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What happened to jobs at high risk of automation?

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- Abstract and Résumé
- Main findings: 1st bullet point p.9
- Section 4: paragraphs 52 and 67
- Section 5: Table 5.1 column (3) and paragraphs 72, 78, 80, 89, 90
- Section 7: paragraphs 119 and 124

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Abstract

This study looks at what happened to jobs at risk of automation over the past decade and across 21 countries. There is no support for net job destruction at the broad country level. All countries experienced employment growth over the past decade. Within countries, however, employment growth has been much lower in jobs at high risk of automation (6%) than in jobs at low risk (18%).

Low-educated workers were more concentrated in high-risk occupations in 2012 and have become even more concentrated in these occupations since then. In spite of this, the low growth in jobs in high-risk occupations has not led to a drop in the employment rate of low-educated workers relative to that of other education groups. This is largely because the number of low-educated workers has fallen in line with the demand for these workers. Going forward, however, the risk of automation is increasingly falling on low-educated workers and the COVID-19 crisis may have accelerated automation, as companies reduce reliance on human labour and contact between workers, or re-shore some production.

Résumé

Cette étude examine l'évolution des emplois menacés par l'automatisation au cours de la dernière décennie dans 21 pays. Au niveau national, aucun élément ne vient étayer une destruction nette d'emplois. Tous les pays ont connu une croissance de l'emploi au cours de la dernière décennie. Au sein des pays, cependant, la croissance de l'emploi a été beaucoup plus faible dans les métiers à haut risque d'automatisation (6 %) que dans les métiers à faible risque (18 %).

Les travailleurs peu qualifiés étaient davantage concentrés dans les professions à haut risque en 2012 et le sont devenus encore plus depuis lors. Néanmoins, la faible croissance de l'emplois dans les professions à haut risque n'a pas entraîné une baisse du taux d'emploi des travailleurs peu qualifiés relativement à celui des autres groupes d'éducation. Cela s'explique en grande partie par le fait que le nombre de travailleurs peu qualifiés a diminué conformément à la demande de ces travailleurs. Cependant, le risque d'automatisation pèse de plus en plus sur les travailleurs peu qualifiés et, à l'avenir, la crise liée au COVID-19 pourrait avoir accéléré l'automatisation, dans la mesure où les entreprises réduisent leur recours au travail humain et les contacts entre les travailleurs, ou relocalisent une partie de la production.

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Main findings

Policy debates are abuzz with talk of automation. Over the past decade, rapid advances in artificial intelligence, machine learning and robotics have seemed set to transform the world of work. The COVID-19 pandemic has only heightened speculation surrounding automation's transformative power, as the technologies that substitute for human labour are both unaffected by the virus and offer prospects of potentially significant cost savings for firms. Are workers being replaced by automation technologies, bringing society ever closer to a world of massive technological unemployment?

There are several reasons to see current levels of job destruction anxiety as exaggerated. First, employment levels have been rising in most OECD countries for decades (at least up until the pandemic). While employment growth has a variety of different contributing factors, upward trajectories in employment rates are simply at odds with fears around technological unemployment. In addition, empirical evidence on how past instances of technological change have impacted labour markets document positive net effects on job creation. While some jobs may disappear and tasks within jobs change, new jobs are also created, potentially at an even faster pace.

Even supposing that automation produces net employment gains, the benefits of automation are unlikely to be shared evenly among workers. Certain groups may be strictly disadvantaged, facing either worsened job prospects or deteriorations in job quality. It is therefore important to go beyond a consideration of the impact of automation on overall employment levels in order to examine who, in particular, is being affected and how. An understanding of automation's differential impacts can then form a basis for policymakers to decide how to target scarce public resources on those most in need.

This paper looks at what happened to jobs that had previously been estimated to be at high risk of automation, building on prior OECD work on automation risk. In response to a widely cited prediction that 47% of US jobs were at risk of being automated over the next 10-20 years (Frey and Osborne, 2017[1]), the OECD created an alternative measure of automation risk available by occupation (Nedelkoska and Quintini, 2018[2]). The OECD approach placed greater emphasis on the heterogeneity of task content within occupations, resulting in a much-reduced estimate of jobs at high risk of automation: an average of 14% across countries, and 10% for the US (with both estimates pertaining to 2012).

In this paper, the task-based measure of automation risk is used to study three main research questions: first, whether countries and jobs that were said to be at high risk of automation back in 2012 experienced employment declines over the subsequent period; second, whether certain demographic groups have been more vulnerable to these changes; and, third, how job stability has changed in these occupations. Annual data on labour market outcomes is taken from labour force surveys of 21 countries and is available at the occupation-level for 38 occupations. The time period considered is 2012 to 2019.

This paper adds to the existing empirical evidence on automation and labour market outcomes in several ways. It is the first paper to link automation risk to employment levels in a cross-country context (as existing studies have considered only the US) as well as the first to evaluate employment outcomes using the task-based measure of automation risk developed by the OECD.

The main findings are as follows:

- The results show no support for net job destruction at the broad country level. All countries saw employment growth over the past decade, and countries that faced higher overall automation risk back in 2012 did not experience lower employment growth over the subsequent period (2012 to 2019). In fact, countries where occupations faced higher automation risk back in 2012 experienced higher occupational employment growth over the subsequent period. This is consistent with a story in which automation contributes to positive employment growth through productivity growth: increases in labour productivity lead to lower prices on consumer goods; and lower prices boost consumer demand, which in turn increases employment levels (even if the amount of labour per unit has declined). Productivity growth may be observed in occupations and sectors where automating technologies are adopted, but also in other occupations and sectors through spill-over effects.
- Within countries, the majority of occupations also saw employment growth. However, occupations that were at higher risk of automation experienced lower employment growth or even modest declines in employment levels. On average across countries, employment among the riskiest half of occupations grew by 6% compared to 18% among the least risky. Thus, there is evidence that automation has worsened employment prospects for some workers. The occupations that saw employment declines include: skilled agricultural workers; clerical support workers; skilled forestry, fishing and hunting workers; handicraft and printing workers; and metal and machinery workers. These declines are even more striking given that they occur against a backdrop of rising employment across countries.
- On average across OECD countries, the overall employment rate of low-educated workers has not been more negatively affected by these trends than that of other education groups, despite the fact that these workers were considerably more likely to work in high-risk occupations at the start of the period. This is because the fall in job opportunities for these workers has been accompanied by a decline in the number of low-educated workers as part of the general upskilling of the workforce.
- At the same time, however, low-educated workers have become increasingly concentrated in high-risk occupations. In 2012, 74% of low-educated workers were in the riskiest half of occupations, compared to 53% of middle-educated and only 13% of high-educated workers. Between 2012 and 2019, automation risk grew even more concentrated among the low-educated: the cross-country average share of low-educated workers in the six riskiest occupations increased by 5.9%.
- Finally, there is evidence that occupation-level job tenure (i.e. how long a person has been in his/her present job) has fallen more in occupations at high risk of automation. A 10 percentage point higher risk of automation was found to be associated with 0.80 percentage point higher drop in tenure (the equivalent of around one month). This negative effect is particularly pronounced among older workers.

These findings lead to two broad policy conclusions. First, the results demonstrate that anxiety around a jobless future may be overblown. While employment tended to have fallen (or rise less fast) in occupations at high risk of automation, at the country-level there is no indication that higher risk of automation is associated with lower employment growth. Second, however, policy must focus attention on individuals who may not share evenly in the benefits of automation, namely, the low-educated. The potential for automation to produce worse outcomes among occupations at high risk of automation is even more worrisome in the present context of the severe employment declines brought by COVID-19. Now as much as ever, this attention should take the form of training programmes to accompany individuals through job transitions; social protection to cushion workers against the individual and social costs of job transitions; and education programs to prepare young workers for new, higher-skilled jobs.

1. Introduction

1. The impact of technological progress on labour markets has been the subject of a lively debate and academic literature.[1] The question that above all others has grabbed the headlines is how many jobs will be lost due to automation. A widely cited study by two academics at the University of Oxford sparked renewed interest in the subject, as they concluded that 47% of jobs in the United States were at risk of being automated (Frey and Osborne, 2017[1]). Following their study, the OECD shifted the focus towards a task-based analysis of automation, placing greater emphasis on the heterogeneity in task content within occupations, which reduced the estimated share of jobs at high risk to between 9% and 14% (Arntz, Gregory and Zierahn (2016[3]); Nedelkoska and Quintini (2018[2])). An additional 32% of jobs, however, were estimated to be at risk of being deeply changed by technology, potentially requiring a radical transformation in workers' competences and skill sets (Nedelkoska and Quintini, 2018[2]).

2. The OECD also predicted that the risks linked with automation were primarily concentrated in specific industries, occupations, and among workers from certain socio-demographic groups (e.g. the low-educated), who typically belong to the most disadvantaged segments of society. Occupations at highest risk of automation, for instance, include food preparation assistants, cleaners and helpers, labourers in mining, construction, manufacturing and transport (Nedelkoska and Quintini, 2018[2]).

3. These predictions highlight the importance of understanding how automation impacts labour market outcomes. However, they may mask a more complicated relationship between automation and social progress overall. On the one hand, technological advancement offers opportunities for growth, welfare gains and social progress. On the other hand, it may present social and economic risks for certain countries, for workers in certain occupations, and for certain individuals and demographic groups.

4. While there has been a lot of rhetoric around the job destruction narrative and, despite anecdotal evidence that automation is making some jobs obsolete, it is far from obvious that automation will destroy jobs overall; it may also create them, and at an even faster pace. Predictions of job destruction are inevitably subject to uncertainty. They point to the necessity of closely monitoring the employment outcomes of specific industries and groups at risk. This paper aims to provide this analysis by documenting recent trends in occupations that were estimated to be at highest risk of automation by the OECD (Nedelkoska and Quintini, 2018[2]), and by investigating the labour market outcomes of workers in those occupations. Beyond an assessment of changes in employment, the paper also examines the relationship between automation risk and changes in job stability. The paper unpacks how employment outcomes are linked to risk across different countries, occupations and demographics. The objective is to push the debate beyond the potential risks linked to technological progress and to inform policy makers on how those risks are translating into concrete outcomes.

[1] Chapter 2 in OECD (2019[5]) offers a detailed overview.

2. Considering labour market outcomes

5. This section discusses the two main labour market outcomes of focus – changes in employment levels and changes in job stability – and summarises the existing evidence on how each relates to automation.[2] This section also summarises the evolution of each outcome variable over the period of study: 2012 to 2019. The starting year was chosen because the measure of automation risk used as a predictor was estimated for this year, while the ending year allows for the use of the most recent labour force survey data available.

6. Employment levels grew between 2012 and 2019, ranging, on average across occupations, from -2% in Finland (the only country where employment declined over the period) to 29% in Ireland, with an average across countries of 12%. It is important to note that part of this employment growth is attributable to countries' economic recoveries following the global financial crisis. The countries that suffered the greatest employment losses during the crisis are also those that experienced the greatest employment growth between 2012 and 2019 (as shown in Figure 5.3 below). The potential for these economic recoveries to confound the results linking automation risk to employment growth is discussed in Section 5, alongside suggestive evidence that automation has played a role over and above the economic recovery.

7. Looking across occupations rather than across countries, employment levels also grew over the period for the majority of the 38 occupations considered, with the highest growth observed for information and communications technology professionals (43.3% on average across countries). Certain occupations, however, represent exceptions: on average, employment levels declined for skilled agricultural workers; other clerical support workers; skilled forestry, fishing and hunting workers; handicraft and printing workers; and metal and machinery workers. These declines are even more striking given that they occur against a backdrop of rising average employment across countries.

8. Finally, the analysis considers changes in job stability using two measures: change in job tenure and change in job tenure adjusted for age composition. Given the possibility that even the looming threat of automation may weaken workers' bargaining power within firms, it is interesting to investigate whether automation risk holds predictive power for outcomes related to job stability.

2.1. Employment

9. The first labour market outcome of interest, and arguably the most intensively studied, is the evolution in the overall employment level and, in particular, the percentage change in the number of people engaged in productive activities, whether as employees or self-employed, over recent years.[3]

[2] While many other outcome variables were considered in the analysis that follows, these two are highlighted because the results are the more robust.

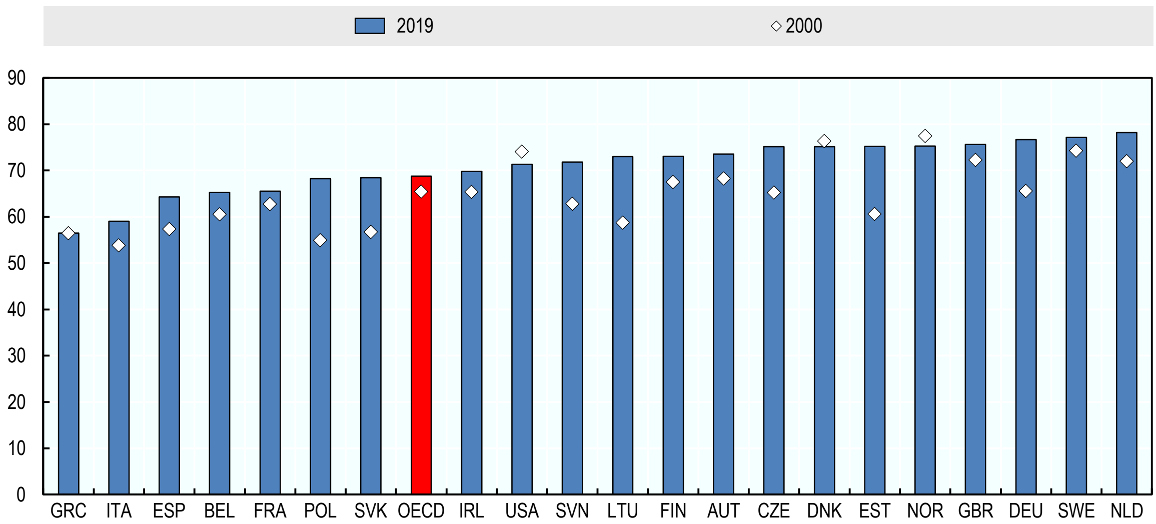
[3] The employment change by country is the percentage change between 2012 and 2019 in the average number of people engaged in productive activities (employed and self-employed) per country (i.e. averaged across occupations within a country). The employment change by occupation is the percentage change over the same period in the average number of people within that occupation (i.e. averaged across countries).

10. While a great deal of public rhetoric and some empirical estimates have fomented fear that automation will destroy jobs and reduce overall employment, it is far from obvious that this is the case. Automation may reduce employment among certain occupations and within certain sectors, and it is certainly changing tasks within jobs. However, at the same time, it may also lead to job creation, potentially at an even faster pace.

11. The view that technology has a positive net impact on employment is perhaps most convincingly bolstered by the fact that the past century of automation and technological progress has not made human labour obsolete. The employment-to-population ratio rose during the 20th century and, although the unemployment rate fluctuates cyclically, there is no apparent long-run increase (Autor, 2015[4]). This has held true over the past two decades (at least up until the COVID-19 crisis) as well. Most OECD countries have seen their employment rates – the share of people of working age in employment – on an upward trajectory over past decades, with the notable exception of the United States (Figure 2.1).

Figure 2.1. Employment rates have been rising in recent decades

Employment-to-population ratio, age 15/16-64



Note: The OECD average in the unweighted average of OECD member countries in the year indicated.
Source: OECD Employment Database, www.oecd.org/employment/database.

12. The literature relating automation to fluctuations in employment is surveyed comprehensively in OECD (2019[5]) (see, in particular, Box 2.1). Two influential studies contributing to the job creation narrative are Bessen (2019[6]) and Autor and Salomon (2018[7]). Bessen (2019[6]) shows that the textile, steel and automotive industries experienced strong employment growth during periods of rapid technological progress and productivity growth (when fears of net job losses also ran high). In essence, automation induced a highly elastic demand response: automation reduced the amount of labour required to produce one unit of a good; in a competitive market, this led to lower prices; under conditions of pent-up demand, lower prices led to greater demand; and the increase

in demand was sufficient to raise total employment. Under these conditions, automation can have positive own-industry employment effects.[4]

13. Another possibility is that certain technologies have a positive impact on employment in industries other than the ones in which they are deployed. Autor and Salomon (2018[7]) estimated the employment impacts of productivity growth (which they use as a proxy for technological adoption) using data on 28 industries for 18 OECD countries since 1970. They found that, by increasing productivity and decreasing consumer prices in one industry, automation technologies boost consumer income and increase demand and employment in other industries. In fact, the positive spillovers to other industries were found to more than offset the negative own-industry employment effects.

14. While automation does not appear to have had a negative net impact on employment over the long run, the job destruction narrative has persisted and perhaps even intensified. The crux of the reasoning underlying it is a belief that the present technological revolution is distinct from those of the past. As such, the evidence cited above may have less relevance for today, as past interactions between automation and employment do not necessarily inform how these factors will interact in the future. In particular, recent technological progress in robotics, machine learning and artificial intelligence (AI) is rapidly extending the range of tasks that machines can perform and permeating the world of work (see Section 2.2.1 of OECD (2019[5])). With greater machine capability, the thinking goes, come greater shares of jobs at risk of automation, followed by job loss.

15. Two prominent voices on this theme have been Brynjolfsson and McAffee, who wrote in 2014: “There’s never been a worse time to be a worker with only ‘ordinary’ skills and abilities to offer, because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate” (Brynjolfsson and McAfee, 2014[8]). While some have suggested that job destruction anxiety is more speculative than evidence-based (Autor (2015[4]); Autor and Salomon (2018[7])), it was further stoked by Frey and Osborne (2017[1]) estimate that 47% of jobs in the US were at risk of being automated over the next 10 to 20 years.

16. Given that a key dividing line between the two perspectives is whether “this time is different,” it is useful to step away from the potential decades-long impacts of automation and to focus instead on recent years. The analysis that follows considers labour market outcomes over the period from 2012 to 2019.[5] Figure 2.2 shows the average percentage change in total employment over this period across occupations for each of the 21 countries considered.[6] It is immediately evident that employment grew over the period, ranging from -2% in Finland (the only country where employment declined over the period) to 29% in Ireland, with an average across countries of 12%.[7]

[4] The mechanism described assumes pent-up demand for a good, which will not always be the case. Bessen also describes how, once demand is satiated, further price declines may generate only modest demand increases, which could fail to offset the labour-saving effect of automation.

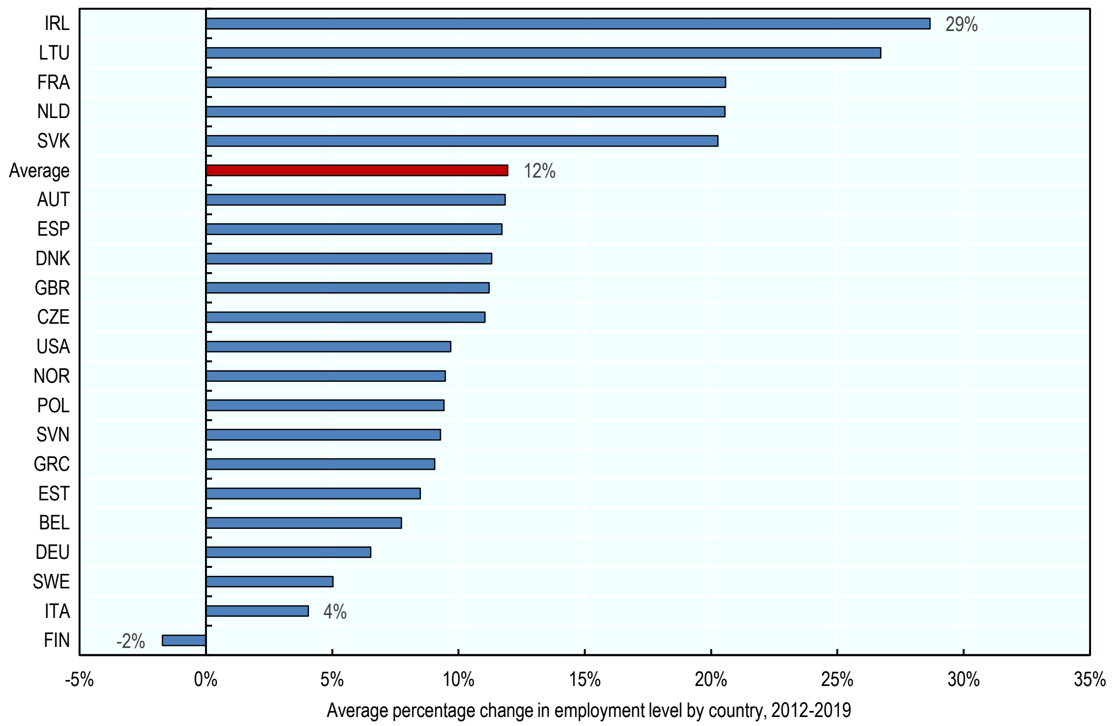
[5] The chosen starting point is 2012 because this is the reference year of the Nedelkoska and Quintini (2018[2]) risk of automation measure used as a predictor (described in detail below).

[6] The data are discussed in detail in Section 3 below.

[7] These growth rates represent unweighted averages of the employment rates in each of the 38 occupations analysed. This is done for consistency with the rest of the analysis in this paper. When weighting for the employment share of each occupation, total employment grew in all countries,

Figure 2.2. Employment has grown across all countries since 2012

Average percentage change in employment level by country (averaged across occupations), 2012 to 2019



Note: This chart reports, by country, unweighted averages across the 38 occupations analysed. Countries are ordered by largest percentage change in employment level (at top) to smallest. The averages presented are unweighted.
Source: EU-LFS and US-CPS.

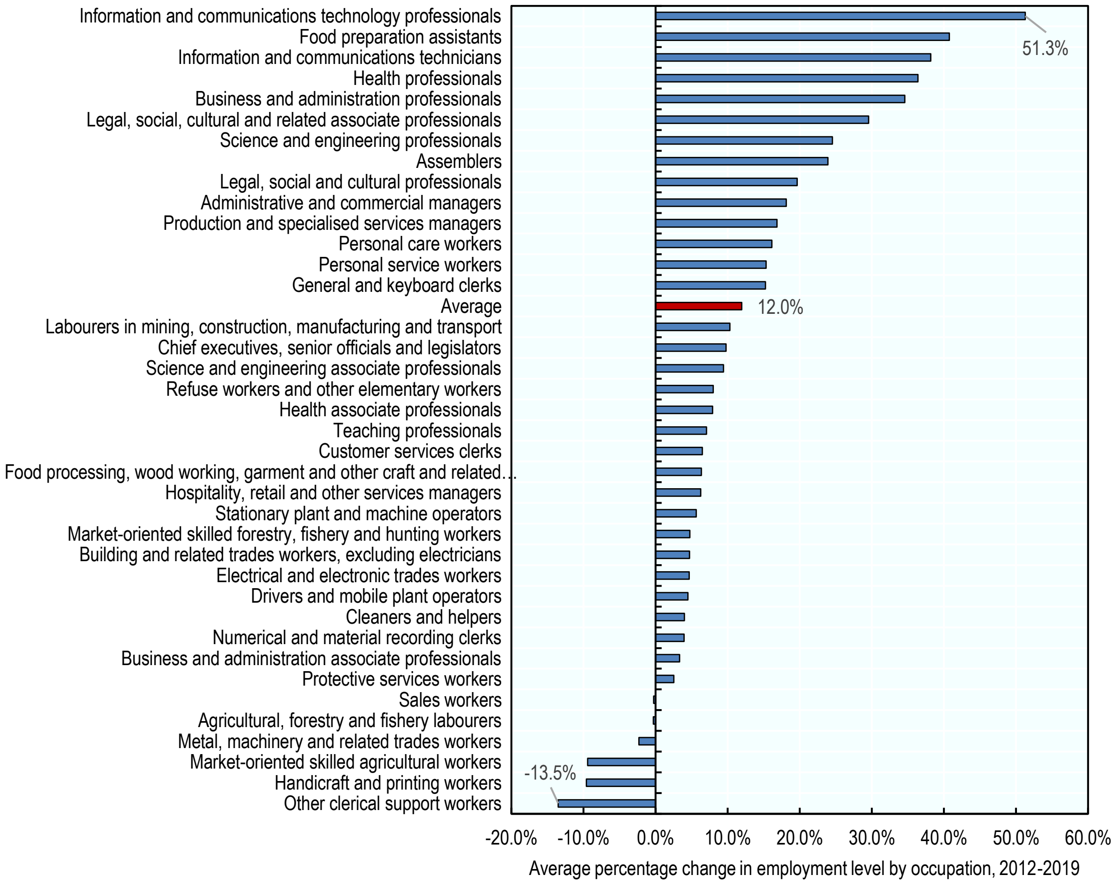
17. The fact that almost all 21 countries experienced positive employment growth on average from 2012 to 2019 is unsurprising given that these years coincide with the economic recovery following the global financial crisis. Indeed, as discussed in Section 5, the countries that suffered the greatest employment losses during the crisis are also those that experienced the greatest employment growth between 2012 and 2019. The potential for recovery-driven employment growth to confound the results linking automation risk to employment growth complicates the analysis. One must be careful in making any conjectures as to what portion of growth could potentially be ascribed to automation. Similarly, potential reductions in employment induced by automation could be obscured by the overall growth that is part of the recovery.

18. Given that automation may have differential effects within industries – increasing employment in one occupation while decreasing it in another – as well as variation across industries within a country, it may be difficult to neatly observe employment level effects at the aggregate country level. As a result, it is informative to look instead at average employment growth by occupation. Figure 2.3 shows the average percentage change in employment between 2012 and 2019 by occupation (across countries), with the highest growth observed for information and communications technology professionals (51.3%).

ranging from 3.3% in Finland to 23.5% in Ireland, with an average of 8.4% across the 21 countries analysed

Figure 2.3. Employment has also grown across most occupations since 2012

Average percentage change in employment level across countries by occupation, 2012 to 2019



Note: Occupations are classified using two-digit ISCO-08. The averages presented are unweighted.
Source: EU-LFS and US-CPS.

19. While the majority of occupations saw employment increases, several occupations – other clerical support workers; handicraft and printing workers; skilled agricultural workers; metal and machinery workers; skilled forestry, fishing and hunting workers; and sales workers – experienced overall reductions over the period 2012-2019 (on average across countries). These declines are even more striking given that they occur against a backdrop of rising employment across countries, and it is natural to wonder whether these examples are harbingers of Brynjolffson and McAffee's warnings. Two recent studies are particularly interesting in this regard: Manning (2019[9]) and Coelli and Borland (2019[10]). As in the analysis that follows, these studies use occupation-level risk of automation measures to evaluate employment growth.

20. In direct response to speculation that the present technological revolution differs from those past, Manning (2019[9]) asks whether "new" forms of technology – information and computer technologies (ICT), AI and robots – have brought about a fundamental change in the way that technology affects labour markets as compared to automating technologies that pre-date the arrival of ICT. Using the risk of automation measure developed by Frey and Osborne (2017[1]) and occupation-level data for the US, he regresses

the change in log employment from 2012 to 2017 on the risk of automation.[8] He finds a significant and negative relationship between automation risk and employment growth, indicating that occupations with a higher risk of automation experienced slower employment growth or employment decreases over the five-year period. Coelli and Borland (2019[10]) also relate Frey and Osborne's risk of automation measure to occupation-level employment changes in the US from 2013 to 2018. Consistent with Manning (2019[9]), they find a significant, negative effect: occupations with higher automation risk experienced slower employment growth or employment decreases over the period considered.

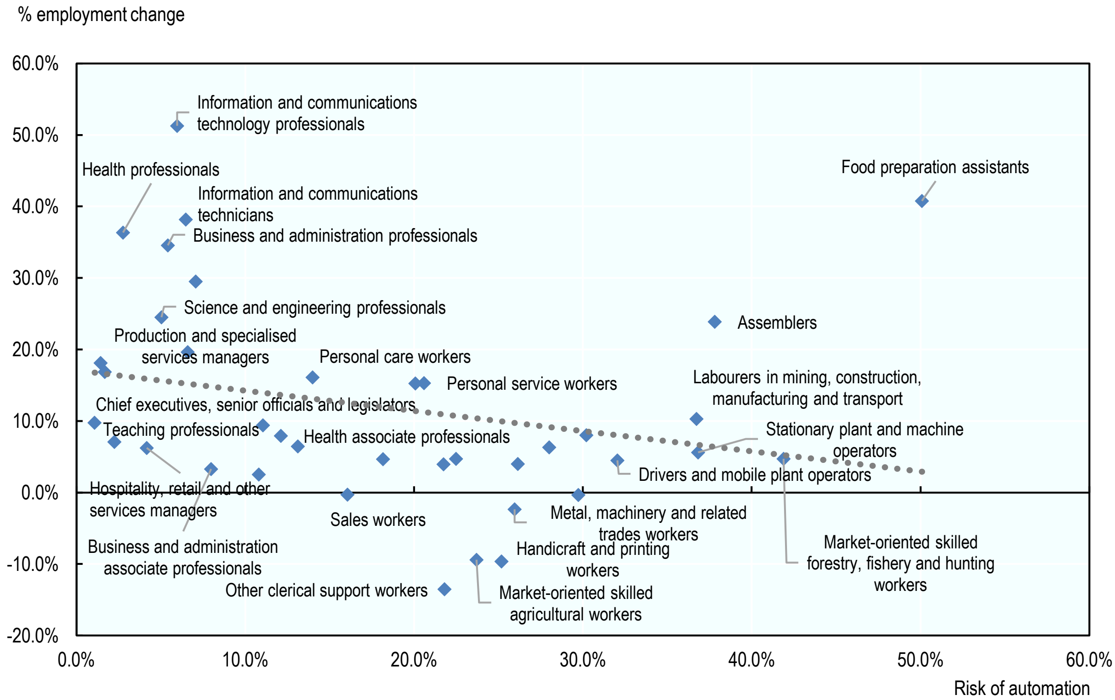
21. A key aspect of the Coelli and Borland (2019[10]) study is their critical view of the Frey and Osborne measure. They focus, in particular, on the limitation that the measure relates to whether an occupation is fully automatable. This binary judgement leaves no scope for the automation of some tasks but not others, which is unlikely to be realistic. This critique, first made by Arntz, Gregory and Zierahn (2016[3]) and Nedelkoska and Quintini (2018[2]), was also the main motivation for these authors to develop task-based measures of the risk of automation as alternatives to Frey and Osborne (discussed in greater detail in Section 3).

22. As there have been no evaluations of the Arntz, Gregory and Zierahn (2016[3]) and Nedelkoska and Quintini (2018[2]) measures thus far, filling that gap is a key objective of this paper. Taking a preliminary look at the relationship between employment growth and risk of automation using the Nedelkoska and Quintini (2018[2]) measure indeed appears to bear out the negative relationship documented by Manning (2019[9]) and Coelli and Borland (2019[10]). The scatter plot in Figure 2.4 shows the average percentage change in employment from 2012 to 2019 for each occupation against that occupation's average risk of automation value. A negative relationship is clearly apparent. While the majority of occupations saw employment growth from 2012 to 2019, those at higher risk of automation appear to have grown by less, while five of the six occupations exhibiting negative employment growth in Figure 2.3 also appear to be occupations at above-average risk of automation. On average across countries, employment among the riskiest half of occupations grew by 6.1% compared to 17.8% among the least risky. The analysis that follows will return to this relationship.

[8] Manning uses the Frey and Osborne (2017[1]) risk of automation measure to encapsulate the impact of new technologies in favour of other automation proxies because it attempts to identify risk of automation due to computerisation, in particular. The measure was constructed using the assessments of machine learning experts as to whether the tasks in an occupation were sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer equipment. The same "new technology" focus can be said to apply to the two other risk of automation measures – Nedelkoska and Quintini (2018[2]) and Arntz, Gregory and Zierahn (2016[3]) – as these measures likewise draw upon these expert assessments.

Figure 2.4. Occupations at higher risk of automation saw lower employment growth

Average percentage change in employment level by occupation (2012 to 2019) and average risk of automation by occupation (2012)



Note: Occupations are classified using two-digit ISCO-08. Not all occupations have marker labels due to space constraints. The averages presented are unweighted averages across countries.
Source: EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

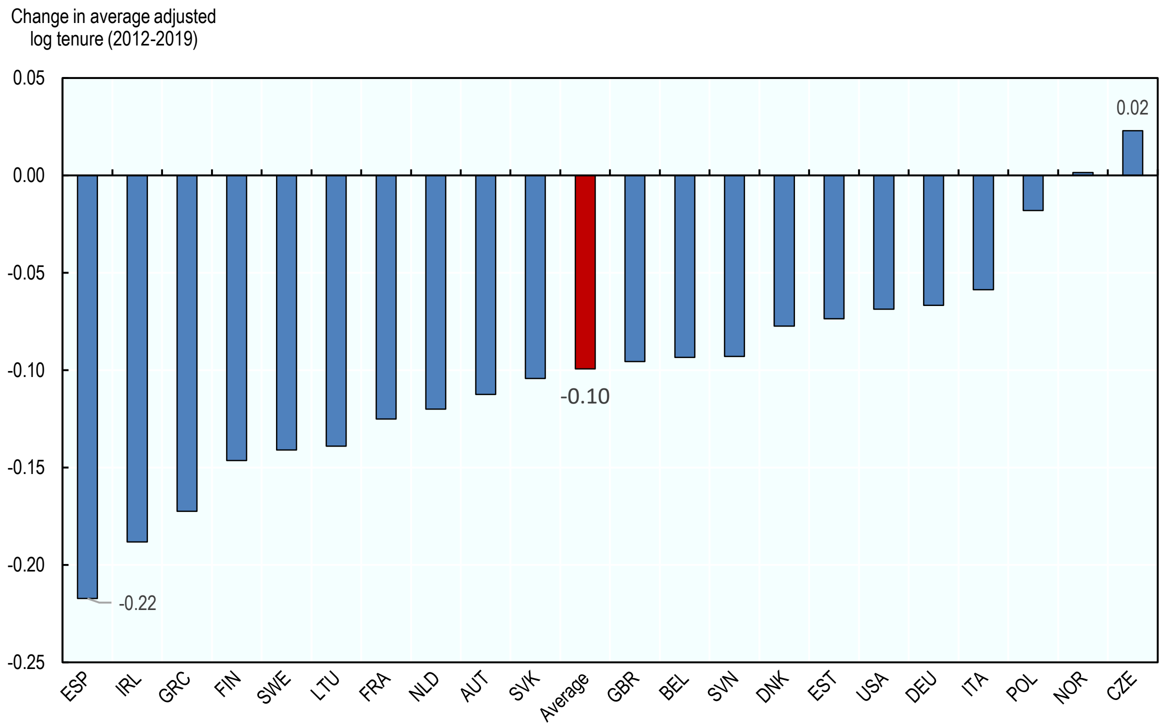
2.2. Job stability

23. In addition to the impact of automation on employment levels, its impact on duration of employment relationships is worthy of investigation. Does automation lead to lower job stability for workers at highest risk? One measure of job stability is job tenure. Figure 2.5 shows the evolution in job tenure between 2012 and 2019, where tenure has been adjusted for composition by age.[9] On average across occupations, all countries (with the exception of Norway and Czech Republic) have experienced declines in job stability. Age-adjusted tenure has dropped by 10% on average across the 21 countries analysed, with a maximum of 22% in Spain.

[9] Population ageing increases the proportion of older workers who usually have longer average job tenure. Not adjusting for the composition effects could lead to bias in the estimates of the impact of automation on job stability.

Figure 2.5. Most countries have experienced declines age-adjusted job tenure

Cross-occupation average percentage change in mean adjusted log tenure across occupations by country, 2012 to 2019



Note: Countries are ordered by largest change in average adjusted log tenure (on the left) to smallest. The averages presented are unweighted. Adjusted log tenure is obtained by taking the residual of country-specific OLS regressions of log tenure over age.
Source: EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

3. Data

24. This section summarises the data used in the analysis. Data relating to the labour market outcomes described in the previous section is from the European Union Labour Force Survey (EU-LFS) and the US Current Population Survey (US-CPS). The combined dataset contains annual information on labour force variables for 38 occupations across 21 countries. Metrics from these surveys were then combined with data on the predicted risk of automation obtained from the work by Nedelkoska and Quintini (2018[2]). Together, these data sources paint a detailed picture of how countries, occupations, and groups at different levels of risk have fared in recent years.

25. The analysis relies on the 2-digit level of the International Standard Classification of Occupations 2008 (ISCO-08). It exploits differences between 2012 and 2019. This period maintains consistency with the risk of automation measure from Nedelkoska and Quintini (2018[2]), which is based on 2012 data.

3.1. EU-LFS

26. The EU-LFS is an extensive cross-country dataset of national labour force surveys that provides annual and quarterly information on individuals of working age (15 years and above). The national surveys are conducted in all Member States of the European Union as well as a few additional countries, including the United Kingdom and three European Free Trade Association countries (Iceland, Norway and Switzerland).[10] In sum, the analysis relies upon data for the following 20 European countries, for which the Nedelkoska and Quintini measure of automation risk is available: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, the Netherlands, Norway,[11] Poland, Slovenia, the Slovak Republic, Spain, Sweden and the United Kingdom.

27. The dataset contains employment status by various characteristics of the individuals covered, including age and sex; information on employed persons by occupation, hours of work and full- or part-time status; and information on job tenure and educational attainment. For the purposes of this analysis, worker-level observations are aggregated into country-occupation-year cells, allowing for analysis of country and occupational heterogeneities.

3.2. US-CPS

28. The US-CPS data provides labour force statistics for a representative sample of the US population on individuals of working age (16 years and above). The dataset contains a

[10] The EU-LFS also provides information for four EU candidate countries (Montenegro, North Macedonia, Serbia and Turkey) (Eurostat, 2019). However, this information has been excluded due to limited data availability and because risk of automation measures specific to these countries are not available.

[11] 2019 data are missing for Norway. Therefore, 2019 employment levels have been imputed assuming that 2018-2019 employment changes were equal to the average annual employment changes between 2012 and 2018. The results are not sensitive to the inclusion of Norway in the analysis.

similar set of information as available in the EU-LFS. As with the EU-LFS, worker-level observations are aggregated into occupation-year cells for the purposes of this analysis.

29. To merge the US-CPS data with the EU-LFS data, the US-CPS occupation census code variable was first mapped to the SOC 2010 classification. Next, it was mapped to the ISCO-08 classification so that the occupation variable would be harmonised with the 2-digit ISCO-08 codes for all countries.

3.3. Measure of the risk of automation

30. The key measure of the risk of automation by occupation is taken from Nedelkoska and Quintini (2018[2]).[12] As mentioned above, an important difference between the Nedelkoska and Quintini measure as an alternative to the Frey and Osborne (2017[1]) measure is that Frey and Osborne's measure potentially exaggerates the extent to which occupations as a whole can be automated. Nedelkoska and Quintini (2018[2]) placed greater emphasis on the heterogeneity of task content within occupations, resulting in a much-reduced estimate of jobs at high risk of automation.

31. The mix of tasks that constitute an occupation may evolve as new technologies are adopted in the workplace, in which case individual workers in an occupation may not undertake the same mix of tasks with precisely the same relative emphasis over time. As a result, the likelihood of their jobs being automated will differ. To construct their measure, Nedelkoska and Quintini estimate the relationship between task measures reported by individual workers in the data available from the Programme for the International Assessment of Adult Competencies (PIAAC) and Frey and Osborne's estimates of the probabilities of occupations being automated. This is done for the full range of countries for which PIAAC was available in 2012 (with additional countries added later). These estimated relationships are then applied to derive predicted probabilities for job loss due to automation for individual workers.[13] The individual-based approach yields a far lower estimated automation risk for the US: Nedelkoska and Quintini estimated that 10% of US jobs were at high risk of automation, compared to Frey and Osborne's 47%.

32. The average risk of automation across occupations by country for the 21 countries in the sample is shown in Figure 3.1. There is considerable variation across countries: while the average share of jobs at high risk is 6.5% in Norway, it reaches 34.6% in the Slovak Republic. In general, jobs in Nordic and Anglophone countries are at less risk compared to jobs in Southern and Eastern European countries. Nedelkoska and Quintini stress the fact that the precise values should be interpreted with caution as actual risk of automation is subject to significant uncertainty. While the findings reliably point to jobs in the Slovak

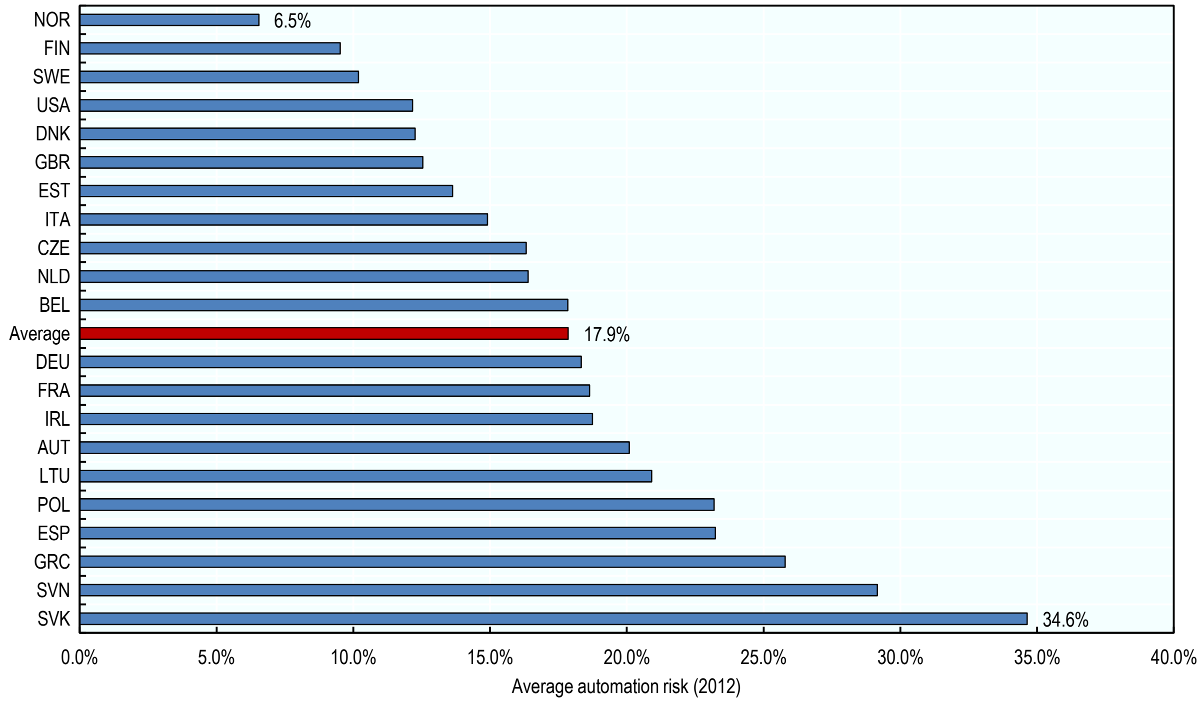
[12] The Nedelkoska and Quintini risk of automation measure is very similar to the measure developed by Arntz, Gregory and Zierahn (2016[3]) for the OECD. The focus here is on Nedelkoska and Quintini (2018[2]) because this paper extended Arntz, Gregory and Zierahn (2016[3]) to a range of different countries (whereas Arntz, Gregory and Zierahn (2016[3]) relates to the US). Another difference between the two approaches is that Nedelkoska and Quintini (2018[2]) undertook a closer matching of the engineering bottlenecks identified by Frey and Osborne (2017[1]), which allows this measure to cover a broader set of workers compared to Arntz, Gregory and Zierahn (2016[3]).

[13] Still, because the underlying automation capabilities used by Nedelkoska and Quintini (2018[2]) are the same as those used by Frey and Osborne (2017[1]), the occupations estimated to be at high risk are more or less the same as well. Note that as both estimates refer to about the same time period, the two measures are also comparable from that perspective.

Republic having a higher risk of automation than jobs in Norway, specific automation probabilities are harder to pin down.

Figure 3.1. Automation risk is relatively low in Nordic and Anglophone countries and relatively high in Eastern and Southern European countries

Average % of jobs at high risk of automation across occupations by country



Note: The percentages represent the share of jobs at high risk of automation, i.e. with more than a 70% automation probability. The averages presented are unweighted.
Source: Nedelkoska and Quintini (2018[2]).

33. The cross-country variation in automation risk is important in identifying the between-country effects. Nedelkoska and Quintini attribute the variation to differences in the organisation of job tasks within economic sectors (rather than to differences in the sectoral structure of economies). They estimate that about 30% of the cross-country variance is explained by cross-country differences in the structure of economic sectors, while 70% is explained by the fact that, within sectors, countries employ different occupational mixes.

34. In countries where automation risk is relatively low, the variation in risk across occupations tends to be lower as well. Figure 3.2 shows the variation in automation risk across occupations for Norway, the country with the lowest average automation risk, and the Slovak Republic, the country with the highest. Average automation risk in Norway is 6.5%, with zero or near-zero risk for occupations such as information and communications technology professionals (0.0%), teaching professionals (0.7%) and health professionals (0.8%) and highest (though still relatively low) risk for labourers in mining, construction, manufacturing and transport (18.5%), drivers and mobile plant operators (23.7%), and food preparation assistants (33.6%).

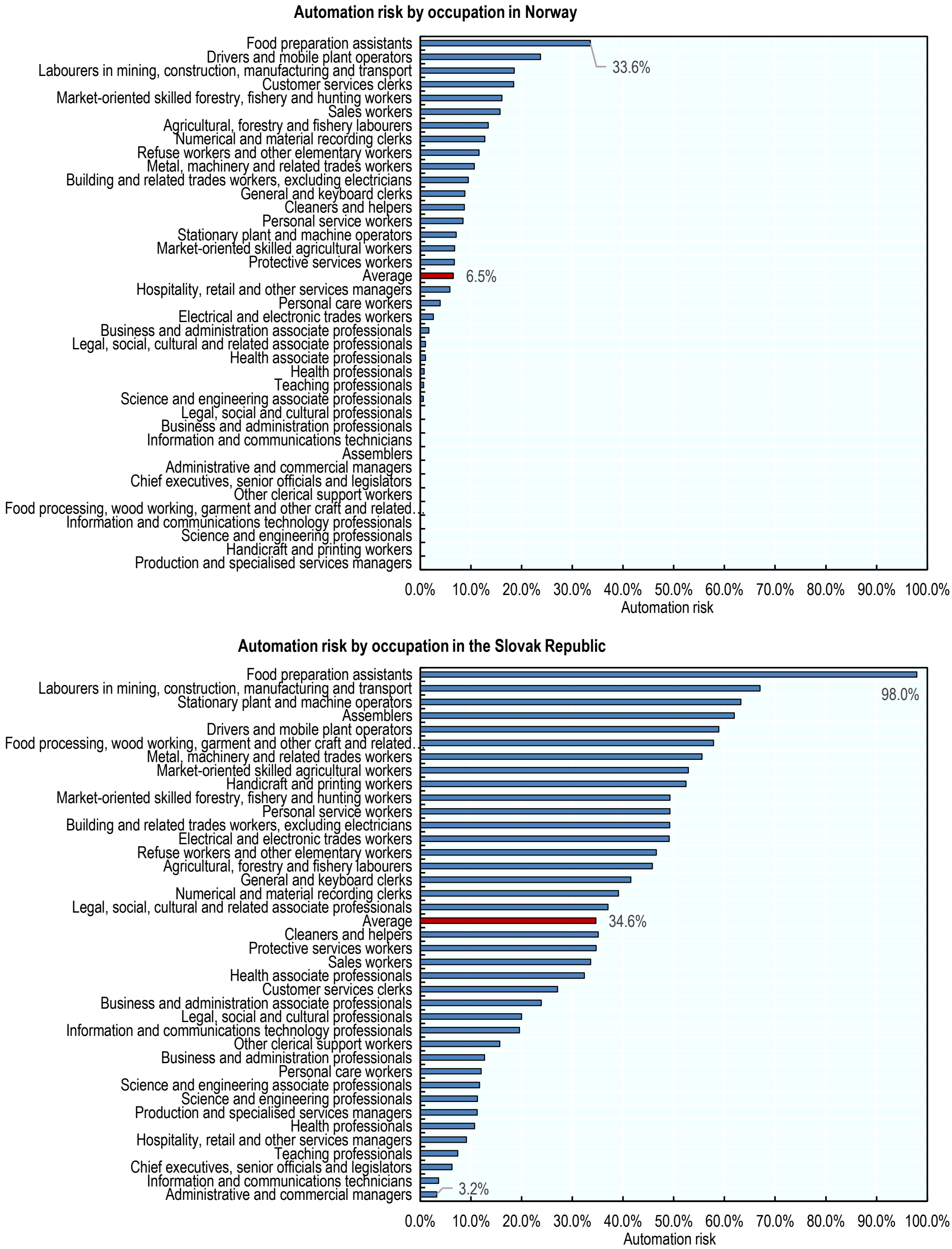
35. Looking at the "riskiest" country in the sample, average automation risk in the Slovak Republic is 34.6%. Low risk occupations include administrative and commercial managers, information and communications technicians, chief executives, senior officials and legislators, and teaching professionals. As each of these occupations has a risk value of under 10%, these occupations within the riskiest country can be said to be "safer" than the riskiest occupations within the safest country. Other occupations, however, are at very high risk: assemblers (62.0%), stationary plant and machine operators (63.4%), labourers in mining, construction, manufacturing and transport (67.0%), and food preparation assistants (98.0%).

36. The key factor contributing to cross-country differences is variation in the frequency of perception and manipulation tasks as well as of cognitive and social intelligence tasks within occupations. Within-occupation differences in the task-content of jobs may also reflect the extent to which automation has already taken place and jobs have adapted as a result. Countries where adoption of labour-substituting technologies has yet to take place would show a structure of job tasks that is more prone to automation as a result. For example, in Figure 3.2, it is notable that Norwegian assemblers face zero automation risk, while in the Slovak Republic assemblers rank as the fourth riskiest occupation. Automation may have already impacted assemblers in Norway, reducing present-day risk to zero, while it may be underway or lie ahead for assemblers in the Slovak Republic. Such differences would be reflected in the measure.

37. Occupations vary in their average automation risk. Some occupations are risky (e.g. market-oriented skilled forestry, fishery and hunting workers), others are not (e.g. health professionals). Turning away from automation risk across countries to consider automation risk across occupations, Figure 3.3 shows the average automation risk for the 38 occupations in the sample. The variation across occupations suggests that the risk of automation is not evenly distributed among workers. Nedelkoska and Quintini found that automation mainly affects jobs in the manufacturing industry and agriculture, although a number of service sectors, such as postal and courier services, land transport and food services were also found to be highly automatable. The occupations with the highest estimated risk of automation typically only require basic to low levels of education. At the other end of the spectrum, the least automatable occupations almost all require professional training and/or tertiary education. Such differences point to the likelihood that automation impacts demographic groups in differential ways. This is explored further in Section 6.

Figure 3.2. In countries where automation risk is relatively low, variation in automation risk across occupations tends to be lower as well

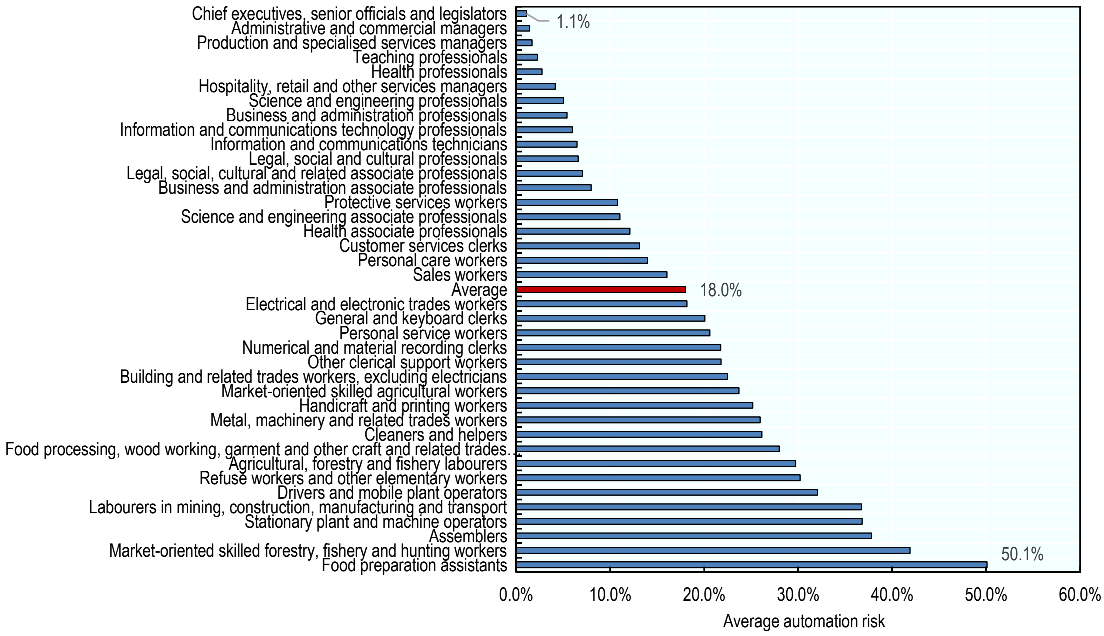
Automation risk by occupation for Norway (low average automation risk) and the Slovak Republic (high average automation risk)



Note: The percentages represent the share of jobs at high risk of automation, i.e. with more than a 70% automation probability.
Source: Nedelkoska and Quintini (2018[2]).

Figure 3.3. Risk of automation distribution by occupation

Average % of jobs at high risk of automation across countries by occupation



Note: The percentages represent the share of jobs at high risk of automation, i.e. with more than a 70% automation probability. The averages presented are unweighted.
Source: Nedelkoska and Quintini (2018[2]).

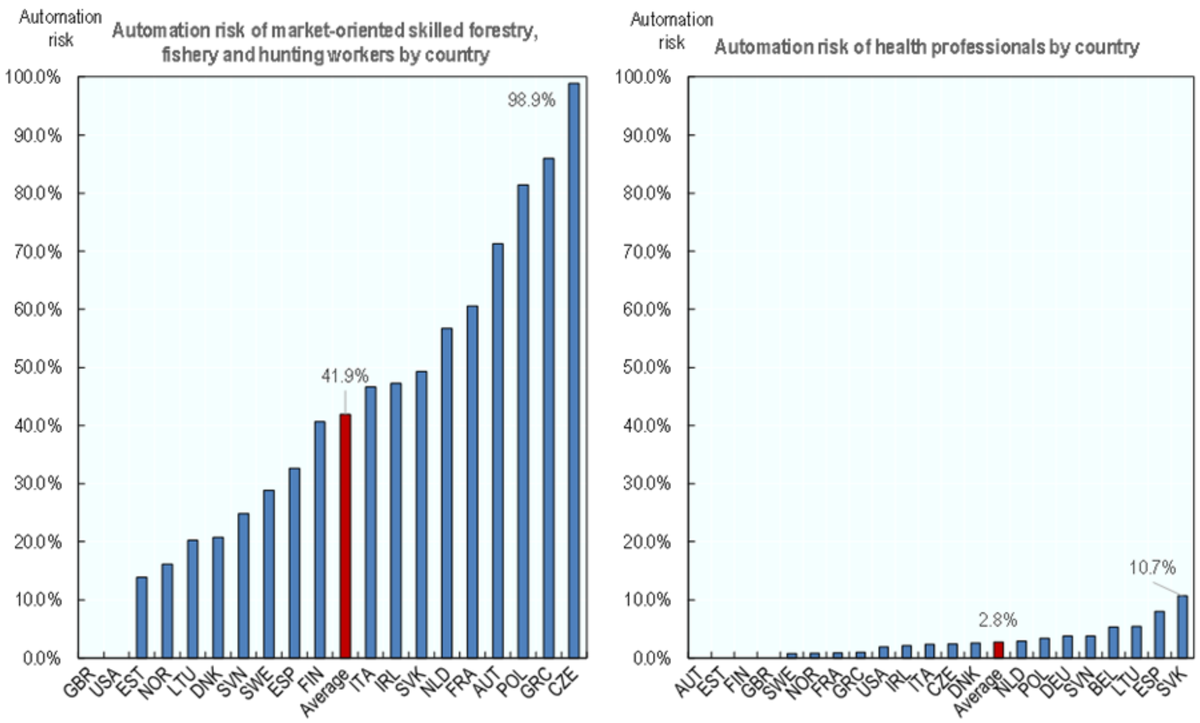
38. Automation risk depends heavily on country context. Figure 3.4 shows automation risk across countries for two occupation examples: market-oriented skilled forestry, fishery and hunting workers, an occupation with relatively high average automation risk across countries, and health professionals, an occupation with relatively low average automation risk.

39. Market-oriented skilled forestry, fishery and hunting workers face relatively low automation risk in Estonia and Norway but relatively high risk in Greece and the Czech Republic. This makes sense: the degree of automation risk depends not just on a job but also on what workers do in that job. Variation in the task content of a given occupation across countries translates into variation in that occupation's cross-country automation risk. But some occupations are "safe" everywhere: automation risk is virtually zero for health professionals in Sweden, Norway and France and highest for health professionals in the Slovak Republic.

40. Again, there is the pattern of more variation where automation risk is highest, suggesting variation in the existing level of automation, as discussed. To take one example: market-oriented skilled forestry, fishery and hunting workers face relatively low automation risk in Estonia (13.9%), Norway (16.1%) and Lithuania (20.3%), while individuals in this same occupation face relative high risk in Poland (81.4%), Greece (86.0%) and the Czech Republic (98.9%). To take another, contrasting example, there is far less variation across countries in the automation risk of health professionals: it is virtually zero in Sweden, Norway and France, and reaches a peak of only 10.7% in the Slovak Republic, followed by Spain (8.0%) and Lithuania (5.4%).

Figure 3.4. In occupations where automation risk is relatively low, variation in automation risk across countries tends to be lower as well

Average % of jobs at high risk of automation by occupation, as estimated by Nedelkoska and Quintini (2018[2]) in 2012



Note: The percentages represent the share of jobs at high risk of automation, i.e. with more than a 70% automation probability.
Source: Nedelkoska and Quintini (2018[2]).

3.4. Other data

41. The effect of automation on jobs may be confounded by other trends at the occupational level, such as offshoring and trade, and so the analysis will attempt to control for those. Offshoring is proxied by an index of offshorability developed by Firpo, Fortin and Lemieux (2011[11]) and made available by Autor and Dorn (2013[12]).[14] The index is an occupation-level task-based measure derived from the O*NET database for the United States. This analysis uses this measure for the 21 countries analysed, assuming that cross-country variations in offshorability for a given occupation are negligible. The analysis also controls for the share of employment within occupations that is in manufacturing and in

[14] The index is available by occupation based on U.S. Census occupation codes. It was first mapped to the SOC 2010 6-digits classification and then to the ISCO-08 4-digit classification. It was finally aggregated at the 2-digit level by using average scores weighted by the number of full-time equivalent employees in each occupation in the United-States, as provided by Webb (2019[23]) and based on American Community Survey 2010 data.

some selected service sectors[15] to capture differences across occupations in exposure to international trade.

42. In controlling for country-specific factors, or investigating whether the relationship between automation risk and employment varies with these factors, the analysis draws on a range of other data, available at the country level. These variables and data sources are described in this sub-section. Firstly, the analysis controls for the employment gap over the financial crisis period (i.e. the percentage point change in the employment rate from the onset of the financial crisis in Q4 2007 to the country-specific crisis trough) in each country. As mentioned, identifying the impact of automation risk on employment is complicated by the presence of confounding factors, one of which is that the period of study (2012 to 2019) coincides with many countries' economic recoveries from the global financial crisis of 2007-2008. Thus, potential employment gains from the productivity effects of automation could be conflated with recovery growth. Controlling for the employment gap at the trough of the crisis attempts to control for this growth.

43. Another important factor in this context is the degree of wealth in a country, which proxies for many factors contributing to a more favourable climate for automation, such as the ability of firms to afford the large capital investments associated with automation, well-functioning capital markets to aid such investment, and so on. The analysis takes into account country-level wealth using GDP per capita in each country.

44. The analysis also considers minimum wage levels across countries using real hourly statutory minimum wage data available from the OECD, and including a dummy for countries that do not have a statutory minimum wage.[16] Investigating whether the effect of risk varies with the minimum wage is of interest because minimum wage levels may induce substitution away from workers whose jobs are more easily automated (Lordan and Neumark, 2018[13]): the higher the labour cost, the greater the potential cost savings resulting from substituting machines for human labour.

45. Beyond the minimum wage, the analysis also looks at whether the effect of risk varies with average wage levels and tax-related labour costs. These investigations follow logic similar to that applied in looking at minimum wage levels: the higher the costs per unit of human labour, the greater the potential cost savings resulting from automation. Data on average wages is available from the OECD.[17] Tax-related labour costs are measured using the tax wedge, which measures the extent to which tax on labour income discourages

[15] The service sectors considered are those potentially more exposed to international trade: construction, wholesale and retail trade, transportation and storage, information and communication, and financial and insurance activities.

[16] OECD (2020), "Earnings: Real minimum wages (Edition 2019)", OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/522a6b71-en (accessed on 26 September 2020). The minimum wages are converted into a common hourly pay period for countries for which they are available. The resulting estimates are deflated by national Consumer Price Indices (CPI) and converted into a common currency unit using either US dollar exchange rates.

[17] Average wages are obtained by dividing the national-accounts-based total wage bill by the average number of employees in the total economy, which is then multiplied by the ratio of the average usual weekly hours per full-time employee to the average usually weekly hours for all employees. The indicator is measured in USD constant prices using 2019 base year and Purchasing Power Parities (PPPs) for private consumption of the same year. OECD average wages are accessible at the following link: https://doi.org/10.1787/cc3e1387-en.

employment (as a percentage of labour costs). Data on tax wedges is also available from the OECD.[18]

46. Next, a range of employment protection and product market national policies may influence employment dynamics and automation's impact on employment outcomes. These include employment protection legislation (EPL), product market regulation (PMR) and the coverage of collective agreements.

47. Whether job protection is motivated by protecting workers against arbitrary dismissals or by having the firm bear some of the dismissal costs, the intended effect of job dismissal regulation is to slow the frequency of layoffs (OECD, 2020). While the interaction between EPL and automation has not been thoroughly studied, one would expect the presence of EPL to slow automation and thus dampen any negative effects of automation on employment outcomes. Alternatively, EPL could encourage automation as it makes it relatively more expensive for firms to reduce production following demand shocks. The analysis proxies for EPL in a country using an OECD indicator of the strictness of employment protection legislation for employees on regular/indefinite contracts and the conditions that pertain to their dismissals and the use of temporary contracts.[19]

48. Interactions between PMR and automation are uncertain. While the automation of production processes may displace certain workers, raising the possibility of technological unemployment, any displacement effects could be offset by productivity effects (to the extent that automation-driven productivity gains increase market demand and the scale of production, and in turn increase labour demand) (Aghion et al., 2020[14]). The analysis considers the country-level regulatory barriers to firm entry and competition in a broad range of key policy areas using an indicator of economy-wide PMR.[20] The PMR indicator measures the degree to which policies promote or inhibit competition in areas of the product market where competition is viable.

49. The analysis considers the coverage of collective agreements in a country using the collective bargaining coverage rate.[21] The collective bargaining coverage rate corresponds to the ratio of employees covered by collective agreements, divided by all wage earners with the right to bargain.

50. Finally, the analysis considers the adoption of industrial robots in different countries using data from the International Federation of Robotics (IFR).[22] The IFR

[18] The tax wedge is defined as the ratio between the amount of taxes paid by an average single worker without children earning 67% of average worker earnings and the corresponding total labour cost for the employer, and is also available from the OECD. OECD tax wedges are accessible at the following link: https://doi.org/10.1787/76e12892-en.

[19] The strictness measure ranges from 0 to 6, with higher scores representing stricter regulation. OECD (2020), "Employment Protection Legislation: Strictness of employment protection legislation: regular employment," OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/data-00318-en (accessed on 23 August 2020).

[20] The OECD PMR indicator is accessible at: https://doi.org/10.1787/data-00593-en.

[21] OECD, http://stats.oecd.org/Index.aspx?DataSetCode=CBC, and ICTWSS database (Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts), http://www.uva-aias.net/en/ictwss/.

[22] The IFR provides data on shipments of industrial robots from almost all existing robot suppliers worldwide. Industrial robots are defined as "automatically controlled, reprogrammable,

calculates the operational stock of robots by accumulating annual deployments and assuming that robots operate 12 years and are immediately withdrawn after 12 years, and the analysis considers the change in operational stock from 2012 to 2019. The stock of robots is interesting in this context because it is a proxy for the actual take-up of automation technologies as opposed to a measure of hypothetical automation risk.

multipurpose manipulators programmable in three or more axes, which may be fixed in place or mobile for use in industrial automation applications" (International Organization for Standardization code 8373). Each element of the definition is essential for a machine to be considered an industrial robot. For instance, a manipulator that is not reprogrammable or that has a single purpose is not considered an industrial robot. Typical applications of industrial robots include assembling, dispensing, handling, processing (for instance, cutting) and welding, all of which are prevalent in manufacturing industries; as well as harvesting (in agriculture) and inspecting of equipment and structures (common in power plants).

4. Empirical strategy

51. This section describes the empirical strategy used in the paper. The overall goal is to understand whether countries and occupations estimated to be at high risk of automation in 2012 have experienced different evolutions in labour market outcomes over the subsequent period (2012-2019) compared to countries and occupations estimated to be at low risk of automation.

52. This is done by way of a regression analysis using data at the occupation-country level, where the main dependent variable is the percentage change in employment from 2012 to 2019 and the main independent variable is the Nedelkoska and Quintini (2018[2]) automation risk measure discussed in the section above. In considering how automation risk may affect labour market outcomes, it is important to note that the measure of automation risk contains variation between and within occupations (that is, within and across countries), as discussed above. This allows for a consideration of the impact of automation both within and between countries.

53. The empirical strategy first uses a classic fixed effects regression approach, controlling for country-specific factors using country fixed effects. This approach controls for any country-specific factors that are constant across occupations. In a second step, a multilevel modelling (MLM) approach is employed as an alternative means to modelling country-specific factors. This offers a few advantages over the more standard fixed effects regression approach in this context, the primary one being an ability to look at the impact of automation risk both within and between countries using a single specification.

54. As a final step, the analysis also considers how automation may affect labour market outcomes in different ways for different socio-demographic groups. This follows a similar regression approach.

4.1. Fixed effects regression model

55. A simple regression model of the occupation-level percentage change in employment from 2012 to 2019 including country fixed effects is estimated as follows:

$$Y_{ij} = \alpha_j + \beta X_{ij} + u_{ij} \quad (1)$$

where Y_{ij} is the percentage change in the number of workers engaged in productive activity (both dependent employed and self-employed) for occupation i in country j over the period 2012-2019, X_{ij} is the risk of automation for occupation i in country j as measured in 2012, β is the coefficient on the risk of automation, α_j is the unobserved occupation-invariant country effect, and u_{ij} is the error term.[23] If automation is a key driver of labour market outcomes, and the risk of automation measure accurately represents how actual automation outcomes will vary between occupations, then the results should point to a relationship between automation risk and labour market outcomes.

56. While the approach above is a standard method in empirical economics, it has some drawbacks in the present context. First, the country fixed effects in equation (1) are modelled as within-group estimates. This is equivalent to the transformation of each

[23] While the analysis focused on this single outcome for now for purposes of exposition, changes in job tenure are also considered, where the same methodological approach is taken.

observation into a deviation from its country mean. Thus, this fixed effects regression only relies on within-country variation for identification, discarding between-country variation. It therefore makes it difficult to consider the impact of automation across countries and to investigate the impact of country-level variables.[24] Second, low variance in automation risk within countries may lead to poor estimates of the country fixed effects (Gelman and Hill, 2006[15]). This presents a problem in this analysis, as the variance of automation risk for some countries can be quite small.

57. These shortcomings prompt consideration of an alternative approach: the multilevel modelling approach (MLM). The next sub-section provides an overview of the MLM approaches employed, followed by an explanation of some benefits of this approach in the present context.

4.2. Multilevel regression models

58. In the most general sense, MLMs are a regression framework designed to analyse data with a multilevel structure, building on random effects models that are well-known alternative to fixed effects models.[25] The nature of the data structure is important in part because variables can be related at more than one level in a hierarchy, and the relationships at different levels are not necessarily equivalent. For example, employment growth (Y_{ij}) may be related to occupation-level automation risk X_{ij} very differently than to the average automation risk in a given country. To see this, consider the possibility that while the overall employment level in a country may rise on account of the positive productivity effects brought by automation, it is not guaranteed that all occupations will exhibit net employment gains. Occupations at high risk may see job declines. MLMs facilitate the investigation of these effects separately.

4.2.1. Basic MLM specification: random intercept model

59. The most basic MLM approach considers a simple model with random intercepts, as follows:

$$Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + r_{ij} \; (2)$$

where Y_{ij} is the dependent variable for occupation i and country j, β_{0j} is the intercept, β_1 is the slope, X_{ij} are occupation-country values of risk of automation and r_{ij} is the residual. This equation is known as the level 1 equation, where β_{0j} can be considered to be random effects in typical terminology. The key difference between this model and that described in equation (1) above is the modelling of the intercept, β_{0j}. Rather than being modelled as a fixed effect, it is instead explicitly modelled in the following country-level (level 2) equation:

$$\beta_{0j} = \gamma_{00} + u_{0j} \; (3)$$

[24] One means of investigating the determinants of the country-specific parameters α_j and β_j is to take them as dependent variables in their own rights and to estimate linear regressions at the country level.

[25] In fact, random effects models can be considered a special case of MLMs (Bell, Fairbrother and Jones, 2018[17]).

60. In this equation, β_{0j} is now the dependent variable, γ_{00} is the level 2 intercept and u_{0j} is the level 2 residual. In the level 2 equation, γ_{00} represents the mean of the intercepts (i.e. the mean of the group means) and u_{0j} represents the deviation of each group mean from the overall mean. Combining the two equations gives:

$$Y_{ij} = \gamma_{00} + u_{0j} + \beta_1 X_{ij} + r_{ij} \quad (4)$$

where γ_{00}, β_1, and $u_{01} \ldots u_{0J}$ are all parameters to be estimated, and r_{ij} is the residual for the entire model.[26]

It is useful to note that the MLM summarised in equations (2) and (4) is similar to the fixed effects specification in equation (1) above, except that the group specific effects β_{0j} are assumed to be uncorrelated with the other explanatory variables in the equation.[27]

4.2.2. MLM including level 2 predictors

61. By extending the simple model discussed above in equations (2)-(4), it is also possible to have the level 2 variable of interest be a function of other predictors. This enables the explicit modelling of country-specific intercepts (β_{0j}), by making them the dependent variables in a level 2 regression with independent variables of its own.

62. This approach is described using equations (5)-(7), as follows:

$$Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + r_{ij} \quad (5)$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \quad (6)$$

$$Y_{ij} = \gamma_{00} + \gamma_{01} W_j + u_{0j} + \beta_1 X_{ij} + r_{ij} \quad (7)$$

where equation (5) describes the level 1 model with country-specific intercepts β_{0j}. Next, the intercepts in equation (5) are themselves modelled in equation (6), the level 2 model. Equation (6) is similar to the level 2 model in equation (3), with the key difference being the inclusion of a group-level predictor W_j, which is assumed to vary between (though not within) groups. Finally, the combined model is described in equation (7).

63. In other words, the system of equations can be understood as follows. A first equation models the within-country effects – in this case, the differences in employment outcomes for occupations of different risk levels. Since these occupation-level outcomes are also impacted by overall country-level factors (e.g., GDP growth, policy factors, or overall levels of automation), a second equation models these effects. The combined model can then be seen in the third equation.

64. In particular, this analysis systematically includes the average risk by country as a level 2 predictor, making it possible to relax the assumption that the group specific effects β_{0j} are uncorrelated with the risk of automation (Oshchepkov and Shirokanova, 2020[16]).

[26] The normality assumptions and details of the variance and co-variance with respect to the residuals u_{0j} and r_{ij} in MLMs are discussed further in Oshchepkov and Shirokanova (2020[16]).

[27] Another common extension of MLMs is the incorporation of random slopes. A random slope MLM is a model in which the slopes are allowed to vary across groups. In this context, the negative relationship between automation risk and employment levels would not be fixed at β_1 for all countries but would be estimated separately for each country. While interesting in principle, this approach is not pursued in this paper due to the limited number of observations available in the data.

Under this condition, the coefficient β_1 will be the same as the fixed-effect coefficient (Bell, Fairbrother and Jones, 2018[17]).

65. A common technique applied to MLMs is centring the predictors using group or overall means (i.e. demeaning the predictors). This analysis applies group centring to the above specification, which, combined with the use of the average risk by country as a level 2 predictor, allows for a direct interpretation of the coefficients in terms of the effects of risk within and between countries (Bell, Fairbrother and Jones (2018[17]) Algina and Swaminathan (2011[18])).

66. Interactions among the predictor variables, particularly interactions between level 1 and level 2 variables, can be very important in the application of MLMs. This is because they allow for an investigation of whether the effect of risk varies with country-specific factors. These cross-level interactions occur when the impact of a level 1 variable on an outcome (i.e. occupation-country automation risk) differs based on the value of the level 2 predictor (i.e. a country-level variable). The cross-level interaction term is simply the product of two predictors. Equation (7) above remains as is, with an additional term.

67. MLM approaches are favoured in the present context, as they allow for more intuitive modelling of relationships at different levels (e.g. within and between countries) relative to the fixed effects regression approach described above. Researchers have always been interested in phenomena that occur at different theoretical levels. In the present context, the interest is in occupation-level outcomes within different countries, where the impact of automation risk on employment outcomes may be different across different occupations or countries. MLM approaches allow researchers to investigate the interconnections between these two separate levels using a single specification.

5. Automation risk and labour market outcomes

68. This section presents the key results relating automation risk to subsequent labour market outcomes. The first sub-section presents results for each of the models discussed in Section 4 above, taking the percentage change in employment from 2012 to 2019 as the dependent variable. The second sub-section examines the relationship between automation risk and job stability.

5.1. Employment

69. This sub-section examines the relationship between automation risk (as estimated in 2012) and the percentage change in employment growth from 2012 to 2019. It first describes the results for the fixed effects model and the basic MLM specification (the random intercept model), followed by a discussion of the results under additional MLM approaches.

5.1.1. The effects of automation within and between countries: fixed effects model and basic MLM specification results

70. The first approach is a simple regression model of the occupation-level percentage change in employment from 2012 to 2019 including country fixed effects. The results, presented in Column 1 of Table 5.1, show a negative and statistically significant coefficient on automation risk. Columns 2 and 3 show that these results hold even after including the occupation-level sectoral shares and an index offshorability.

Table 5.1. Fixed effects model and basic MLM specification results

Dependent variable: 2012-2019 % change in employment level

	(1)	(2) Fixed effects (FE) model	(3)	(4) Basic MLM specification
Risk	-0.172**	-0.147*	-0.162**	
	(0.0728)	(0.0768)	(0.0768)	
Risk (demeaned/country)				-0.172**
				(0.0727)
Average risk/country				0.409*
				(0.222)
Share of manufacturing	No	Yes	Yes	
Share of service sector	No	Yes	Yes	
Offshorability	No	No	Yes	
R-squared	0.007	0.009	0.018	
Observations	792	792	792	792
Number of countries	21	21	21	21

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Offshorability is an occupation-level measure developed by Autor and Dorn (2013[12]) based on data from the United States. For each country-occupation cell, the share of the manufacturing sector represents the share of workers in that cell working in the manufacturing sector in 2012. The share of service sector represents the 2012 share of workers in the country-occupation cell working in service sectors potentially more exposed to international trade: construction, wholesale and retail trade, transportation and storage, information and communication, and financial and insurance activities.
Source: Author's calculations using data from EU-LFS, US-CPS, Nedelkoska and Quintini (2018[2]) and Autor and Dorn (2013[12]).

71. The negative sign indicates that occupation-level employment grew by less (or potentially declined) for occupations with higher automation risk, which is consistent with the results from Manning (2019[9])) and Coelli and Borland (2019[10]) discussed in Section 2. The size of the coefficient (-0.172) indicates that, for each occupation and holding country effects constant, occupation-level employment growth over the period was 1.72 percentage points lower for every ten point increase in occupation-level automation risk.

72. Turning to the results of the basic MLM specification, recall that the MLM approach, using the average risk by country as a level 2 predictor, resembles the fixed effects model in certain ways. Both estimate the between-occupation effect of automation, i.e. the extent to which an increase in the automation risk of an occupation is associated with different occupation-level employment outcomes, holding country-specific factors constant. By construction, the corresponding coefficients are therefore the same in both models. The MLM approach then extends the fixed effects model by estimating, within the same regression framework, the between-country effect, i.e. the extent to which an increase in average country-level automation risk is associated with different employment outcomes.

73. To model these two effects, the MLM specification includes two independent variables measuring automation risk. The first is occupation-country automation risk centred by average country-level automation risk (i.e. the level 1 predictor centred by the group mean, associated with β_1 in equation (4) above). The second is occupation-country automation risk centred by overall average automation risk and averaged by country (i.e. a level 2 predictor consisting of an average of risk at the group level). These are discussed in turn.

74. The coefficient on the between-occupation effect is negative, statistically significant and equal in magnitude to the coefficient on risk in the fixed effects model. To explore this result by way of a country example, it is useful to consider Germany. In Germany, average employment growth between 2012 and 2019 for the five highest risk occupations (5.7 %) was less than half of average employment growth for the five lowest risk occupations (12.1 %).

75. The five occupations at greatest risk of automation in Germany according to the Nedelkoska and Quintini (2018[2]) measure are food preparation assistants, followed by labourers in mining, construction, manufacturing and transport, then drivers and mobile plant operators, then other clerical support workers, and then stationary plant and machine operators.[28] These occupations had employment growth between 2012 and 2019 that ranged from 4.0 to 10.2 %, with an unweighted average employment growth of 5.7 %. In contrast, the five occupations at lowest risk of automation according to the Nedelkoska and Quintini (2018[2]) measure are administrative and commercial managers, production and specialised services managers, hospitality, retail and other services managers, chief executives, senior officials and legislators and teaching professionals..[29] These occupations had employment growth between 2012 and 2019 that ranged from -8.7 to 28.0 %, averaging

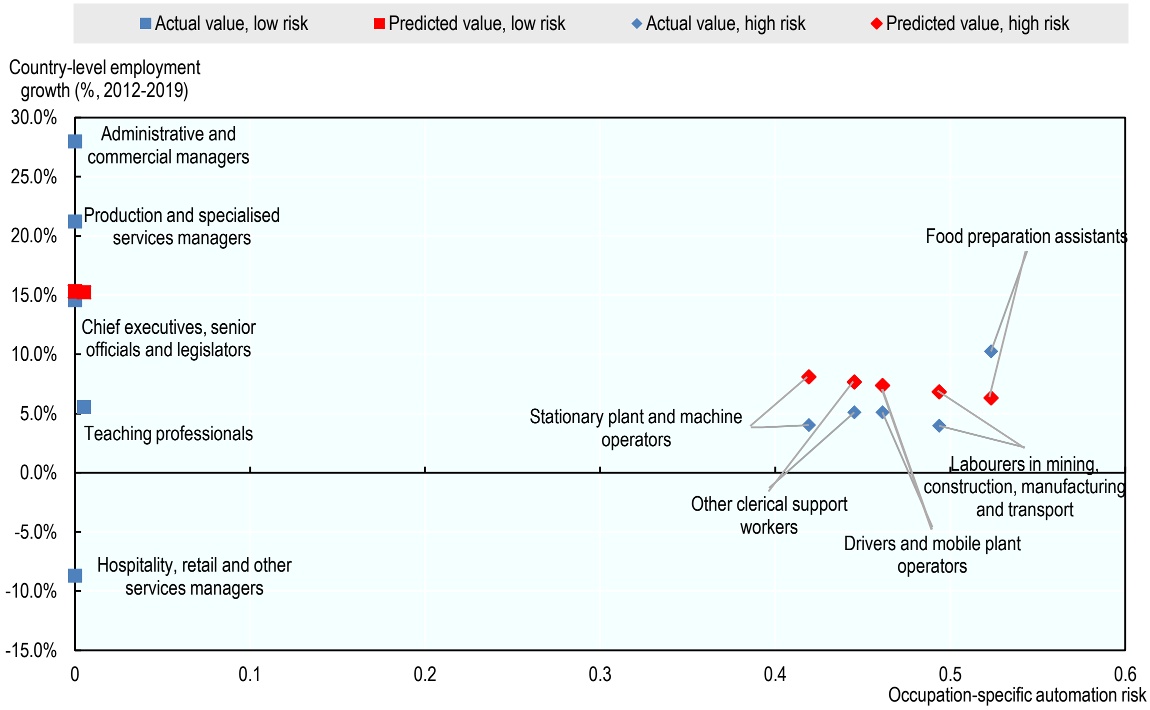
[28] In the 2-digit ISCO-08, classification, food preparation assistants are category 94, labourers in mining, construction, manufacturing and transport are category 93, drivers and mobile plant operators are category 83, other clerical support workers are category 44, and stationary plant and machine operators are category 81.

[29] In the 2-digit ISCO-08, classification, Administrative and commercial managers are category 12, Production and specialised services managers are category 13, Hospitality, retail and other services managers are category 14, Chief executives are category senior officials and legislators are category 11 and Teaching professionals are category 23.

12.1 %. This highlights the manner in which within-country variation in occupation risk is associated with differential employment outcomes.

76. It is also useful to compare these values at the country level with the model's predictions. The model finds an average of 7.2 % employment growth over the same period for the five highest risk occupations (compared to an actual value of 5.7 %) and an average of 15.3 % employment growth for the five lowest risk occupations (compared to an actual value of 12.1 %). Average expected employment growth among the five occupations at lowest risk of automation was therefore twice as high relative to average expected employment growth among the five occupations at highest risk, as can be seen in Figure 5.1 below.

Figure 5.1. Low-risk occupations in Germany saw higher employment growth (2012-2019) relative to high-risk occupations



Note: This figure presents the actual and predicted values for the five least risky occupations in Germany and the five riskiest occupations.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

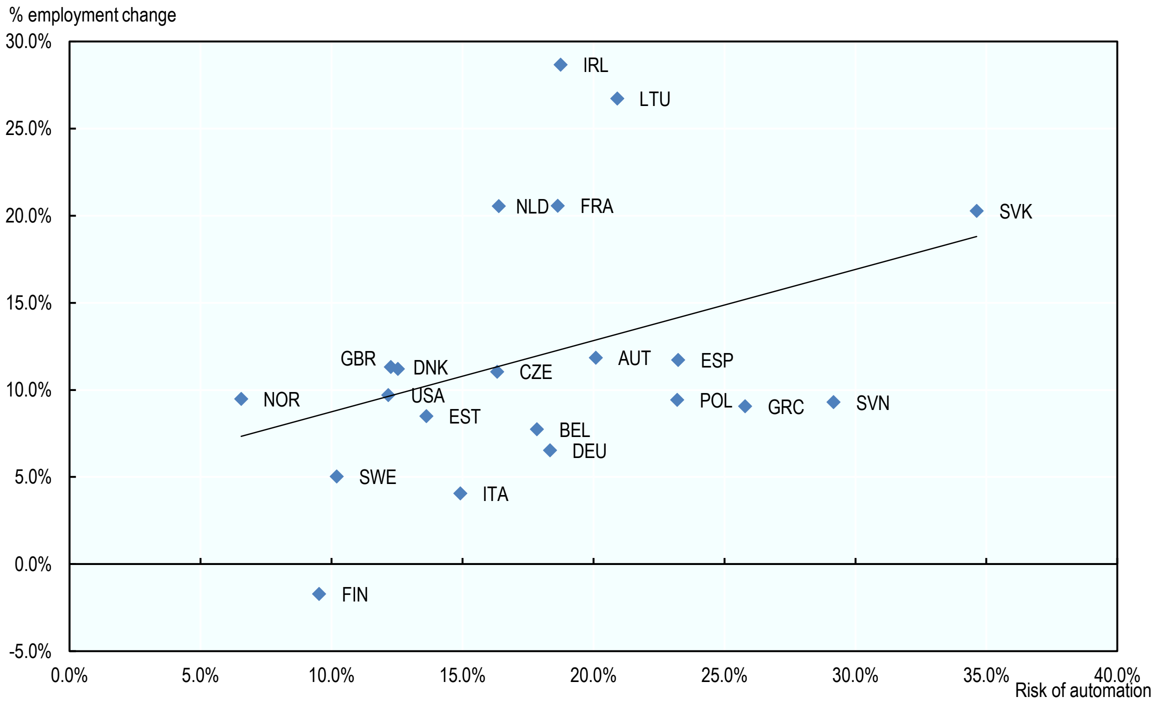
77. The second independent variable in the most basic MLM specification is occupation-country automation risk centred by overall average automation risk and averaged by country (i.e. the level 2 predictor averaged at the group level). While this model specification takes the coefficient on the level 1 predictor (β_1) as equal across countries, the model intercepts (β_{0j}) are allowed to vary by country and are explicitly modelled in the level 2 equation. The coefficient on the level 2 predictor (average risk/country), expressed as γ_{01} in equation (6) above, reflects the slope of the relationship between employment change and risk between countries, i.e. the average expected percentage change in employment growth for a one point increase in average automation risk in each country relative to the overall automation risk in the sample. This coefficient

is positive and significant at the 10 % level, suggesting that there was higher expected employment growth among countries with higher average automation risk.

78. This relationship can be seen in Figure 5.2, which plots the average employment growth between 2012 and 2019 on the y-axis and average automation risk on the x-axis for each of the 21 countries in the sample. The positive relationship between country average risk and employment outcomes is clear, suggesting stronger average employment growth in countries with higher average automation risk relative to countries with lower average risk.[30] This finding suggests that between-country variation is as important to examine in closer detail as between-occupation variation. It is further important to examine between-country variation because other variables operating at the country level could be correlated with the overall country-level average risk. This is the subject of the next section.

Figure 5.2. Countries with higher average automation risk saw higher employment growth

Average percentage change in employment level (2012 to 2019) and average risk of automation (2012), by country



Note: The averages presented are unweighted.
Source: Author’s calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

79. In summary, there is a negative employment effect when looking across occupations, and a positive effect when looking across countries. These two results are not necessarily contradictory. One could imagine that the positive effect of automation on productivity at the country level may be spread across occupations, thereby explaining how

[30]Growth rates and automation risk represent unweighted averages across the 38 occupations analysed. When weighting for the employment share of each occupation, there is still no indication that higher risk of automation is associated with lower employment growth.

the negative effect could allow for a positive country effect. This is explored further in the following subsection.

5.1.2. Investigating the cross-country relationship between automation risk and employment: results of MLM adding level 2 predictors

80. While the results in the previous section point to a negative effect with respect to between-occupation outcomes (in which higher automation risk is associated with lower employment growth), the results at the country-level point to a positive effect. The positive coefficient on average country-level risk indicates that occupations in riskier countries experienced higher levels of employment growth. This finding highlights the importance of understanding the impact of country-level factors on employment, to exclude the role of potential confounding factors at the country level. To do this, additional predictors are included at the second (country) level in the results presented in Table 5.2.[31] Here, the focus is on other factors that may impact employment outcomes at the country level. In Table 5.3 the analysis considers other factors that may interact with automation risk.

81. Each specification includes occupation-country automation risk and the country-average risk measure, as in Column 4 of Table 5.1. Column 1 controls for the share of workers in the each industry in 2012 (at the country level) and the results show that the sectoral composition of employment of countries does not drive the positive relationship between the risk of automation and employment growth.

82. Column 2 of Table 5.2 includes the employment gap over the financial crisis period (i.e. the percentage point change in the employment rate from the onset of the financial crisis in Q4 2007 to the country-specific crisis trough) given that countries most affected by the crisis are likely to have experienced higher subsequent employment growth. The associated coefficient is negative - meaning that countries that were most affected by the crisis indeed saw higher subsequent employment growth (after controlling for automation risk) - but not statistically significant.

[31] By construction of the model, the inclusion of country-level (or level 2) variables does not change the estimate of the between-occupation effect (coefficient on *Risk demeaned/country*), but only affects the estimate of the between-country effect (coefficient on *Country-average risk*).

Table 5.2. MLM results inclusive of country-level control variables at the second level

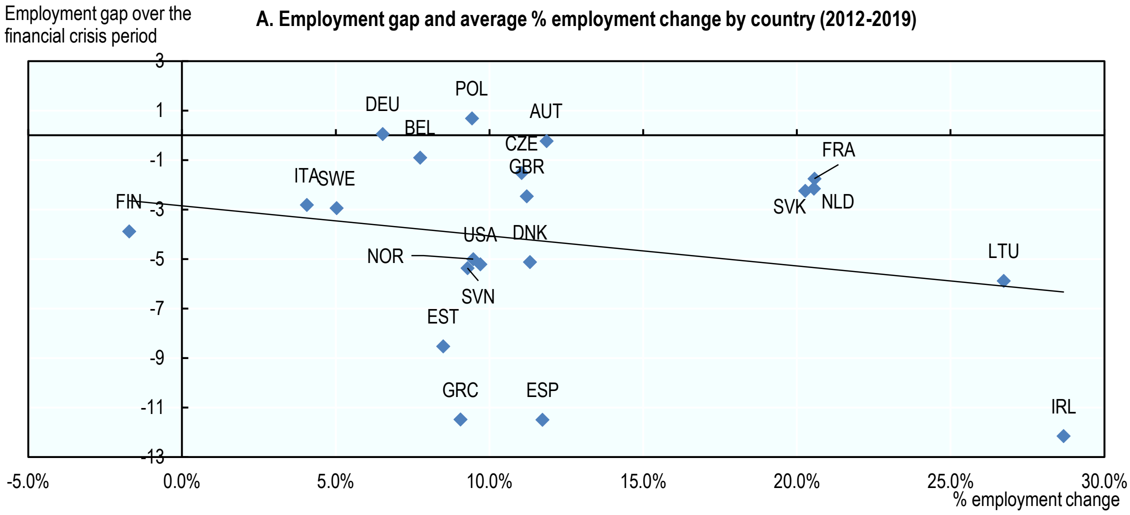
Dependent variable: 2012-2019 % change in employment level

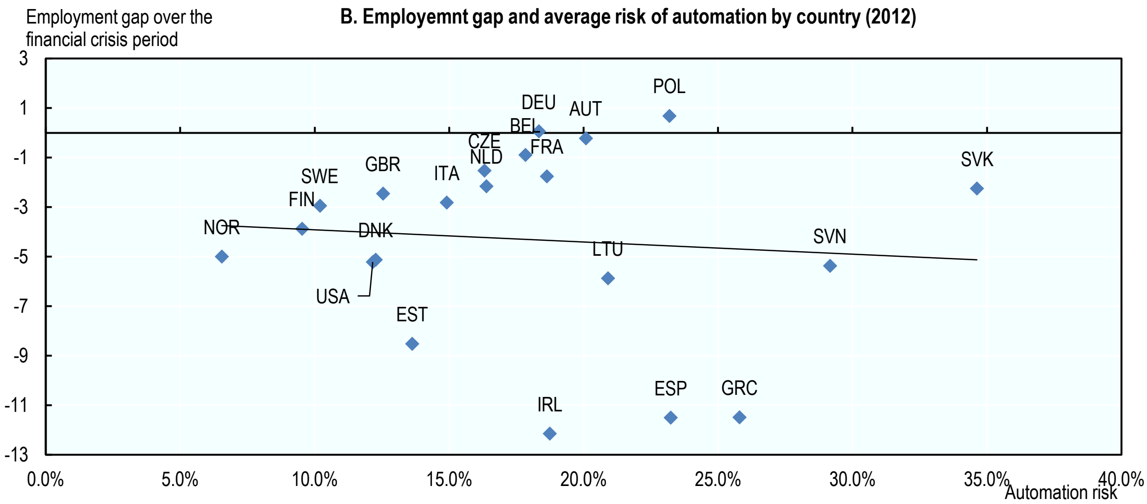
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Risk (demeaned/country)	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**	-0.172**
	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0727)	(0.0718)
Country-average risk	0.652**	0.390*	0.276	0.469*	0.473**	0.608**	0.440*	0.431*	0.471**	0.372*	1.026
	(0.318)	(0.217)	(0.246)	(0.257)	(0.206)	(0.278)	(0.233)	(0.237)	(0.227)	(0.212)	(0.696)
Employment gap (crisis trough)		-0.00405									-0.0330
		(0.00387)									(0.0246)
Minimum wage (2012)			0.00583								-0.110
			(0.00495)								(0.0675)
Average wage (2012)				6.06e-07							1.13e-05
				(1.35e-06)							(1.46e-05)
Tax Wedge (2012)					-0.00424**						-0.0207
					(0.00215)						(0.0131)
GDP per capita (2012)						2.03e-06					1.85e-06
						(1.80e-06)					(1.39e-05)
EPL Permanent (2012)							-0.0125				0.356
							(0.0302)				(0.239)
EPL Temporary (2012)								-0.00484			0.309*
								(0.0189)			(0.159)
Product Market Regulation (2013)									-0.0710		-0.444
									(0.0764)		(0.378)
CB Coverage (2012)										-0.000683	-0.00360
										(0.000462)	(0.00219)
Industry shares (2012)	Yes	No	No	No	No	No	No	No	No	No	Yes
Observations	792	792	792	792	792	792	792	792	792	792	792
Number of countries	21	21	21	21	21	21	21	21	21	21	21

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. A dummy variable equal to 1 for countries that have a minimum wage is included in Specifications 3 and 11. The industry shares represent ten controls for the sectoral composition of the workforce of the countries in 2012 with respect to the following breakdown: Agriculture, forestry and fishing; Mining and quarrying and other industry; Manufacturing; Construction; Accomodation and food service activities; Wholesale and retail trade, transportation and storage, information and communication; Financial and insurance activities; Real estate, renting and business activities; Public administration, defence, education, human health and social work activities; Other services. The tax wedge is the wedge between the labour cost for the employer and the corresponding net take-home pay of the employee for single persons without children earning 67% of average worker earnings. It is expressed as the sum of personal income tax and all social security contributions as a percentage of total labour cost. The real hourly minimum wage is expressed in 2019 constant prices at 2019 USD exchange rates. The average annual wage is expressed in 2019 constant price at 2019 USD PPPs. The aggregate indexes of anti-competitive product market regulations come from the OECD Regulatory Database and vary from 0 to 6 from the least to the most restrictive. The aggregate Employment Protection Legislation (EPL) indexes on regulations with respect to the dismissals of workers on open-ended contracts (including additional provisions for collective dismissals) and the use of temporary contracts come from the OECD Indicators of Employment Protection. Both indicators vary from 0 to 6 from the least to the most stringent. The employment gap is the percentage-points change in the employment rate between the onset of the crisis (Q4 2007) and the country-specific crisis trough, as computed in the OECD 2016 Employment Outlook. Collective bargaining coverage rate corresponds to the ratio of employees covered by collective agreements, divided by all wage earners with the right to bargain.
Source: Author’s calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]), OECD Taxing Wages Database, OECD Indicators of Product Market Regulation, OECD Employment Protection Database, OECD Employment Database, OECD 2016 Employment Outlook, OECD National Accounts, ICTWSS database (Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts).

83. Looking into this relationship a bit further, there is indeed little evidence that some of the positive relationship between automation risk and employment growth is accounted for by countries' economic recoveries from the financial crisis.

Figure 5.3. Countries with more severe contractions in employment during the financial crisis also grew the most over the subsequent period





Note: The averages presented are unweighted. The employment gap is the percentage point change in the employment rate from the onset of the financial crisis in 2007 to the country-specific crisis trough.
Source: EU-LFS, US-CPS, Nedelkoska and Quintini (2018[2]) and (OECD, 2016[19]).

84. Figure 5.3. shows the relationship between the employment gap over the financial crisis period and average employment growth by country from 2012-2019 in the top scatter plot. The negative relationship suggests that countries with more severe contractions in employment during the financial crisis also grew the most over the subsequent period. In addition, the bottom scatter plot in Figure 5.3 shows the relationship between the employment gap and average automation risk by country. Here, however, it is less clear that countries hit hardest by the financial crisis tended to be those that faced higher automation risk. This second chart provides some evidence that the positive employment-

risk relationship observed does not seem driven by recovery from the financial crisis. To summarise: countries that saw the greatest hit from the crisis also saw the greatest subsequent employment growth, but they were not necessarily the countries at highest risk of automation.

85. The next several columns in the table consider various other country-level factors that may help explain patterns in employment growth that are correlated with country-level risk. To investigate this in the context of the MLM framework, a variety of other policy variables that may affect automation risk through a relative cost of labour channel are added one by one (Columns 2-4). These include the minimum wage, the average wage, and the average tax wedge. While tax wedge is negatively associated with employment growth, there is little evidence in this analysis in support of the hypothesis that relative labour costs explain the positive relationship between automation risk and employment growth at the country level.

86. One potential explanation could be that average automation risk in a country relative to overall automation risk (*Country-average risk* in the regressions) could be correlated with wealth. To investigate this, Column 5 explicitly includes a proxy for GDP per capita, which is not statistically significant. This suggests that wealth may not be driving employment outcomes separately from automation risk.

87. It is also useful to consider whether the coefficient on *Country-average risk* is statistically significant when controlling for characteristics of labour market institutions or public policies that may also affect labour market outcomes. The expected signs on these variables are theoretically ambiguous. In particular, while highly regulated labour markets may limit employment growth, lighter regulation could lead to expanded investment in automation, which could limit employment growth. To examine this, Columns 6-8 include variables for the coverage of collective bargaining agreements, employment protection legislation, and product market legislation. None of the coefficients on these variables are statistically significant.

88. The inclusion of additional country-level variables is difficult due to data limitations. There is a relative lack of variation and observations in the data at the second level with which to identify many coefficients. This can also be seen in the final regression (Column 11), in which the full slate of control variables is added. In this regression, while the first-level result remains significant, most of the second level variables are statistically insignificant. This highlights the need to engage in further research to expand the sample (e.g. by adding additional countries). Thus, the evidence presented in Table 5.2 should be considered suggestive and preliminary only.

89. Finally, it is useful to consider whether proxies for actual changes in automation are associated with different employment outcomes. While controlling for the average level of automation risk in a given country points to the risk of automation affecting employment outcomes, it does not control for the overall level of investment in automating technologies that actually occurred. This is assessed using the change in the stock of industrial robotics technologies over the period 2012-2019 (Table 5.3). Interestingly, the results suggest a positive and statistically significant relationship between increases in the stock of robots and employment growth, while the variable for the risk of automation stays positive but is no longer statistically significant. This relationship is shown in Figure 5.4. Countries that increased their stock of robots had higher job growth on average, even though those occupations where risk of automation is high experienced lower growth.

Table 5.3. MLM results using an alternative automation measure at the country level

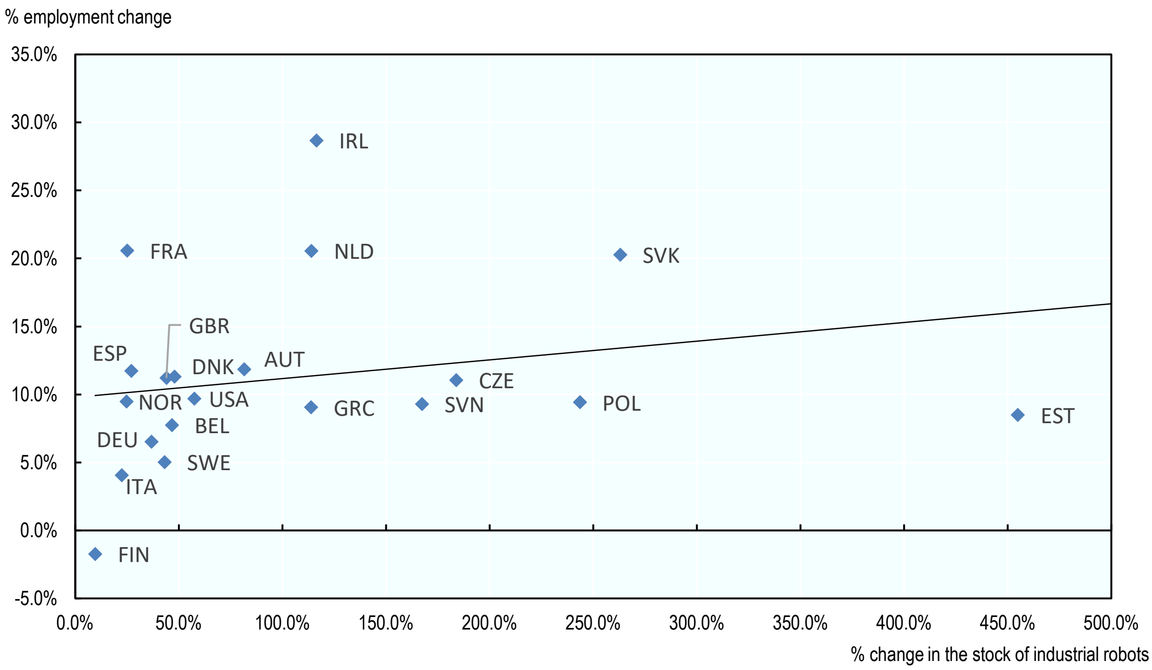
Dependent variable: 2012-2019 % change in employment level

	(1)	(2)	(3)
Risk (demeaned/country)	-0.172**	-0.172**	-0.172**
	(0.0727)	(0.0727)	(0.0727)
Country-average risk	0.409*		0.299
	(0.222)		(0.206)
Industrial robot (% change, 2012-2019)		0.0138**	0.0118**
		(0.00551)	(0.00542)
Observations	792	792	792
Number of countries	21	21	21

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell.
Source: Author's calculations using data from EU-LFS, US-CPS, Nedelkoska and Quintini (2018[2]) and International Federation of Robotics.

Figure 5.4. Countries with greater uptake of industrial robots experienced higher employment growth

Average percentage change in employment level by country and percentage change in the stock of industrial robots (2012-2019)



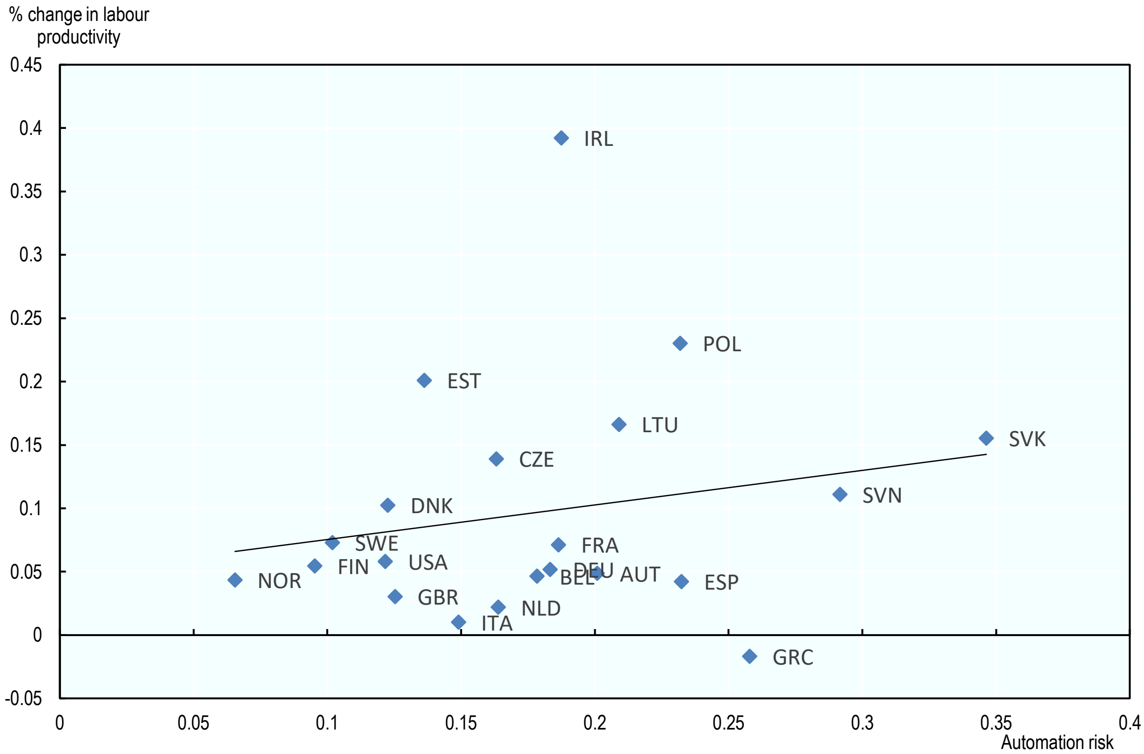
Note: The International Federation of Robots calculates the operational stock of robots by accumulating annual deployments and assuming that robots operate 12 years and are immediately withdrawn after 12 years. The variable here reflects the average change in the stock of industrial robots between 2012 and 2019 per country. Lithuania has been excluded for readability reasons, but the results are qualitatively the same when Lithuania is included.
Source: Nedelkoska and Quintini (2018[2]) and the International Federation of Robots.

90. Overall, this analysis suggests several broad trends. First, a negative relationship between occupation-level automation risk and employment outcomes is evident. Riskier occupations have experienced lower employment growth. Second, the patterns of employment growth vary substantially across countries. Looking at the country level, automation risk matters. Countries with higher levels of automation risk experienced higher occupational employment growth. Further investigation is challenging, but the evidence presented here does not suggest that labour cost variables play a key role in this relationship. In addition, there is some evidence that, overall, investment in automation is associated with higher job growth on average at the country level. This may suggest that while some jobs are more exposed to automation risk, automation at the country-level may have positive impacts on employment.

91. As described in Section 2, automation may be positively linked to employment growth through labour productivity. To the extent that automation increases labour productivity, prices on consumer goods will fall. Lower prices, in turn, boost consumer demand, which in turn grows employment (even if the amount of labour per unit has declined). Higher levels of employment could occur in the same occupations experiencing automation but also in other occupations, with the potential for both negative employment effects of automation within countries and positive effects across countries. Looking into changes in productivity over the period considered does seem to offer at least suggestive support for this narrative. Figure 5.5 shows the relationship between changes in labour productivity between 2012 and 2019 and average risk per country. Consistent with the labour productivity story, labour productivity growth was indeed higher in countries that faced higher risk of automation. While this is not definitive proof that automation is driving positive employment growth at the country level through a positive effect on labour productivity, it is encouraging.

Figure 5.5. Increased labour productivity in countries with higher average automation risk suggests that automation may have positive employment effects

Percentage change in labour productivity (2012-2019) and risk of automation (2012)



Note: The averages presented are unweighted. Labour productivity is measured by GDP (in USD, constant prices) per hour workers. For Belgium, the productivity level in 2019 has been imputed assuming that the 2018-2019 change in productivity was equal to the average annual change in productivity between 2012 and 2018.
Source: OECD Productivity Database and Nedelkoska and Quintini (2018[2]).

5.1.3. The within-country relationship between automation risk and employment varies across countries: results of MLM including cross-level interaction terms

92. The previous sub-section explored the explanatory power of country-level factors in explaining employment growth under the assumption that there was no interaction between the effect of country-level factors and that of automation risk. This sub-section returns to examine the explanatory power of automation risk within countries (level 1) while interacting automation risk with each of the country-specific (level 2) dependent variables.

93. As described in Section 4 above, the inclusion of cross-level interaction terms allows for consideration of whether country-level factors (policy variables, macroeconomic variables, investments in automation) increase or reduce the impact of country-level risk on employment outcomes. For example, one could conjecture that the risk of automation could have differential impacts in countries where investment in robots (which was found to be associated with higher employment growth in the previous section) is high relative to where investment in robots is low. Similarly, automation risk may have differential impacts depending on whether labour markets are more or less regulated.

94. The key results are presented in Table 5.4. The negative relationship between the risk of automation and employment growth is stronger in countries where restrictions on the use of temporary employment are looser, as highlighted by the significant positive interaction coefficient between risk and the indicator of employment protection legislation for temporary employment. The risk of automation was also associated with stronger negative employment effects in countries where employment declined less during the financial crisis. One possible explanation could be that, shortly after the global financial crisis, firms had a greater capacity to invest in automation technologies in countries that were less affected by the crisis.

95. Caution should nonetheless be exercised in interpreting the results due to a relative lack of explanatory power. This is due to the limited number of countries at the second level with which to identify the coefficients.

Table 5.4. MLM results inclusive of country-level control variables at the second level and interaction terms

Dependent variable: 2012-2019 % change in employment level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risk	-0.172**	-0.315***	-0.107	0.0103	-0.475	0.208	-0.627	-0.610***	-0.889*	-0.220	-0.216**	-0.214***
	(0.0727)	(0.106)	(0.162)	(0.226)	(0.483)	(0.281)	(0.440)	(0.227)	(0.504)	(0.158)	(0.0893)	(0.0806)
Country-average risk	0.409*	0.390*	0.269	0.469*	0.473**	0.608**	0.440*	0.431*	0.471**	0.372*	0.299	0.409*
	(0.222)	(0.217)	(0.316)	(0.257)	(0.206)	(0.278)	(0.233)	(0.237)	(0.227)	(0.212)	(0.206)	(0.222)
Employment gap (crisis trough)		-0.00405										
		(0.00387)										
Employment gap x risk		-0.0325*										
		(0.0178)										
Minimum wage (2012)			0.00577									
			(0.00566)									
Minimum wage (2012) x risk			0.00354									
			(0.0265)									
Average wage (2012)				6.06e-07								
				(1.35e-06)								
Average wage (2012) x risk				-4.92e-06								
				(5.79e-06)								
Tax Wedge (2012)					-0.00424**							
					(0.00215)							
Tax Wedge (2012) x risk					0.00793							
					(0.0125)							
GDP per capita (2012)						2.03e-06						
						(1.80e-06)						
GDP per capita (2012) x risk						-1.04e-05						
						(7.46e-06)						
EPL Permanent (2012)							-0.0125					
							(0.0302)					
EPL Permanent (2012) x risk							0.181					
							(0.173)					
EPL Temporary (2012)								-0.00484				
								(0.0189)				
EPL Temporary (2012) x risk								0.196**				
								(0.0962)				
Product Market Regulation (2013)									-0.0710			

									(0.0764)			
Product Market Regulation (2013) x risk									0.501			
									(0.349)			
CB Coverage (2012)										-0.000683		
										(0.000462)		
CB Coverage (2012) x risk										0.000826		
										(0.00243)		
Industrial robots (% change, 2012-2019)											0.0118**	
											(0.00542)	
Industrial robots x risk											0.0233	
											(0.0278)	
Country-average risk x risk												1.265
												(1.059)
Observations	792	792	528	792	792	792	792	792	792	792	792	792
Number of countries	21	21	14	21	21	21	21	21	21	21	21	21

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. The risk variable is centred using country means in all specifications. The tax wedge is the wedge between the labour cost for the employer and the corresponding net take-home pay of the employee for single persons without children earning 67% of average worker earnings. It is expressed as the sum of personal income tax and all social security contributions as a percentage of total labour cost. The real hourly minimum wage is expressed in 2019 constant prices at 2019 USD exchange rates. The average annual wage is expressed in 2019 constant price at 2019 USD PPPs. The aggregate indexes of anti-competitive product market regulations come from the OECD Regulatory Database and vary from 0 to 6 from the least to the most restrictive. The aggregate Employment Protection Legislation (EPL) indexes on regulations with respect to the dismissals of workers on open-ended contracts (including additional provisions for collective dismissals) and the use of temporary contracts come from the OECD Indicators of Employment Protection. Both indicators vary from 0 to 6 from the least to the most stringent. The employment gap is the percentage-points change in the employment rate between the onset of the crisis (Q4 2007) and the country-specific crisis trough, as computed in the OECD 2016 Employment Outlook. Collective bargaining coverage rate corresponds to the ratio of employees covered by collective agreements, divided by all wage earners with the right to bargain.

Source: Author’s calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]), OECD Taxing Wages Database, OECD Indicators of Product Market Regulation, OECD Employment Protection Database, OECD Employment Database, OECD 2016 Employment Outlook, OECD National Accounts, ICTWSS database (Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts).

5.2. Job stability

96. In addition to the impact of automation on employment levels, its impact on the duration of employment relationships is an important factor contributing to automation anxiety, as duration is closely tied to the probability of job loss. It should be noted that, although related, the impacts of automation risk on job quantity and job stability are not necessarily connected. For example, a reduction in the employment share of high-risk occupations might occur without any change in hiring and separations for those occupations (as long as the difference between the two account for the change in employment). Similarly, an increase in separations can co-exist with a constant employment level. To investigate the relationship between the risk of automation and job stability, the analysis of the previous section is replicated using job tenure as the dependent variable of interest.

97. The results suggest that automation risk appears is negatively associated with changes in job stability at the occupational level. Table 5.5 highlights a negative relationship between the risk of automation and changes in job tenure from 2012 to 2019[32], especially when tenure is adjusted for age. On average, a 10 percentage point higher risk of automation is associated with 0.80 percentage point higher drop in age-adjusted tenure (equivalent to around one month).[33] These results are robust to the inclusion of occupation-level sectoral employment shares and an index offshorability.

[32] Tenure data for the United States are from the CPS January Supplement, available every two years and most recently in 2018. Therefore, 2019 tenure levels for the United-States have been imputed assuming that 2018-2019 tenure changes were equal to the average annual tenure changes between 2012 and 2018.

[33] Estimated at the average tenure the sample (9.9 years).

Table 5.5. There is a negative relationship between automation risk and job stability

Variables of interest are 2012-2019 change

	Tenure (% change)	Age-adjusted log tenure (change)			
	Fixed effects (FE) model	FE model	FE model	FE model	Basic MLM specification
Risk	-0.0588*	-0.0796**	-0.0729**	-0.0675*	
	(0.0306)	(0.0347)	(0.0365)	(0.0369)	
Risk (demeaned/country)					-0.0796**
					(0.0347)
Country-average risk					-0.233
					(0.184)
Share of manufacturing	No	No	Yes	Yes	
Share of service sector	No	No	Yes	Yes	
Offshorability	No	No	No	Yes	
R-squared	0.005	0.007	0.012	0.014	
Observations	792	792	792	792	792
Number of countries	21	21	21	21	21

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Adjusted log tenure is obtained by taking the residual of country-specific OLS regressions of log tenure over age. Offshorability is an occupation-level measure developed by Autor and Dorn (2013[12]) based on data from the United States. For each country-occupation cell, the share of the manufacturing sector represents the share of workers in that cell working in the manufacturing sector in 2012. The share of service sector represents the 2012 share of workers in the country-occupation cell working in service sectors potentially more exposed to international trade: construction, wholesale and retail trade, transportation and storage, information and communication, and financial and insurance activities.
Source: Author's calculations using data from EU-LFS, US-CPS, Nedelkoska and Quintini (2018[2]) and Autor and Dorn (2013[12]).

5.3. Null results

98. The presentation of results in this section has focused on two labour market outcomes: changes in employment levels and changes in job stability. These two have been highlighted because the results are the most robust in terms of statistical significance and consistency when examining different time periods (e.g., 2012-2018, 2013-2019, etc.). However, many other outcome variables were considered in the analysis and led to null results. In particular, the analysis also considered changes in: the level of average working hours; the prevalence of part-time work contracts; the share of workers who are self-employed; the share of workers on temporary contracts; the level of wages; and measures of inequality. Null results for these outcomes could be a matter of the limited data available for use in this analysis.

6. Who is affected by automation?

99. This section sheds some light on the socio-demographic profile of the workers most affected by the trends described in the previous section. The section first examines the profile of workers who were most concentrated in occupations at high risk of automation in 2012. It then assesses whether the lower employment growth in high-risk occupations has disproportionately affected the labour market prospects for some categories of individuals. Finally, the section examines how exposure to automation risk has changed for different socio-demographic groups over the period 2012-2019. This section also analyses whether the relative decline in job tenure in high-risk occupations has affected job stability for certain workers more than for others.

100. Low-educated workers were more likely to work in occupations at high risk of automation in 2012. However, the lower employment growth in these occupations has not resulted in significantly lower growth in the employment rate of the low-educated compared to other education groups. This is due to the general upskilling of the workforce: there were relatively fewer jobs in risky occupations in 2019 than in 2012, but also fewer low-educated people. At the same time, the low-educated have not managed to move away from high-risk into lower-risk occupations. In fact, low-and middle-educated workers have become disproportionately more concentrated in high-risk occupations.

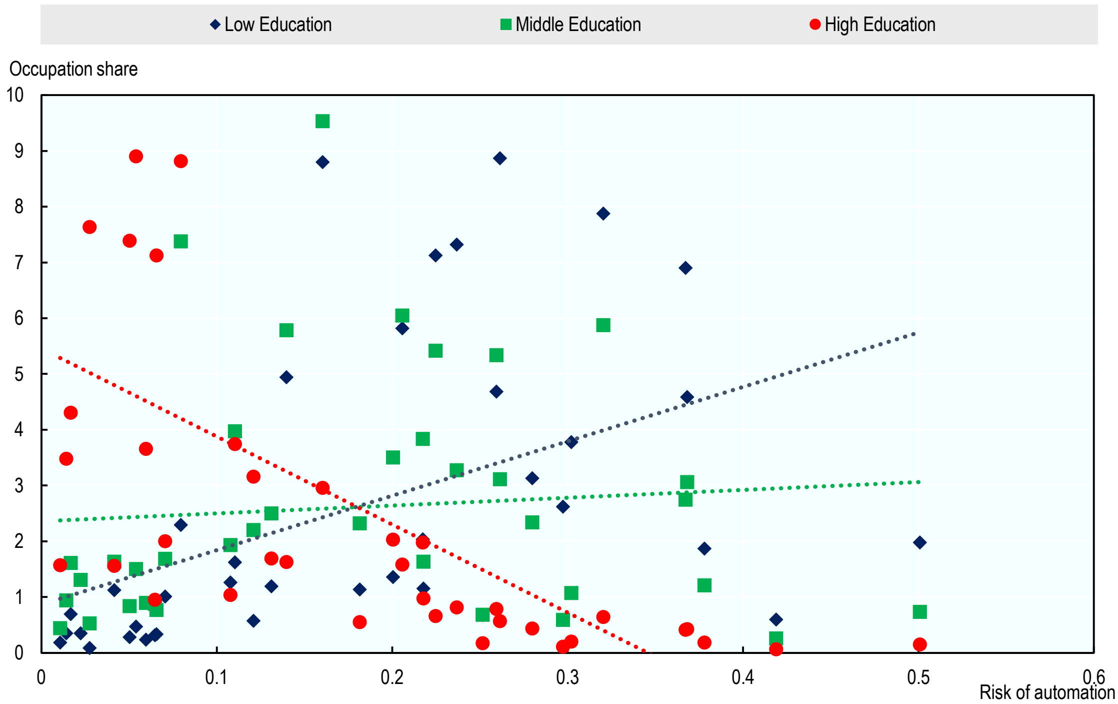
6.1. Low-educated workers were more likely to be concentrated in occupations at high risk of automation

101. Low-educated workers were more likely to work in occupations at high risk of automation in 2012. Figure 6.1 shows a clear positive relationship between the share of low-educated workers in a certain occupation in 2012 and the risk of automation in that occupation in that year. The relationship is still positive, although flatter, for middle-educated workers. By contrast, high-educated workers were more likely to work in occupations at low risk of automation. In 2012, 74% of low-educated workers were in the riskiest half of occupations, compared to 53% of middle-educated and only 13% of high-educated. These findings are in line with Nedelkoska and Quintini (2018[2]), who find that high-risk occupations only require basic to low levels of education, while low risk occupations almost all require professional training or tertiary education.[34]

[34] It useful to consider whether the relationships between automation risk and the occupation share taken among all workers of an education group are statistically significant. To test this, Table A A.1 replicates the previous MLM specification and uses the occupation share taken among all workers of an education group in a certain occupation in 2012. The analysis is done separately for each of the three education groups. The tables provide evidence in support of the results shown in Figure 6.1 by displaying three statistically significant relationships: a positive relationship between the share of low-educated workers in an occupation and the risk of automation in that occupation, a positive but weaker relationship for the middle-educated and a negative relationship for the high-educated. Table A A.2 presents results from a more disaggregated analysis by education, age and gender. This analysis shows that the positive relationship for the middle-educated is concentrated on men.

Figure 6.1. Low-educated workers have been disproportionately exposed to the risk of automation

Cross-country average occupation shares (by level of education) versus average risk of automation by occupation (2012)

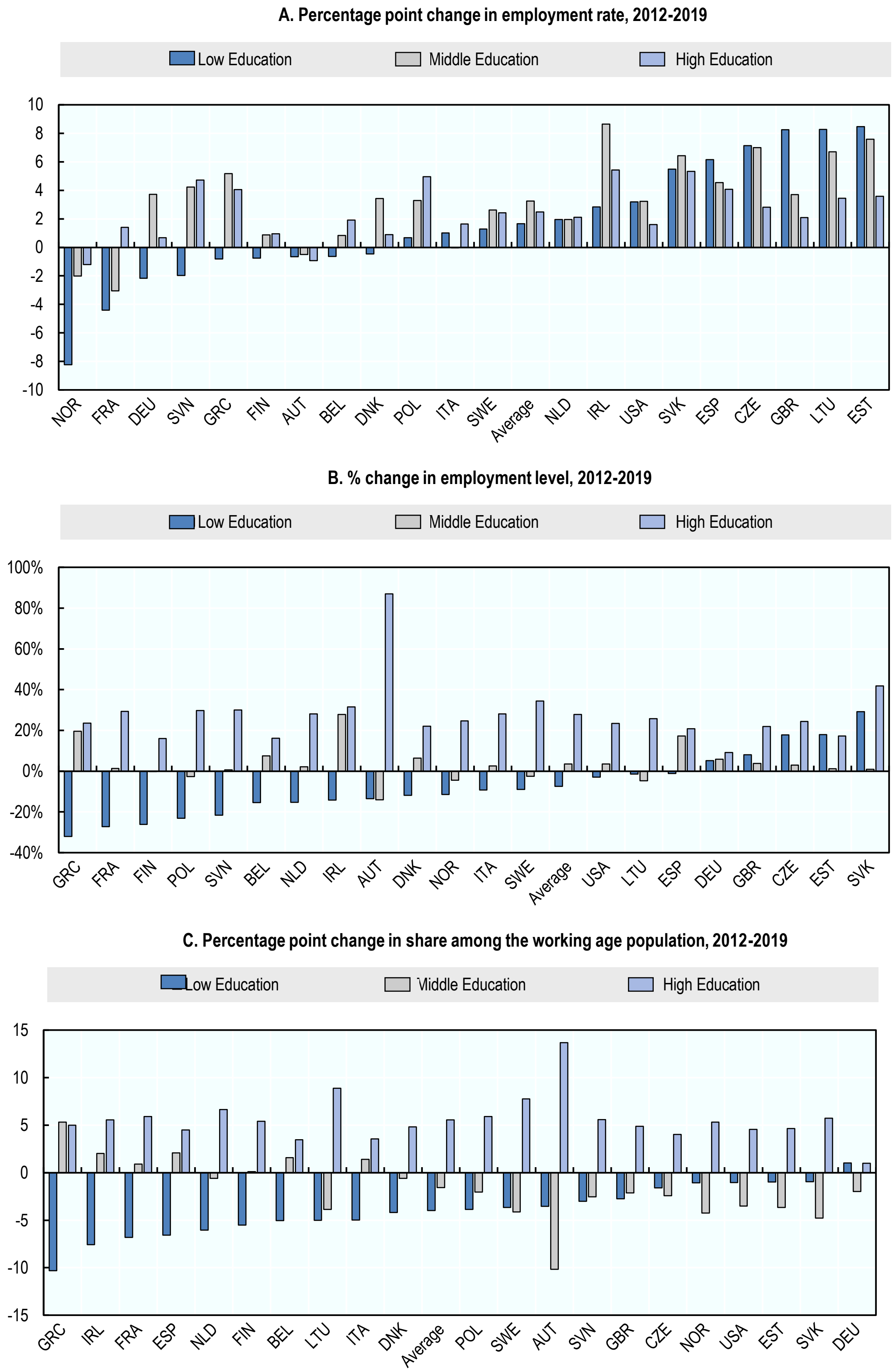


Note: Each dot reports the unweighted average across the 21 countries analysed of the share of workers with a particular education in that occupation. For each education group, occupation shares represent the share of workers of that group in a particular occupation. Among highly educated individuals, teaching professionals are excluded from the chart for readability reasons.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

6.2. Lower employment growth in high-risk occupations did not result in lower growth in the employment rate of the low-educated relative to other groups

102. The lower employment growth in occupations at high risk of automation has not resulted in significantly lower growth in the employment rate of the low-educated compared to other education groups (Figure 6.2 Panel A), despite the fact that low-educated workers were considerably more likely to work in those occupations (Figure 6.1). Figure 6.2 Panel C provides suggestive evidence reconciling these two findings: the lower employment growth in high-risk occupations has coincided with changes in the demographic composition of the workforce. In particular, the general level of education of the workforce has been rising for several decades, including in more recent years (Figure 6.2 Panel C). This means that the share of highly educated individuals has grown while the share of low-educated individuals has fallen. Therefore, even if there are now, in relative terms, fewer jobs for low-educated workers (Panel B), there are also fewer low-educated people to fill those jobs (Panel C), so that the employment rate of the low-educated has not grown less than that of the more educated.

Figure 6.2. Growth in the employment rate has been similar across educational groups



Note: The averages presented are unweighted.

Source: EU-LFS and US-CPS.

103. The suggestive evidence presented above indicates that the general upskilling of the labour force has meant that the lower employment growth in occupations at high risk of automation has not led to a lower growth in the employment rate for the low-educated. The analysis that follows presents a more formal test of this hypothesis and confirms the results. It also shows that, lower employment growth in high-risk occupations has not been accompanied by a move of the low-educated away from high-risk and into lower-risk occupations.

104. The analysis that follows decomposes the change in the share of the working-age population in a given occupation into propensity and composition effects.[35]

105. The *composition effect* captures what the employment change in a given occupation would have been based solely on changes in the education composition of the workforce. For example, if low-educated individuals were more likely to work as assemblers, and low-educated individuals have declined as a share of the total working-age population, then the share of assemblers in the workforce would correspondingly decline. The composition effect holds the likelihood that an individual works as an assembler constant.

106. By contrast, the *propensity effect* captures what the employment change in a given occupation would have been based solely on changes in the likelihood that an individual with a certain level of education works in a particular occupation (holding the composition of the workforce constant). For example, if the share of low-educated individuals in the workforce stays constant but they become less likely to work as assemblers, then the share of assemblers in the workforce would fall.

107. The results show that, on average across countries, the lower employment growth observed in high-risk occupations has not led to a relative decline in the propensity of individuals with a certain level of education to work in high-risk occupations. This is because these trends have coincided with changes in the education composition of the workforce. As discussed above, there were relatively fewer jobs in risky occupations in 2019 than in 2012, but also fewer low-educated people (Figure 6.2 Panel C), who are more likely to work in those occupations (Figure 6.1). This can be seen clearly in Figure 6.3, which, for each occupation, decomposes the growth in the share of the working age population in that occupation into the composition and propensity effects (averaged across countries). Occupations are ranked according to the cross-country average risk of automation, from lowest risk (left) to highest risk (right). The relationship between automation risk and total change in occupation shares[36] is similar to that between automation risk and change in employment levels observed in Figure 2.4. That is, there was

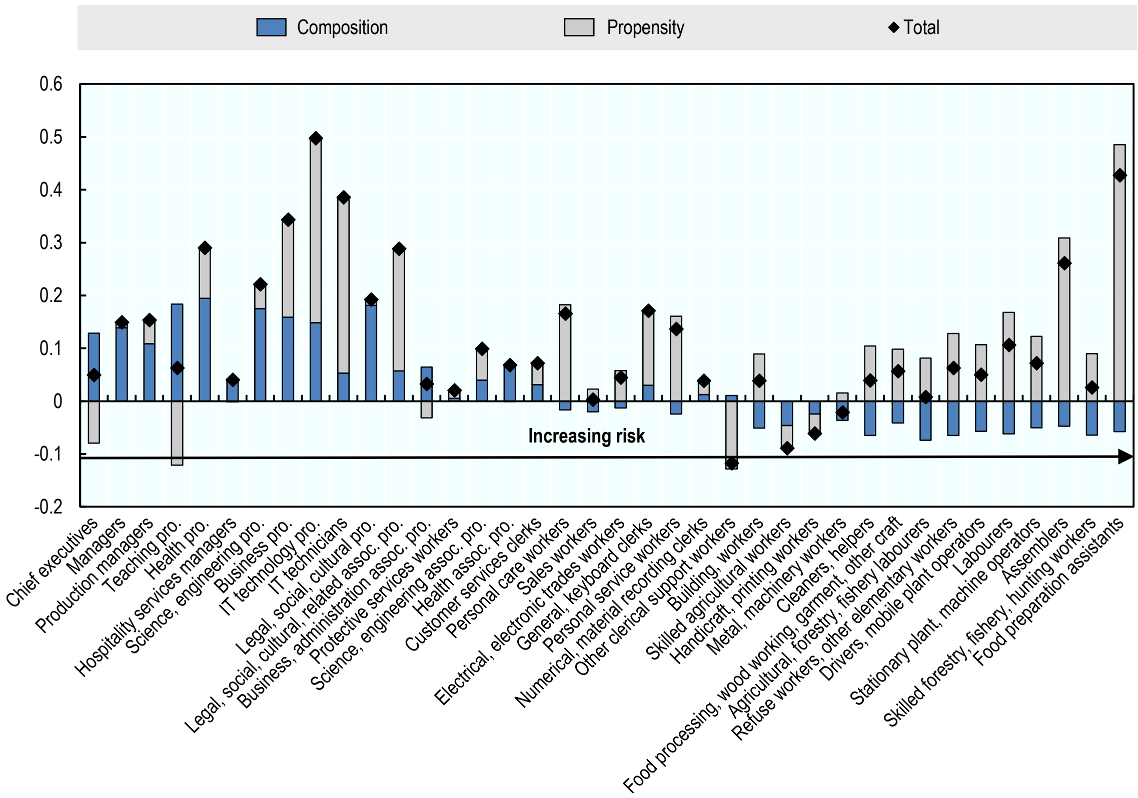
[35] This is done via a shift-share analysis, which decomposes the change in the share of individuals employed in each occupation according to: $\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g \Delta w_{g1}\, \pi_{g0}^j + \sum_g w_{g0}\, \Delta\pi_{g1}^j$. The term $\bar{\pi}_t^j$ is the share of the population in occupation j at time t. The term w_{gt} is the share of the population in education group g at time t, and π_{gt}^j is the share of group g in occupation j at time t. The left-hand side of the equation is the change in the share of the population in occupation j. The two terms on the right-hand side of the equation are (from left to right) the composition and propensity effects, respectively.

[36] Occupation shares represent the share of individuals in a particular occupation, and are calculated based on the entire working age population of the country (including the non-employed). The analysis includes the non-employed because it attempts to provide insights on the employment rates by education group.

lower employment growth in occupations that were at higher risk of automation. However, the decomposition shows that this was driven mainly by the composition effect: the relative decline in employment in high-risk occupations has been counterbalanced by changes in the composition of the workforce.

Figure 6.3. Lower employment growth in high-risk occupations coincides with changes in the demographic composition of the workforce

Cross-country average percentage change in occupation share associated with composition and propensity effects, 2012-2019



Note: This chart reports unweighted averages across the 21 countries analysed. Occupations are ranked according to the cross-country average risk of automation, from lowest (left) to highest (right). Occupation shares represent the share of individuals in a particular occupation, and are calculated based on the entire working age population of the country (including the non-employed). The composition and propensity components are the result of the shift-share decomposition of percentage employment change with respect to education.

Source: Author’s calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

108. A formal test of the statistical significance of these effects confirms this conclusion. Table 6.1 displays the coefficients obtained from applying the MLM specifications of the previous section on each term of the decomposition.[37] The results only show a statistically significant negative relationship between automation risk and the composition effect. The results also show a positive and statistically significant coefficient on the propensity effect, which suggests that, on average across education groups, the likelihood of an individual

[37] As in previous section, all MLM specifications in this section include the country-average risk measure as a control.

working in high-risk occupations has increased more than the likelihood of working in low-risk occupations. In other words, the composition effects have more than offset the lower employment growth in high-risk occupations, so that, for some workers, there has been a higher increase in the likelihood to work in high-risk occupations. This finding is explored further as part of the next subsection.[38]

Table 6.1. Lower employment growth in high-risk occupations coincides with changes in the demographic composition of the workforce

The variables of interests are the 2012-2019 percentage change in occupation share associated with composition and propensity effects

	Total	Composition	Propensity
Risk (demeaned/country)	-0.152**	-0.403***	0.251***
	(0.0707)	(0.0180)	(0.0690)
Observations	792	792	792
Number of countries	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. Occupation shares represent the share of individuals in a particular occupation, and are calculated based on the entire working age population of the country (including the non-employed). All MLM specifications include controls for the average risk by country. The composition and propensity components are the result of the shift-share decomposition of percentage employment change with respect to education.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

109. To conclude, the general upskilling of the labour force has meant that the lower employment growth in occupations at high risk of automation has not resulted in lower growth in the likelihood for individuals with a given level of education level to work in high-risk occupations. As a result, lower employment growth in high-risk occupations has not led to a lower growth in the employment rate for the low-educated. At the same time, the low-educated have not managed to move from occupations at high risk of automation and into lower risk occupations.[39]

110. These results have policy implications related to the mix of skills of individuals entering and leaving the workforce. To maintain alignment between the skills demanded and those supplied, policymakers' attention should focus on the future pipeline of workers, making sustained investment in education to ensure that individuals leave school with the right skills to take up the kinds of jobs that will be available to them.

[38] A similar analysis has been carried out using age, gender and education simultaneously to define the demographic groups in the shift-share decomposition. It provides similar results (see Table A A.3). In addition, the MLM specification in Table 6.1 has been tested using the composition components with respect to age and gender considered separately. This shows that the composition component with respect to education is the only one associated in a statistically significant manner with the risk of automation (Table A A.4).

[39] These findings contrast with recent evidence showing clear implications of the decline in middle skill employment since the mid-1990s in terms of labour market prospects within demographic groups (Chapter 4 in OECD (2020[22])). However, the present analysis focuses only on the 2012-2019 period, and automation is only one of the multiple drivers of shrinking middle skill employment.

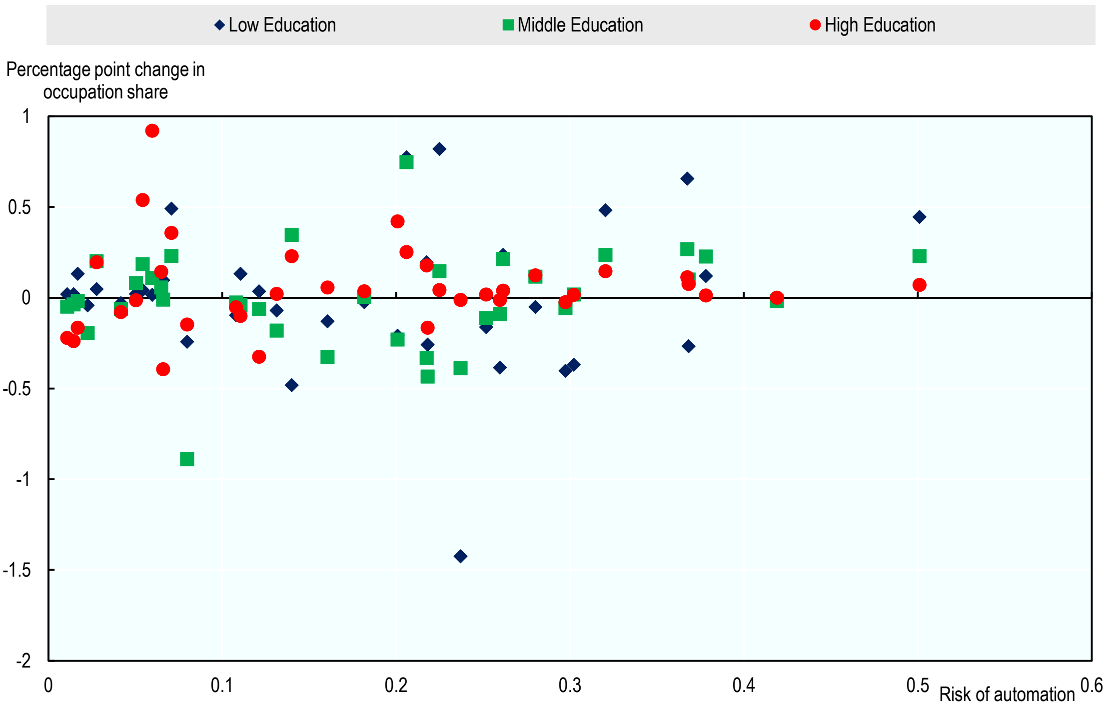
6.3. Low- and middle-educated workers have become disproportionately more concentrated in high-risk occupations

111. In spite of lower employment growth in high-risk occupations, the upskilling of the workforce has meant that, on average across demographic groups, the likelihood of an individual working in high-risk occupations has increased more than the likelihood of working in low-risk occupations over the period 2012-2019 (Table 6.1).

112. In particular, low- and middle-educated workers have become disproportionately more concentrated in the six riskiest occupations in terms of automation. Looking at averages across countries, Figure 6.4 shows that half of these six occupations exhibit very strong growth in the share of low-educated workers employed in them: Food preparation assistants, Labourers and Drivers and mobile plant operators. The picture is very similar for the middle-educated (Figure 6.4). As a result, the share of low-educated workers in the six riskiest occupations has increased by 1.4 percentage points over the period 2012-2019 (from 23.8% to 25.2%) and the share of middle-educated workers in these same occupations has increased by 1 percentage point (from 13.9% to 14.9%), compared to a 0.4 percentage point increase among the high-educated (from 1.9% to 2.3%).

Figure 6.4. Low-educated workers have become more concentrated in high-risk occupations

Cross-country average percentage point change in occupation share of an education group (2012-2019) and average risk of automation by occupation (2012)



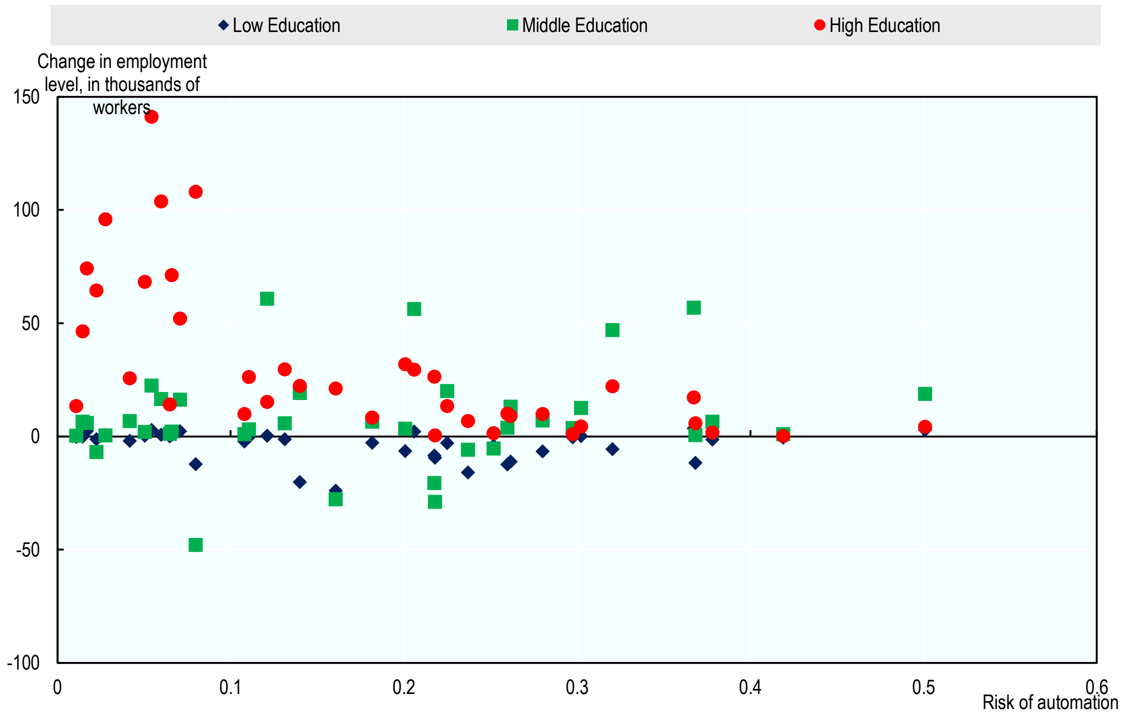
Note: Each dot reports the unweighted average across the 21 countries analysed for one occupation. For each education group, occupation shares represent the share of workers of that group in a particular occupation, and are calculated based on the population of workers of that group in the country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

113. While middle- and low-educated workers have both experienced a strong increase in their concentration in the six riskiest occupations, the mechanisms behind these trends are different. For middle-educated workers, this stems from a strong increase in job opportunities in the three occupations mentioned above: Food preparation assistants, Labourers, and Drivers and mobile plant operators (Figure 6.5). In contrast, there has not been an increase in the number of low-educated workers in these three occupations (Figure 6.5) but the combined facts that *i)* they were already more concentrated in these occupations (Figure 6.1), *ii)* the overall number of low-educated workers is falling (Figure 6.2, Panel C) and *iii)* the number of low-educated workers in these five occupations has not decreased (Figure 6.5) mean that, mechanically, the share of low-educated workers who are in these three occupations has increased considerably.[40]

[40] For the same given change in employment level N_g^j in an occupation j for a declining workers category *g* of overall size N_g, employment share S_g^j of group *g* in occupation *j* will increase more (or decrease less) in occupations with a higher initial employment share. More precisely, $\Delta S_g^j = \left(\frac{-N_g * \Delta N_g}{N_g + \Delta N_g}\right) * S_g^j + \frac{\Delta N_g^j}{N_g + \Delta N_g}$ increases with S_g^j if $\Delta N_g < 0$. This can be illustrated using the following simple example. Assume two occupations O1 and O2 and assume there are 100 low-educated workers in total. Further assume that 10 of these low-educated individuals work in O1 and 20 work in O2. This means that the share of low-educated workers employed in O1 = 10/100 = 0.1 and the share of low-educated workers working in O2 = 20/100 = 0.2. If the number of low-educated workers drops from 100 to 80, but the numbers of workers remain the same in O1 and O2, the share of low-educated workers in occupation O1 will have increased to 10/80=0.125 while the share of low-educated workers employed in occupation O2 will have increased to 20/80=0.25. Previously, 10% of the low-educated worked in O1, now 12.5% do. Similarly, 20% used to work in O2, but now 25% do. So merely by the underlying population dropping, the share of low-educated workers in O2 has increased more than their share in O1.

Figure 6.5. The increased concentration of the middle-educated in high-risk occupations stems from a strong increase in job opportunities for them in these occupations

Cross-country average change in employment levels by education (2012-2019) and average risk of automation (2012), by occupation



Note: Each dot reports the unweighted average across the 21 countries analysed for one occupation.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

114. These results have major implications for policy. Low-educated individuals, who were already disproportionately exposed to the risk of automation, seem to have become even more concentrated in occupations at very high risk of automation. It also looks like these occupations, despite automation in recent years, have remained high-risk occupations, as evidence from the United States shows.[41] Similarly, middle-educated individuals are increasingly concentrated in very high-risk occupations. Given the particular vulnerabilities of the low- and middle-educated to automation, it is crucial that social protection systems adequately protect these workers in the event of job transitions. In addition, adult learning programmes should help them to adapt their skills to changing labour market needs. This is especially true in light of prior findings that workers in high-risk occupations are less likely to participate in training (Nedelkoska and Quintini, 2018[2]).

[41] Calculations based on two waves of PIAAC data for the United States give a share of jobs at high risk of automation of 9.9% in 2017, compared to 10.0% in 2012. Of course, there is no guarantee that the same holds for the other countries included in the analysis, and this is an assumption that has to be made.

6.4. Stronger declines in job stability among workers in high-risk occupations have mostly affected older workers

115. The analysis now returns to the issue of declining job stability discussed in Section 5 and asks whether some socio-demographic groups were more affected than others. Results from a decomposition exercise[42] suggest that, in this case, composition effects account for only a minor part of the stronger decline in job stability in occupations at high risk of automation (Table 6.2). In contrast, propensity effects play a larger role. In other words, the relative average decline in job stability among workers in high-risk occupations is a function of workers experiencing actual decreases in job stability (rather than being the result of changes in the composition of workers in these occupations).

116. The stronger declines in job stability among workers in high-risk occupations have mostly affected older workers. Results from MLM analyses of tenure within demographic groups are presented in Annex A.[43] They show a statistically significant negative coefficient on the risk variable for older workers only (Table A A.5, Table A A.6 and Table A A.7). In other words: a higher risk of automation is associated with a relative decline in job stability mainly among older workers.

Table 6.2. The relative decline in job stability in high risk occupations is due primarily to higher drops in job stability within groups (rather than to compositional changes within occupations)

The variables of interest are the 2012-2019 change in average age-adjusted log tenure due to composition and propensity effects

	Composition	Propensity
Risk (demeaned/country)	0.0286	-0.0641**
	(0.0177)	(0.0324)
Observations	792	792
Number of countries	21	21

Note: Standard errors in parentheses. All MLM specifications include controls for average risk by country. The composition and propensity components are the result of the shift-share decomposition of the change in average age-adjusted log tenure with respect to education and gender.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

[42] This shift-share decomposition considers changes in the demographic composition of occupations. It is based on gender and education, as age composition effects have already been taken into account by using age-adjusted log tenure as a proxy for job stability. It decomposes the change in the average log of age adjusted tenure in each occupation according to: $\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g \Delta w_{g1}^j \pi_{g0}^j + \sum_g w_{g0}^j \Delta\pi_{g1}^j$. The term $\bar{\pi}_t^j$ is the average log of age-adjusted tenure in occupation j at time t. The term w_{gt}^j is the share of occupation j in demographic group g at time t, and π_{gt}^j is the average log of age adjusted tenure of group g in occupation j at time t. The left-hand side of the equation is the change in the average log of age-adjusted tenure in occupation j. The two terms on the right-hand side of the equation are (from left to right) the composition and propensity effects, respectively.

[43] Analyses focusing on age, education and gender one by one are favoured in this case for sample size reasons. In addition, the absence of a significant coefficient on the composition component in Table 6.2 suggests that the results focusing on one demographic variable only do not hide correlations between risk and composition effects with respect to the other variables.

7. Conclusion

117. This paper has presented an assessment of what has happened in occupations that were at high risk of automation in Europe and the United States. Using novel and granular occupation-country level data on automation risk, it provides the first cross-country evidence of the relationship between automation risk and employment outcomes. The evidence points to significant commonalities in how automation risk is affecting occupations across countries; technological progress knows no borders.

118. The results suggest that higher automation risk in a certain occupation is associated with worse employment outcomes for workers in those occupations. Overall employment levels in riskier occupations saw declines or lower levels of growth relative to less risky occupations. Riskier occupations also saw worse outcomes in job stability, which is often associated with job security.

119. The paper built on its cross-country approach by using an empirical approach that is novel in the study of automation risk on employment outcomes: multilevel modelling. This approach allows disaggregation of the impact of automation within countries (i.e. between different occupations) and between countries. Here the results suggest that while riskier occupations are associated with lower employment growth within countries, countries where occupations were riskier on average experienced higher occupational employment growth. These results are robust to the inclusion of a variety of controls. The paper is the first to disaggregate the relationship between automation risk and employment outcomes into a between-country and within-country effects, and to show these contrasting effects.

120. The paper also examines the relationship between automation risk and differing demographics in the labour markets. Overall, while low-educated workers have been most concentrated in occupations at high risk of automation, the lower employment growth in these occupations has not resulted in lower growth in their employment rate relative to other groups. Rather, the negative effect of automation risk on employment goes hand-in-hand with the general upskilling of the workforce, through composition effects: less educated workers retire and are replaced by more educated workers, who are less likely to work in risky occupations. However, as the labour force as a whole becomes more educated, those with lower educational levels are becoming even more concentrated in high-risk occupations, turning their labour market prospects even more uncertain. The potential for automation to destroy jobs is even more worrisome in the present context of severe employment declines worldwide due to the COVID-19 crisis.

121. In addition to the impact of automation on employment levels, its impact on the duration of employment relationships is another important factor contributing to automation anxiety, as employment duration is closely tied to the probability of job loss. There is evidence that higher automation risk is associated with greater reductions in occupation-level job tenure (i.e. how long a person has been in his/her present job). This negative effect is particularly pronounced among older workers, and is not associated with changes in the demographic composition of occupations.

122. The results have important implications for policy. They provide evidence that automation risk is associated with uncertain employment prospects for specific demographic groups. However, the analysis also suggests that automation risk is associated with improved outcomes for workers across the economy on average. This suggests that, rather than bringing about a “jobless future,” automation has the prospect of a future with different jobs. Managing the transition from existing jobs to future jobs is a crucial goal for

policymakers. Policymakers should thus focus on managing job transitions to new jobs for affected workers, and ensure that skills investments for younger workers match anticipated job availability, including by forecasting skill needs in light of automation trends.

123. The paper suggests several important avenues for future research. Throughout, the analysis is hampered by limited sample size at the country level with which to disentangle country-level risk of automation from other factors, including policy variables. In addition, although the analysis attempts to control for occupation-level offshorability and exposure to international trade, other potential confounding factors within countries cannot be excluded, such as a different post-crisis recovery for different occupations. Expanding the set of countries and taking into account additional occupation-level confounding factors would be an important avenue of future research.

124. The paper also raises important puzzles. While negative relationships between automation risk on employment were found within countries, positive relationships were found across countries. There is an important need to unpack the mechanisms behind these relationships. One obvious channel could be that automation raises worker productivity in affected sectors, leading to increased growth and employment. Higher levels of employment could occur in occupations other than those experiencing automation, with the potential for both negative employment effects of automation within countries and positive effects across countries. This channel could potentially be examined using employer-employee datasets.

125. Finally, the paper evaluated the impact of the Nedelkoska and Quintini (2018[2]) measure of automation risk at the occupation-level, but was only able to evaluate the impact of actual automation at the country level and for one particular type of technology due to data availability. Future work could combine subsequent iterations of PIAAC (the survey on which the measure is based) to examine whether the task content of occupations changed where automation risk was highest, and examine whether such changes were associated with different employment outcomes.

Annex A. Additional results

Table A A.1. Low-educated workers have been disproportionately exposed to the risk of automation

The variables of interest are the 2012 occupation shares taken among all workers of an education group

	Low Education	Middle Education	High Education
Risk (demeaned/country)	6.881***	1.224**	-10.44***
	(0.765)	(0.593)	(0.710)
Observations	792	792	792
Number of countries	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. For each education group, occupation shares are taken among all workers of that group in the country. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.2. Exposure to the risk of automation varies mostly by education and slightly by gender

The variables of interest are the 2012 occupation shares taken among all workers of an education group

	Women								
	Older High Education	Older Middle Education	Older Low Education	Prime High Education	Prime Middle Education	Prime Low Education	Young High Education	Young Middle Education	Young Low Education
Risk (demeaned/country)	-11.97***	-1.473	4.704***	-11.15***	-0.706	6.183***	-9.165***	0.0954	5.044***
	(1.135)	(0.928)	(1.269)	(0.941)	(0.908)	(1.126)	(0.855)	(1.135)	(1.309)
Observations	792	792	792	792	792	792	792	792	792
Number of countries	21	21	21	21	21	21	21	21	21

	Men								
	Older High Education	Older Middle Education	Older Low Education	Prime High Education	Prime Middle Education	Prime Low Education	Young High Education	Young Middle Education	Young Low Education
Risk (demeaned/country)	-11.25***	1.291*	6.933***	-10.32***	2.424***	8.029***	-7.790***	4.043***	8.821***
	(0.769)	(0.738)	(1.043)	(0.672)	(0.695)	(0.870)	(0.709)	(0.684)	(0.884)
Observations	792	792	792	792	792	792	792	792	792
Number of countries	21	21	21	21	21	21	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. For each education group, occupation shares are taken among all workers of that group in the country. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.3. Lower employment growth in high-risk occupations coincides with changes in the demographic composition of the workforce

The variables of interests are the 2012-2019 percentage change in occupation share (taken among the entire working age population) associated with composition and propensity effects

	Total	Composition	Propensity
Risk (demeaned/country)	-0.152**	-0.438***	0.286***
	(0.0707)	(0.0194)	(0.0701)
Observations	792	792	792
Number of countries	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. Occupation shares are taken among the entire working age population of the country and include non-employment as a possible category. All MLM specifications include controls for the average risk by country. The composition and propensity components are the result of the shift-share decomposition of percentage employment change with respect to age, education and gender.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.4. The relative reduction employment in high-risk occupations corresponds to education-related compositional effects

The variables of interest are the 2012-2019 percentage change in occupation share (taken among the entire working age population) associated with composition with respect to each demographic variable considered separately

	Age	Education	Gender
Risk (demeaned/country)	-0.00495	-0.403***	-0.000272
	(0.00313)	(0.0180)	(0.000986)
Observations	792	792	792
Number of countries	21	21	21

Note: Standard errors in parentheses. Occupation shares are taken among the entire working age population of the country and include non-employment as a possible category. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.5. The negative relationship between automation risk and job stability is concentrated on low-educated workers

2012-2019 change in age adjusted log tenure

	All	Low Education	Middle Education	High Education
Risk (demeaned/country)	-0.0890**	-0.192	0.0463	-0.0472
	(0.0356)	(0.119)	(0.0507)	(0.0947)
Observations	721	721	721	721
Number of countries	21	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.6. The negative relationship between automation risk and job stability is concentrated on older workers

2012-2019 change in age adjusted log tenure

	All	Young	Prime	Older
Risk (demeaned/country)	-0.0920***	0.0478	-0.0865	-0.209***
	(0.0346)	(0.0781)	(0.0558)	(0.0656)
Observations	784	784	784	784
Number of countries	21	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

Table A A.7. There is no major difference in the relationship between the risk of automation and job stability by gender

2012-2019 change in age adjusted log tenure

	All	Women	Men
Risk (demeaned/country)	-0.0840**	-0.117	-0.0326
	(0.0343)	(0.0724)	(0.0488)
Observations	788	788	788
Number of countries	21	21	21

Note: Standard errors in parentheses. Each observation is a country-occupation cell. All MLM specifications include controls for the average risk by country.
Source: Author's calculations using data from EU-LFS, US-CPS and Nedelkoska and Quintini (2018[2]).

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