). Therefore, we can, without loss of generality, refer to percentage employment decrease or loss instead of difference. This makes the interpretation of the signs in Tables 3 to 6 relatively more straightforward, as a positive (negative) sign for a correlation or a coefficient indicates that the respective variable is negatively (positively) associated with employment loss due to the pandemic.

([10]) Some of these categories are further divided into subcategories; see Eurofound (2016).

([11]) The results of these regressions should be interpreted with caution. Their coefficient estimates should not be taken at face value, as the sample in each case is not large enough to secure high degrees of freedom.

Figures 2 and 3 depict the relation between employment loss and WFH and automation risk respectively, for the 27 EU Member States. Overall, countries in which job positions have greater remote working potential and lower shares of high automation risk appear to suffer less employment loss due to the emergence of the pandemic. This relation, however, is statistically significant only for the initial period examined, 2020-21. For the next two years (2022-23), during which EU economies are expected to gradually recover, the respective correlation coefficients are statistically significant at the 1% level, but the regression coefficient estimates are not (Table 3). These results indicate that, in countries in which the labour market allows for more work-from-home opportunities, employment is more safeguarded from the pandemic shock and the return to pre-COVID levels is expected to occur relatively faster and smoother. On the other hand, we see that Romania, the country with the minimum WFH potential, has also the largest expected employment loss in both the shock and the recovery period. Romania has also the largest estimated share of jobs at high risk of automation (Figure 3). Nevertheless, we see that employment in the country is forecast to recover somewhat faster compared to, e.g. Spain, Croatia and Ireland, which have lower levels of both WFH potential and share of jobs at high automation risk.

A more detailed view of the skills requirements which will allow individuals in different countries to better buffer the shock of the crisis can be gauged from relating employment loss to the intensity of different tasks performed at work. In Table 3 we see that tasks requiring social skills and the use of ICT tools appear to be very important for safeguarding against employment loss in the initial stages of the COVID-19 pandemic. The importance of ICT skills remains significant even in the long term (Table 4). On the other hand, countries in which a lot of jobs require physical skills appear to suffer larger employment losses. Also, employment in these countries is expected to recover at a slower pace than in countries in which a large portion of jobs require non-physical skills. Nevertheless, the related coefficient is not statistically significant in any of the country regression specifications (see Table 3). Other tasks that in general relate more to jobs susceptible to automation risk, such as routine tasks and the operation of machine tools, are not significantly related to employment loss due to COVID-19. These results, along with the overall insignificant effects of the mean probability of automation, may be viewed as an indication that, at least from the perspective of different countries, COVID-19 does not seem to accelerate the ongoing trend of job automation.

On the other hand, both remote working potential and automation risk appear to be significant determinants of employment loss for different occupations across the EU. In Tables 3 and 5, we see that higher WFH potential is significantly associated with less employment loss due to COVID-19, but not at the initial stages of the pandemic, i.e. 2020-21. This might reflect the effect of protective measures taken by governments across the EU (e.g. furlough schemes for workers, employment support and rescue packages for businesses) with the aim of restraining employment loss. When these protective measures start to be gradually lifted (which is expected to occur after 2021 as economies recover from the pandemic), remote work potential becomes a significant determinant of employment loss. In general, occupations benefitting from their high amenability to work from home are mostly related to the services sector. They include teaching, business and administration, and ICT technology professionals. All have WFH levels above 90% and are expected to suffer only moderate employment loss in 2020-2021 and then recover rapidly to pre-COVID employment levels. However, occupations which are recognised as essential for battling with the pandemic do not seem to suffer employment loss despite their low WFH potential. See, for example, the three occupations at the top-left corner of the charts in Figure 3 (health professionals, health associate professionals, and personal care workers) which combine very low WFH with the least employment loss in all three periods examined.

Also, occupations with a greater probability of automation or larger shares of workers at high automation risk appear to suffer significantly more as well as lasting employment loss because of the pandemic (Table 3) ([12]). This indicates that some in these occupations may become permanently lost as a result of greater adoption of automation, accelerated by the pandemic. Examples include food processing, woodworking, garment and other craft and related trades, and food preparation assistants. In both types of occupations, the mean probability of automation is greater than 50% and the share of workers at high automation risk is more than 10%. Both are forecasted to experience a long and persistent decrease in employment as a result of the pandemic (over 7% on average in 2020-21, and about 5% and 3% in 2022-23 and 2024-30 respectively). The same is expected to occur for sales workers, for whom the swift shift to online retailing during the pandemic is expected to have long-lasting adverse effects.

Employment in occupations where social, intellectual and ICT skills are important seems to be more safeguarded from temporary or permanent loss due to COVID-19 (Table 3). In a similar fashion to WFH potential, this relation appears to become significant after the pandemic's initial shock. On the other hand, routinisation of work or the use of machine tools appear to be related to larger and more persistent employment losses in occupational employment. Such occupations (e.g. assemblers, stationary plant and machine operators, and metal, machinery and related trades workers) are also the ones associated with less remote work potential, more

([12]) Notice, however, that the regression coefficients in Table 5 are not statistically significant for the first two time periods examined, while for 2024-2030 they have a positive sign, indicating that more automation risk contributes to less employment loss.

automation risk, and the primary or secondary economic sectors ([13]). Therefore, we may infer that, when viewed from the perspective of occupational employment, COVID-19 appears to accelerate the ongoing EU megatrends of job automation and the structural shift towards the services sector.

The same appears to hold for the job polarisation trend. The variable reflecting the major occupational group of each ISCO two-digit occupation (which takes the value of 1 for elementary, 2 for skilled manual, 3 for skilled non-manual and 4 for highly skilled non-manual occupations) appears to be a significant determinant of employment loss due to COVID-19 (Table 5). Its positive sign indicates that high-skilled occupations face less employment loss in the initial stages of the pandemic, while they also manage to recover relatively faster compared to medium- or low-skilled occupations. This finding is consistent with those of other studies that have analysed data from the initial stages of the pandemic (Adams-Prassl et al., 2020; Fana et al., 2020). Also, in the occupational averages in Table 3 we see that high-skill occupations are more amenable to remote operation and are also associated with less automation risk.

In contrast to the observations made for occupational and country-level employment, expected employment loss due to the pandemic does not appear to be driven by either remote work potential or automation risk. In Table 3 we see that the respective correlations have the expected signs but are not statistically significant. The same holds for the correlations between employment loss and the intensity of performing different tasks at work. In Table 1 we see that employment in certain industries is expected to fall by 11% (manufacturing) in 2020-21 and 6% in 2022-23, and on average be as much as 4.2% lower than pre-COVID forecasts for 2024-30 for the accommodation and food service activities industry. However, the WFH potential of the manufacturing sector is almost the same as that of the human health and social work activities industry, in which employment is expected to remain mostly unharmed through the pandemic (see Figure 3). The real estate, arts, recreation, and other service activities, and public administration and defence industries have roughly the same levels of automation risk, but employment in the latter is forecasted to drop considerably less. Both the human health and social work activities and the public administration and defence industries have been considered essential for battling against the pandemic, while the rest were forced to partly or fully cease operation. Thus, employment loss at the sectoral level might be driven more by the restrictions imposed by governments rather than automation risk or the remote work potential in these sectors.

([13]) This is an expected outcome, as both the WFH measures and automation risk are constructed following task-based approaches; that is, accounting for the relative intensity of certain tasks that are frequently performed in different job positions.

CHAPTER 4.
Concluding remarks

In this paper we have provided a first assessment of potential determinants of the future effects of COVID-19 on employment in the EU. More specifically, we concentrated on two factors: remote working potential and automation risk. The former appears to be a significant driver of employment loss, due to the restrictions on mobility and the exercise of social distancing across the EU. The latter might indirectly affect certain job positions lost during the pandemic (which are related to the onsite operation of machines and routine work) as well as after its end (through changes in investment decisions towards faster adoption of automation). We employed estimates of employment differences from 2020 to 2030 between two separate scenarios conducted by Cedefop's skills forecast: one that incorporated the pandemic effects and one that did not, as well as remote working potential and automation risk estimates provided by recent literature

Overall, our results suggest that less potential to operate 'from home' and greater risk of automation are associated with greater expected employment loss due to the emergence of COVID-19, but only at the country or EU-wide occupational level. This relation is significant at the country level only at the initial stages of the pandemic, while the reverse holds for employment in different occupations. Further, COVID-19 appears to significantly accelerate the ongoing megatrends of job polarisation and automation, as well as the shift towards the service sectors, but only when it is examined from the perspective of different occupations. Also, employing data on the intensity of performing different tasks at work across the EU, we found that intellectual, ICT and social skills appear to be those that will allow individuals to better buffer the shock of the COVID-19 crisis in the short- and medium-term future. Jobs that are highly dependent on these skills are expected to suffer less employment loss and recover faster after the pandemic has ended.

The results of this paper are based on employment forecasts and not actual data, and thus provide merely a partial glance at the likely effects of the COVID-19 pandemic on EU employment and their potential determinants. It is likely that some of the employment loss forecasted by the skills forecast COVID-19 scenario for occupations, countries and industries will not be realised because of additional future measures implemented by EU and individual country authorities. Also, as actual data become available in the coming years, the above results can be reassessed in light of new and updated information on employment. For example, a valuable addition to the present paper would be to relate the actual loss in employment in different EU countries, occupations and industries between pre- and post-pandemic years (e.g. between 2019 and 2020-2022) to remote working potential and the risk of automation. This would provide valuable insights that would complement the findings of the present paper.

Table 1. **Descriptive statistics of the study variables**

	Employment decrease (%)				Intensity of performing different tasks at work						Automation risk	
	WFH	$D_{2020-21}$	$D_{2022-23}$	$D_{2024-30}$	Physical tasks	Social tasks	Intellectual tasks	Routine methods	Use of machine tools	Use of ICT tools	Mean risk	High risk
(a) 27 EU Member States												
average	36.370	-5.546	-3.036	-2.285	28.926	48.111	39.593	49.852	20.407	38.000	50.765	8.824
maximum	53.420	-2.370	-1.340	-0.776	35.000	52.000	41.000	52.000	28.000	48.000	51.862	11.024
minimum	21.760	-9.525	-6.885	-6.460	23.000	45.000	35.000	47.000	15.000	29.000	49.346	7.710
median	36.690	-5.240	-2.625	-1.827	29.000	48.000	40.000	50.000	20.000	38.000	50.959	8.851
standard deviation	5.989	1.982	1.394	1.314	1.979	1.476	1.309	1.322	2.707	3.453	0.651	0.748
(b) 39 EU-wide ISCO 2-digit occupations												
average	32.872	-5.857	-3.150	-2.474	29.577	47.533	38.810	49.859	21.772	38.254	50.615	8.718
maximum	100.000	-0.740	-0.785	-0.626	43.300	65.400	62.500	72.300	51.000	84.700	57.000	18.000
minimum	0.000	-11.225	-4.985	-3.903	9.900	24.800	20.700	17.500	3.000	7.300	42.000	2.000
median	17.000	-5.875	-3.075	-2.477	32.500	45.600	37.300	49.400	17.500	38.700	50.000	8.000
standard deviation	35.475	2.363	1.045	0.801	11.190	10.929	10.652	9.953	13.599	21.849	3.760	4.690
(c) 17 EU-wide NACE industries												
average	36.888	-4.525	-2.601	-2.070	28.244	38.877	48.401	50.046	20.837	39.814	50.851	8.741
maximum	77.487	0.320	0.000	0.000	40.533	49.741	57.438	60.018	36.193	64.988	54.437	12.585
minimum	7.716	-11.495	-6.160	-4.244	16.298	29.715	40.854	42.046	8.814	21.498	47.291	4.406
median	30.091	-4.505	-3.185	-2.563	29.144	39.013	46.813	49.201	17.454	37.343	51.032	8.567
standard deviation	21.227	3.559	1.881	1.514	6.677	4.699	4.945	4.885	8.753	12.237	2.081	2.533

NB: We consider 39 out of 41 ISCO two-digit occupations. One occupation (Armed Forces) was not considered in Gottlieb et al. (2020) and two occupations (Armed Forces, Subsistence farmers, fishers, hunters and gatherers) were not considered by Eurofound (2016).

Source: Authors' calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb et al. (2020), Pouliakas (2018) and Eurofound (2016).

Table 2. **Averages values of the study variables over four major occupational groups**

		Employment decrease (%)			Intensity of performing different tasks at work						Automation risk	
	WFH	$D_{2020-21}$	$D_{2022-23}$	$D_{2024-30}$	Physical tasks	Social tasks	Intellectual tasks	Routine methods	Use of machine tools	Use of ICT tools	Mean risk	High risk
High-skilled non-manual	60.133	-4.967	-2.598	-2.030	21.200	58.967	48.167	45.853	13.960	58.573	47.933	5.133
Skilled non-manual	39.125	-5.294	-2.966	-2.470	26.913	45.513	39.025	46.575	12.150	41.300	48.500	6.625
Skilled manual	4.500	-7.802	-3.940	-2.945	41.100	41.280	29.660	60.710	40.330	20.870	54.800	14.600
Elementary	3.667	-5.588	-3.462	-2.801	34.867	32.067	30.383	46.167	23.200	12.367	53.167	10.667

NB: We consider 39 out of 41 ISCO 2-digit occupations. One occupation (Armed Forces) was not considered in Gottlieb et al. (2020) and two occupations (Armed Forces, Subsistence farmers, fishers, hunters and gatherers) were not considered by Eurofound (2016).

Source: Authors' calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb et al. (2020), Pouliakas (2018) and Eurofound (2016).

Table 3. **Pearson correlation coefficients of the study variables**

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	
1. WFH		0.518***	0.415***	0.291	-0.949***	0.918***	0.842***	-0.784***	-0.854***	0.940***	-0.734***	-0.901***	Upper diagonal: 27 EU Member States
2. $D_{2020-21}$	0.242		0.644***	0.659***	-0.516***	0.589***	0.421**	-0.326*	-0.338*	0.563***	-0.216	-0.390**	
3. $D_{2022-23}$	0.415***	0.819***		0.861***	-0.438**	0.425***	0.360*	-0.274	-0.287	0.430***	-0.306	-0.373*	
4. $D_{2024-30}$	0.419***	0.664***	0.925***		-0.255	0.366**	0.140	-0.072	-0.021	0.310*	-0.120	-0.169	
5. physical tasks	-0.847***	-0.204	-0.329**	-0.290*		-0.866***	-0.859***	0.790***	0.889***	-0.945***	0.652***	0.880***	
6. social tasks	0.718***	0.204	0.357**	0.352**	-0.682***		0.821***	-0.662***	-0.705***	0.936***	-0.631***	-0.792***	
7. intellectual tasks	0.433***	0.330**	0.326**	0.243	-0.590***	0.766***		-0.681***	-0.853***	0.843***	-0.696***	-0.893***	
8. routine methods	-0.369**	-0.632***	-0.519***	-0.396**	0.607***	-0.273*	-0.475***		0.889***	-0.699***	0.694***	0.815***	
9. use of machine tools	-0.617***	-0.534***	-0.495***	-0.395**	0.800***	-0.449***	-0.613***	0.815***		-0.819***	0.769****	0.934***	
10. use of ICT tools	0.856***	0.189	0.373**	0.368**	-0.798***	0.897***	0.573***	-0.313*	-0.545***		-0.725***	-0.878***	
11. mean automation risk	-0.552***	-0.528***	-0.558***	-0.510***	0.623***	-0.606***	-0.726***	0.608***	0.789***	-0.593***		0.879***	
12. high automation risk	-0.611***	-0.542***	-0.542***	-0.421***	0.751***	-0.630***	-0.747***	0.720***	0.845***	-0.661***	0.910***		
	Lower diagonal: 39 EU-wide ISCO two-digit occupations												
1. WFH		0.208	0.347	0.373	-0.949***	0.698***	0.887***	-0.642***	-0.713***	0.902***	-0.662***	-0.803***	Upper diagonal: 17 NACE industries
2. $D_{2020-21}$			0.907***	0.824***	-0.112	0.154	0.309	-0.206	-0.040	0.212	-0.208	-0.204	
3. $D_{2022-23}$				0.966***	-0.265	0.211	0.448**	-0.149	-0.070	0.370	-0.248	-0.244	
4. $D_{2024-30}$					-0.294	0.214	0.479**	-0.118	-0.085	0.407	-0.296	-0.275	
5. physical tasks						-0.702***	-0.827***	0.651***	0.783***	-0.906***	0.677***	0.826***	
6. social tasks							0.633***	-0.765***	-0.888***	0.536**	-0.899***	-0.901***	
7. intellectual tasks								-0.435	-0.538**	0.938***	-0.575**	-0.681***	
8. routine methods									0.900***	-0.483**	0.835***	0.902***	
9. use of machine tools										-0.592**	0.927***	0.957***	
10. use of ICT tools											-0.557**	-0.696***	
11. mean automation risk												0.952***	
12. high automation risk													

NB: Three, two and one stars denote statistical significance at the 1%, 5% and 10% level respectively.
Source: Authors' calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb et al. (2020), Pouliakas (2018) and Eurofound (2016).

Table 4. **Regression estimations, percentage difference in EU Member States employment against Work from Home potential, automation risk, and intensity of performing different tasks at work**

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $D_{2020-21}$						
intercept	-11.783***	-19.529	-25.749	-16.050	-71.086	-122.07
WFH	0.172***					0.099
intensity of performing:						
physical tasks		-0.369	-0.188			0.631
intellectual tasks		-0.044	-0.417			-0.196
social tasks		0.398	0.856*			-0.279
routine tasks		-0.156		-0.358		-0.607
use of machine tools		0.389		0.441		0.468
use of ICT tools		0.186		0.510***		0.097
mean automation risk					-1.697	2.009
high automation risk					-2.333**	-1.094
adjusted R^2	0.239	0.206	0.282	0.293	0.159	0.141
F-statistic	9.175***	2.123*	4.407**	4.588**	3.449**	1.475
heteroscedasticity	no	No	no	no	no	no
Dependent variable: $D_{2022-23}$						
intercept	-6.551**	11.117	-0.662	-7.178	-5.667	87.113
WFH	0.097					-0.218
intensity of performing:						
physical tasks		-0.515	-0.249			-1.542
intellectual tasks		0.288	-0.135			-0.331
social tasks		-0.211	0.211			0.719
routine tasks		-0.274		-0.181		0.187
use of machine tools		0.452		0.187		0.487
use of ICT tools		0.104		0.246*		-0.502
mean automation risk					0.199	-0.942
high automation risk					-0.848	-1.300
adjusted R^2	0.139	0.028	0.100	0.100	-0.036	-0.022
F-statistic	5.208**	1.127	1.967	1.970	0.899	0.919
heteroscedasticity	yes	No	no	no	no	no
Dependent variable: $D_{2024-30}$						
intercept	-4.606***	0.956	-12.052	-7.581	-10.734	30.208
WFH	0.064					-0.070
intensity of performing:						
physical tasks		-0.379	-0.041			-0.819
intellectual tasks		0.019	-0.523			-0.455
social tasks		0.082	0.658			0.465
routine tasks		-0.299		-0.373		-0.062
use of machine tools		0.576		0.518**		0.756
use of ICT tools		0.163		0.350***		-0.176
mean automation risk					0.252	0.042
high automation risk					-0.489	-2.092
adjusted R^2	0.048	0.106	0.112	0.197	-0.048	0.049
F-statistic	2.311	1.513	2.087	3.132**	0.399	1.151
heteroscedasticity	no	no	no	no	no	no

NB: Three, two and one stars denote statistical significance at the 1%, 5% and 10% level respectively. Heteroscedasticity consistent standard errors are used when necessary.

Source: Author’s calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb et al. (2020), Pouliakas (2018) and Eurofound (2016).

Table 5. **Regression estimations, percentage difference in EU-wide ISCO 2-digit occupational employment against Work from Home potential, automation risk, and intensity of performing different tasks at work**

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: $D_{2020-21}$							
intercept	-6.386***	-5.830	-7.341*	1.391	-7.604***	2.210	-12.957
WFH	0.016						0.040**
intensity of performing:							
physical tasks		0.223**	-0.015				0.289***
intellectual tasks		0.094	-0.034				0.087
social tasks		-0.048	0.091				0.0352
routine tasks		-0.147		-0.135			-0.142**
use of machine tools		-0.124		-0.016			-0.091
use of ICT tools		0.020		-0.004			-0.021
occupational group (1)					0.619*		0.017
mean automation risk						-0.129	0.128
high automation risk						-0.189	-0.252
adjusted R	0.033	0.534	0.042	0.349	0.061	0.262	0.571
F-statistic	2.294	8.265***	1.551	7.811***	3.495*	7.734***	6.054***
heteroscedasticity	no	yes	yes	yes	no	no	no
Dependent variable: $D_{2022-23}$							
Intercept	-3.552***	-3.526*	-3.945**	-1.275	-4.227***	-2.534	-0.845
WFH	0.012***						0.017*
intensity of performing:							
physical tasks		0.070*	-0.014				0.075*
intellectual tasks		0.055	0.017				0.017
social tasks		-0.035	0.010				-0.027
routine tasks		-0.048*		-0.045*			-0.059**
use of machine tools		-0.044		-0.002			-0.002
use of ICT tools		0.010		0.011			-0.008
occupational group					0.417***		0.305
mean automation risk						-0.105	-0.037
high automation risk						-0.044	-0.053
adjusted R^2	0.150	0.334	0.072	0.260	0.178	0.279	0.367
F-statistic	7.689***	4.176***	1.987	5.453***	9.260***	8.385***	3.206***
heteroscedasticity	no	no	yes	no	no	yes	no
Dependent variable: $D_{2024-30}$							
intercept	-2.785***	-3.109**	-3.213**	-1.575**	-3.378***	-5.146	4.413
WFH	0.010***						0.012
intensity of performing:							
physical tasks		0.047*	-0.008				0.035
intellectual tasks		0.062	0.025				0.007
social tasks		-0.042	0.006				-0.027
routine tasks		-0.027		-0.026			-0.049**
use of machine tools		-0.035		0.002			0.013
use of ICT tools		0.001		0.010			-0.007
occupational group					0.321***		0.337
mean automation risk						0.158**	-0.131
high automation risk						0.043	0.058
adjusted R^2	0.154	0.225	0.057	0.156	0.180	0.231	0.315
F-statistic	7.899***	2.836**	1.769	3.348**	9.313***	6.708***	8.748**
heteroscedasticity	no	no	yes	no	no	no	no

NB: Occupational group is a dummy variable that takes the value of 4 for high-skilled non-manual occupations, 3 for skilled non-manual occupations, 2 for skilled manual occupations, and 1 for elementary occupations.

Three, two and one stars denote statistical significance at the 1%, 5% and 10% level respectively. Heteroscedasticity consistent standard errors are used when necessary.

Source: Authors' calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb *et al.* (2020), Pouliakas (2018) and Eurofound (2016).

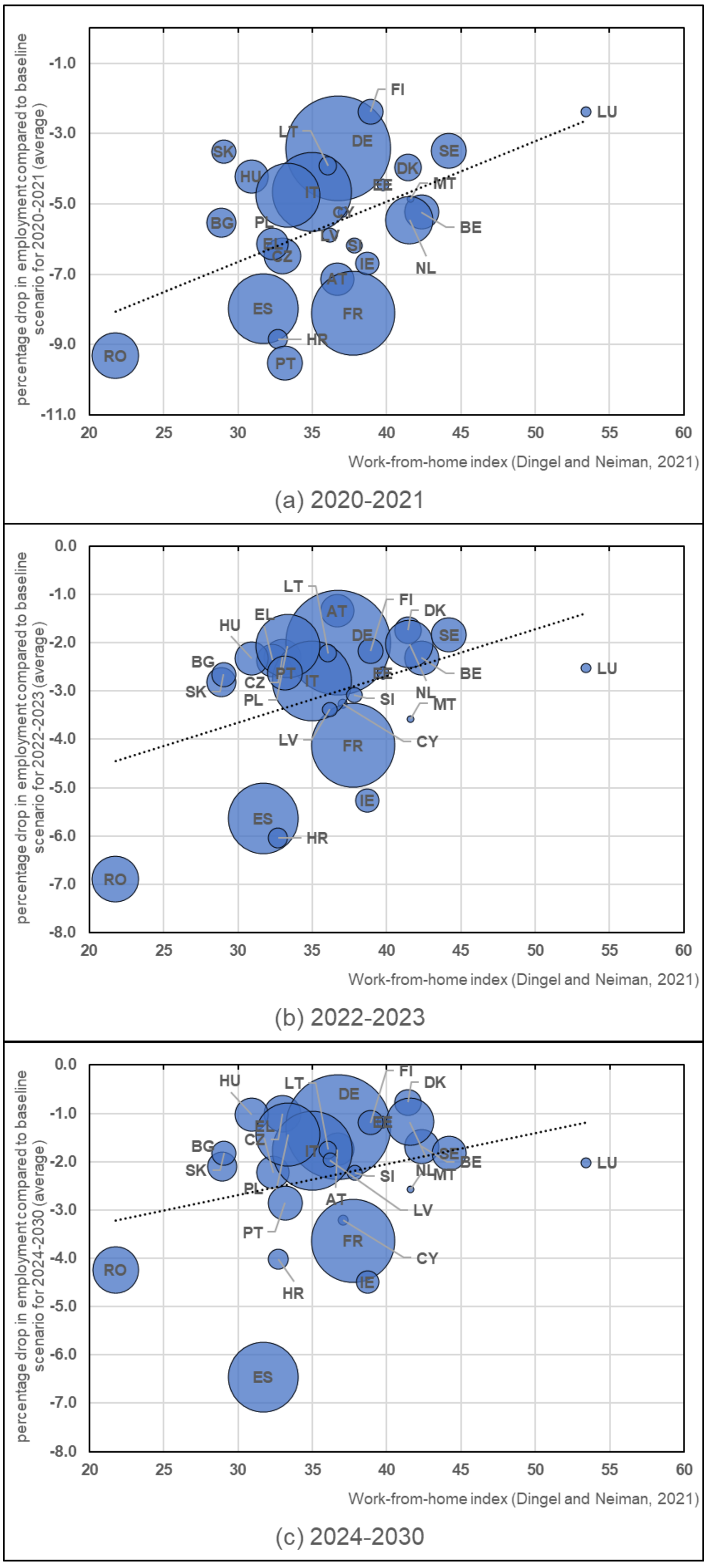
Table 6. **Regression estimations, percentage difference in EU-wide employment forecasts in 17 NACE industries against Work from Home potential, automation risk, and intensity of performing different tasks at work**

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $D_{2020-21}$						
intercept	-5.810***[1]	-11.587	-37.749	18.235	9.389	222.229
WFH	0.035					-0.180
intensity of performing:						
physical tasks		0.166	0.266			-1.028
intellectual tasks		-0.010	0.483			0.151
social tasks		0.551	0.060			0.464
routine tasks		-0.791		-0.270		-1.447
use of machine tools		0.683		0.433		1.441
use of ICT tools		0.171		0.107		0.013
mean automation risk					-0.259	-3.867
high automation risk					-0.084	2.532
adjusted R^2	-0.021	-0.034	-0.029	0.062	-0.093	-0.071
F-statistic	0.677	0.911	0.847	1.354	0.320	0.882
heteroscedasticity	no	no	no	no	no	no
Dependent variable: $D_{2022-23}$						
intercept	-3.736***	-13.090	-18.187	1.987	5.522	148.967
WFH	0.031					-0.078
intensity of performing:						
physical tasks		0.056	-0.090			-0.643
intellectual tasks		-0.462	0.277			-0.516
social tasks		0.659	-0.011			0.685
routine tasks		-0.332		-0.230		-0.786*
use of machine tools		0.527		0.171		1.034**
use of ICT tools		0.283		0.084*		0.238
mean automation risk					-0.149	-2.794*
high automation risk					0.065	2.084
adjusted R^2	0.062	0.020	0.061	0.061	-0.072	0.247
F-statistic	2.058	1.054	1.345	1.349	0.463	1.583
heteroscedasticity	no	no	no	no	no	no
Dependent variable: $D_{2024-30}$						
intercept	-3.052***	-12.536	-14.361	-1.303	11.128	115.865*
WFH	0.027					-0.045
intensity of performing:						
physical tasks		0.047	0.066			-0.458
intellectual tasks		-0.241	0.232*			-0.379
social tasks		0.407	-0.020			0.383
routine tasks		-0.176		-0.115		-0.416
use of machine tools		0.317		0.102		0.779**
use of ICT tools		0.182		0.072*		0.149
mean automation risk					-0.267	-2.164*
high automation risk					0.044	1.006
adjusted R^2	0.082	-0.053	0.095	0.052	-0.042	0.327
F-statistic	2.430	0.866	1.559	1.291	0.679	1.865
heteroscedasticity	no	no	no	no	no	no

NB: Three, two and one stars denote statistical significance at the 1%, 5% and 10% level respectively. Heteroscedasticity consistent standard errors are used when necessary.

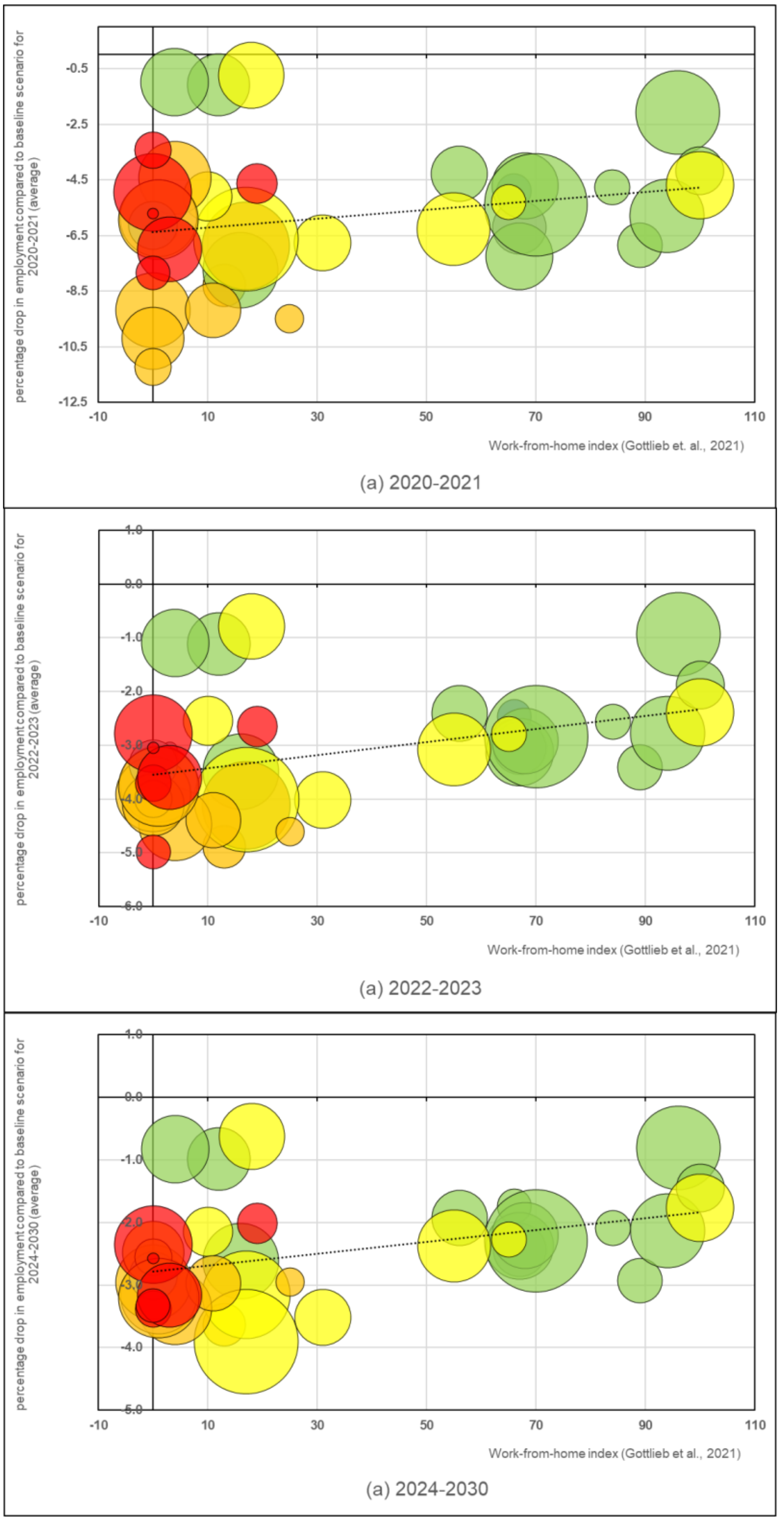
Source: Author's calculations based on data from Cedefop (2021), Dingel and Neiman (2020), Gottlieb et al. (2020), Pouliakas (2018) and Eurofound (2016).

Figure 1. **Percentage difference in the 27 EU Member States total employment forecasts due to COVID-19 and Work from Home potential**



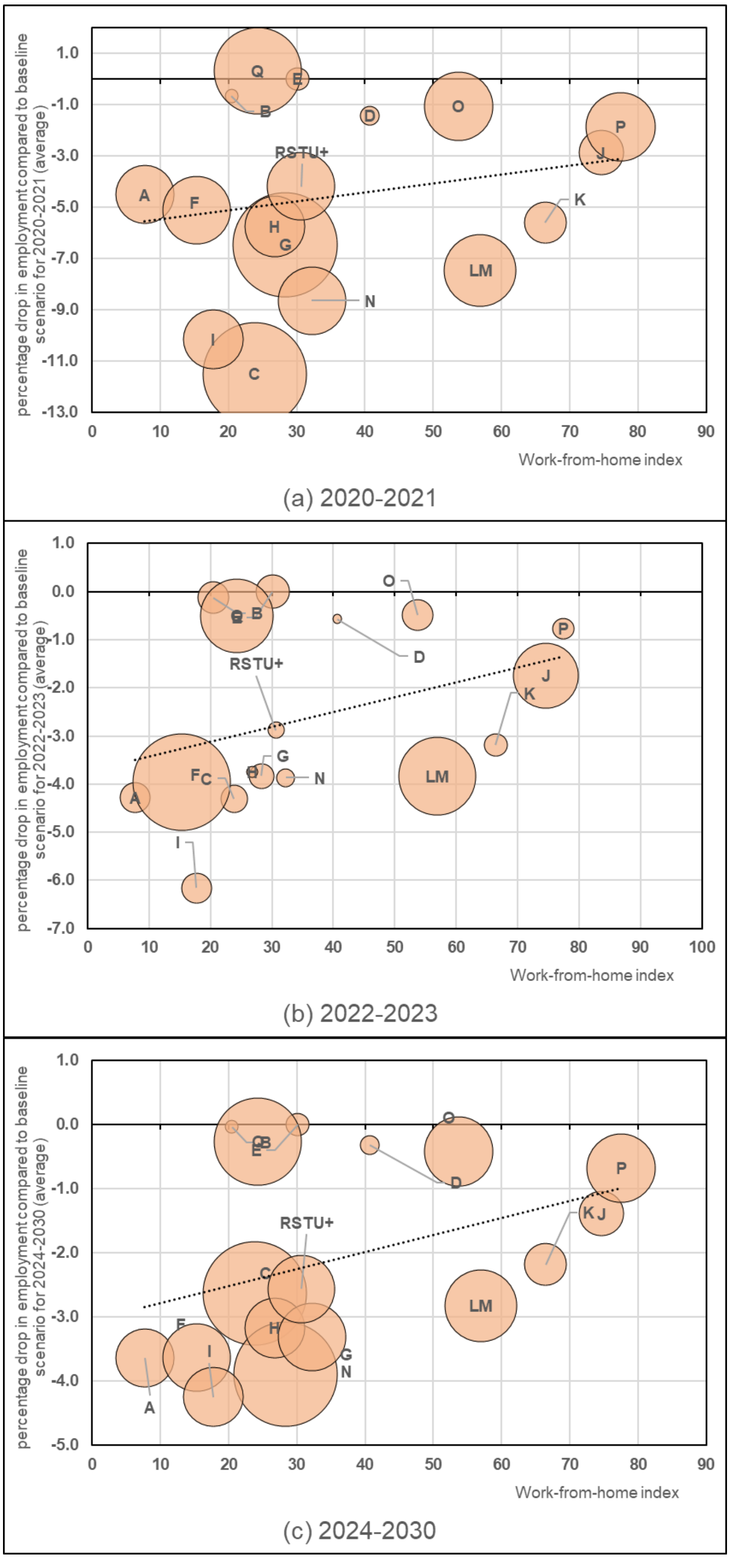
NB: The size of the circles depicts employment in each country as a share of total EU employment forecast in 2019.

Figure 2. **Percentage difference in EU-wide occupational employment forecasts due to COVID-19 and Work from Home potential**



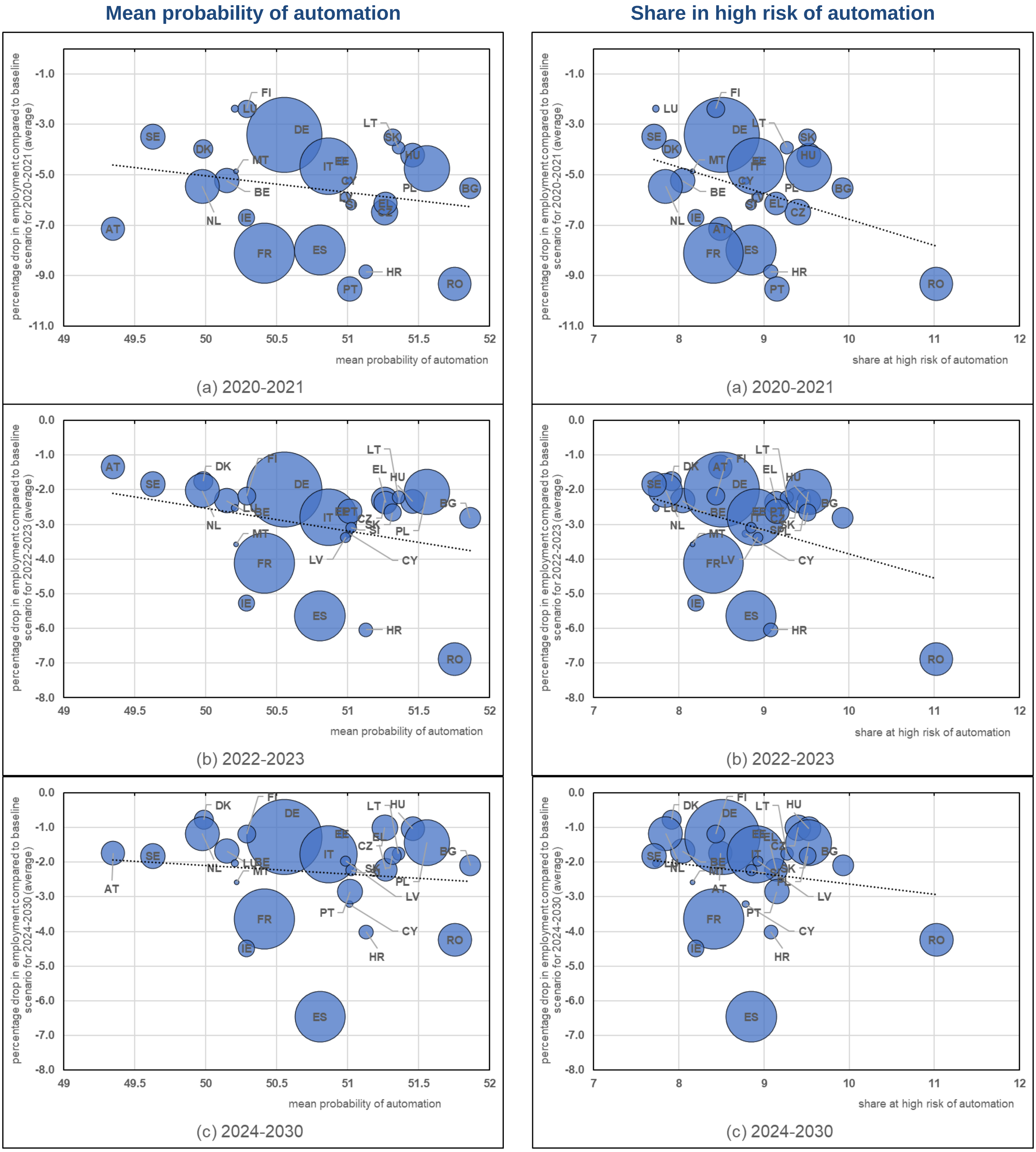
NB: The size of the circles depicts employment in each country or occupation as a share of total EU employment forecast in 2019. The colour in each circle depicts the major occupational group, as follows: green (high-skilled non-manual occupations), yellow (skilled non-manual) occupations, orange (skilled manual occupations), red (elementary occupations).

Figure 3. **Percentage difference in EU-wide employment forecasts in 17 NACE industries due to COVID-19 and Work from Home potential**



NB: The size of the circles depicts employment in each industry as a share of total EU employment forecast in 2019. The letter corresponds to NACE industry classification; see Table A3 in Annex 2.

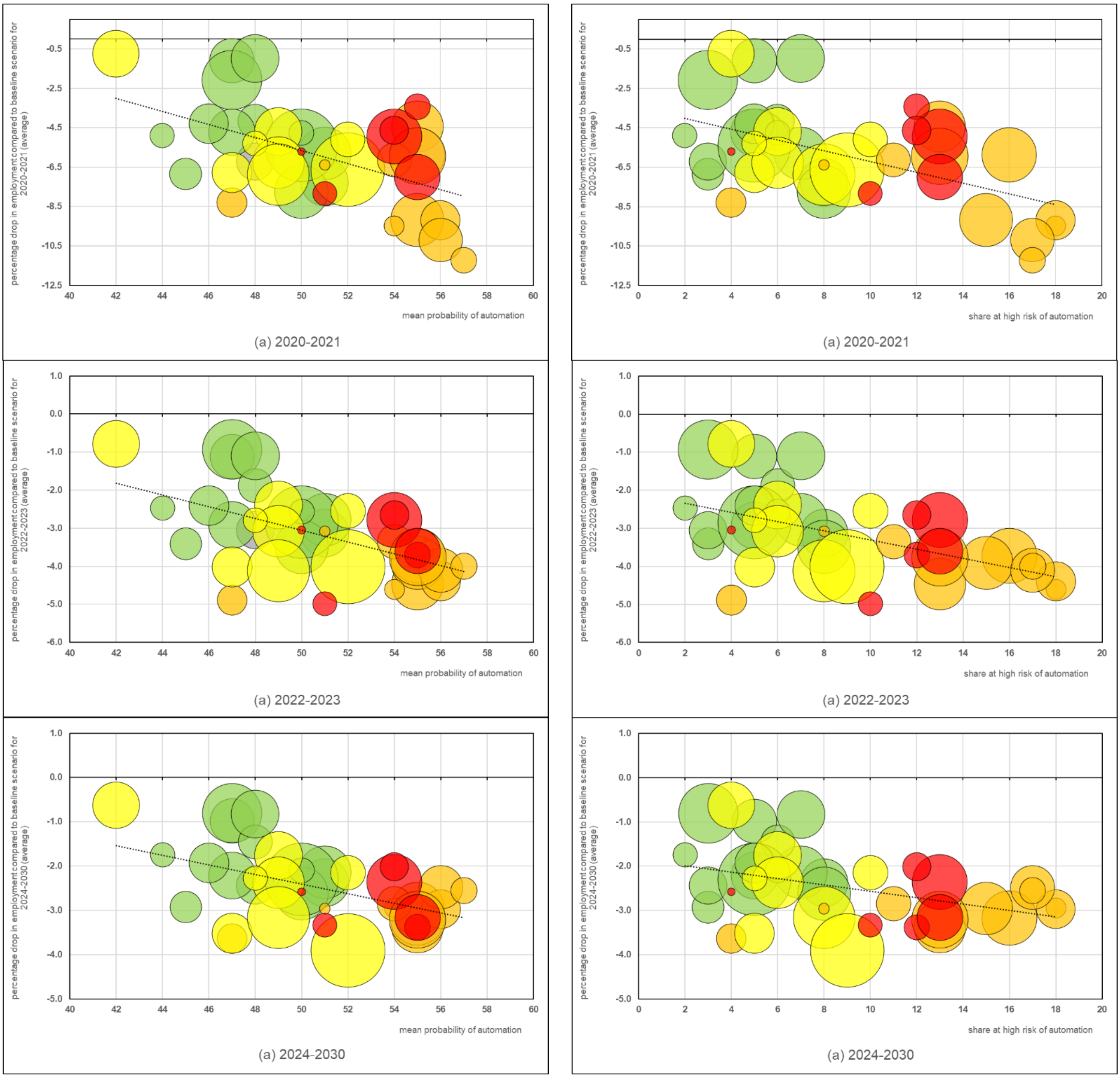
Figure 4. **Percentage difference in the 27 EU Member States total employment forecasts due to COVID-19 and automation risk estimates**



NB: The size of the circles depicts employment in each country as a share of total EU employment forecast in 2019.

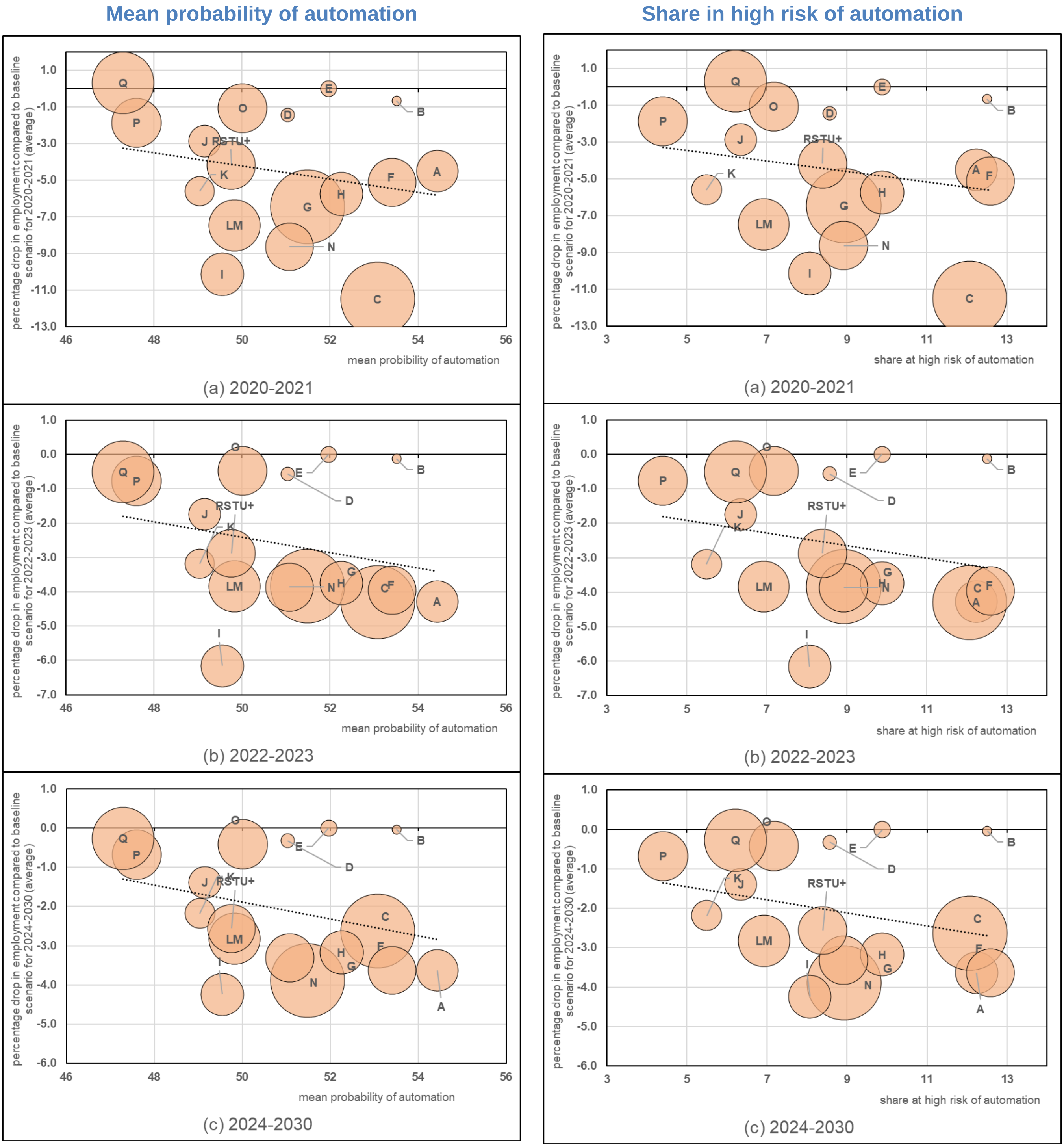
Figure 5. **Percentage difference in EU-wide occupational employment forecasts due to COVID-19 and automation risk estimates**

Mean probability of automation **Share in high risk of automation**



NB: The size of the circles depicts employment in each country or occupation as a share of total EU employment forecast in 2019. The colour in each circle depicts the major occupational group, as follows: green (high-skilled non-manual occupations), yellow (skilled non-manual) occupations, orange (skilled manual occupations), red (elementary occupations).

Figure 6. **Percentage difference in EU-wide employment forecasts in 17 NACE industries due to COVID-19 and Work from Home potential**



NB: The size of the circles depicts employment in each industry as a share of total EU employment forecast in 2019. The letter corresponds to NACE industry classification; see Table A3 in Annex 2.

Acronyms

AI	artificial intelligence
EU	European Union
ICT	information and communication technology
ISCO	International standard for classification of occupations
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne (Statistical classification of economic activities in the European Community)
O*NET	Occupational Information Network
US	United States of America
WFH	work from home

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Annexes

Annex 1.
Additional data

Table A1. **WFH potential in different EU countries**

Country	WFH potential
Austria	36.69
Belgium	42.34
Bulgaria	28.9
Cyprus	37.06
Czech Republic	32.99
Germany	36.73
Denmark	41.42
Estonia	39.75
Greece	32.34
Spain	31.69
Finland	38.92
France	37.74
Croatia	32.69
Hungary	30.92
Ireland	38.71
Italy	34.99
Lithuania	36.05
Luxemburg	53.42
Latvia	36.18
Malta	41.59
Netherlands	41.55
Poland	33.35
Portugal	33.16
Romania	21.76
Sweden	44.19
Slovenia	37.83
Slovakia	29.04

Source: Dingel and Neiman (2020).

Table A2. **WFH potential and risk of automation in different ISCO two-digit occupations**

Occupation	WFH potential	Mean probability of automation	Share at high risk of automation
Chief executives, senior officials and legislators	66	44	2
Administrative and commercial managers	89	45	3
Production and specialised services managers	67	48	3
Hospitality, retail and other services managers	13	47	4
Science and engineering professionals	67	51	8
Health professionals	12	47	5
Teaching professionals	96	47	3
Business and administration professionals	94	51	7
Information and communications technology professionals	100	48	6
Legal, social and cultural professionals	68	47	5
Science and engineering associate professionals	16	50	8
Health associate professionals	4	48	7
Business and administration associate professionals	70	50	5
Legal, social, cultural and related associate professionals	56	46	5
Information and communications technicians	84	50	6
General and keyboard clerks	100	49	6
Customer services clerks	31	47	5
Numerical and material recording clerks	55	49	6
Other clerical support workers	65	48	5
Personal service workers	17	49	8
Sales workers	17	52	9
Personal care workers	18	42	4
Protective services workers	10	52	10
Market-oriented skilled agricultural workers	4	55	13
Market-oriented skilled forestry, fishery and hunting workers	3	51	8
Building and related trades workers, excluding electricians	1	55	16
Metal, machinery and related trades workers	0	55	15

Occupation	WFH potential	Mean probability of automation	Share at high risk of automation
Handicraft and printing workers	25	54	18
Electrical and electronic trades workers	0	54	11
Food processing, wood working, garment and other craft and related trades	11	56	18
Stationary plant and machine operators	0	56	17
Assemblers	0	57	17
Drivers and mobile plant operators	1	55	13
Cleaners and helpers	0	54	13
Agricultural, forestry and fishery labourers	0	55	12
Labourers in mining, construction, manufacturing and transport	3	55	13
Food preparation assistants	0	51	10
Street and related sales and service workers	0	50	4
Refuse workers and other elementary workers	19	54	12

NB: We consider 39 out of 41 ISCO 2-digit occupations. One occupation (Armed Forces) was not considered in Gottlieb et al. (2020) and two occupations (Armed Forces, Subsistence farmers, fishers, hunters and gatherers) were not considered by Eurofound (2016).

Source: Gottlieb et al. (2020); Pouliakas (2018).

Annex 2.
NACE classification in 17 industries

Table A3. **NACE classification in 17 industries**

Industry code	Industry name
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply, Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles
H	Transportation and Storage;
I	Accommodation and Food Service Activities
J	Information and Communication
K	Financial and Insurance Activities
LM	Real Estate, Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
O	Public Administration and Defence, Compulsory Social Security
P	Education
Q	Human Health and Social Work Activities
RSTU+	Arts, Recreation, and Other Service Activities; (Film & TV production/broadcasting)

JOB LOSS AND COVID-19: DO REMOTE WORK, AUTOMATION AND TASKS AT WORK MATTER?

The COVID-19 pandemic is expected to have adverse and non-uniform impacts on future employment prospects for different job positions in the EU. We investigate two possible determinants of the variation of future employment loss due to the pandemic: the potential of a job to be carried out 'from home' and the risk of being substituted by automation. Using unique data provided by a dedicated COVID-19 impact scenario carried out for the latest Cedefop skills forecast, we find that less remote working potential and more automation risk are related to larger expected losses in employment due to COVID-19 for different countries and occupations, but not industries. These links are stronger in the short-term future for different countries, but for occupations they seem to strengthen in the years after 2022, reflecting the removal of protective measures taken by EU governments as the world recovers from the pandemic. Relating expected employment loss to the intensity of performing different tasks at work, we find that such loss is expected to be less for countries and occupations in which social, intellectual and information and communication technology (ICT) skills are important for a larger proportion of jobs.

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