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Automation, skills use and training

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Abstract

This study focuses on the risk of automation and its interaction with training and the use of skills at work. Building on the expert assessment carried out by Carl Frey and Michael Osborne in 2013, the paper estimates the risk of automation for individual jobs based on the Survey of Adult Skills (PIAAC). The analysis improves on other international estimates of the individual risk of automation by using a more disaggregated occupational classification and identifying the same automation bottlenecks emerging from the experts' discussion. Hence, it more closely aligns to the initial assessment of the potential automation deriving from the development of Machine Learning. Furthermore, this study investigates the same methodology using national data from Germany and United Kingdom, providing insights into the robustness of the results.

The risk of automation is estimated for the 32 OECD countries that have participated in the Survey of Adult Skills (PIAAC) so far. Beyond the share of jobs likely to be significantly disrupted by automation of production and services, the accent is put on characteristics of these jobs and the characteristics of the workers who hold them. The risk is also assessed against the use of ICT at work and the role of training in helping workers transit to new career opportunities.

Résumé

Cette étude analyse le risque d'automatisation et ses implications pour la formation professionnelle et l'utilisation des compétences dans le cadre professionnel. En s'appuyant sur les entretiens d'experts conduits par Carl Frey and Michael Osborne en 2013, cette étude détermine un risque d'automation qui est spécifique à chaque emploi. En utilisant l'Enquête sur les Compétences des Adultes (PIAAC). L'analyse perfectionne les résultats obtenus par d'autres études internationaux sur le risque d'automatisation à niveau individuel en utilisant des catégories professionnelles plus désagrégées et en identifiant les mêmes étranglements techniques constatés lors des entretiens d'experts. Par conséquent, cette étude est mieux alignée à l'évaluation du potentiel d'automatisation généré par les développements en Intelligence Artificielle. Aussi, cette étude applique la même méthodologie à des bases de données nationales pour l'Allemagne et le Royaume Uni, ce qui permet de tester la robustesse des résultats.

Le risque d'automatisation est estimé jusqu'à présent pour les 32 pays de l'OCDE ayant participé à l'Évaluation des compétences des adultes (PIAAC). Outre la proportion d'emplois à risque d'être perturbés par l'automatisation de la production et des services, l'étude s'intéresse en particulier aux caractéristiques desdits emplois et des travailleurs qui les occupent. Le risque est également évalué en fonction de l'utilisation des TIC dans le cadre professionnel et du rôle des formations visant à aider les travailleurs à évoluer vers de nouvelles opportunités professionnelles

Main findings

The implications for jobs and skills of the developments in Artificial Intelligence and Machine Learning have dominated recent debates on the Future of Work and the changes brought about by digital technologies. Since Frey and Osborne (2013) shocked analysists and policy makers worldwide with a study suggesting that 47% of jobs in the United States are at high risk of being automated, several other researchers and institutions have contributed to the debate, all produced estimates in the high double digits. All these studies stem from an assessment by experts of the risk of automation for a subset of occupational titles, based on the tasks these occupations involved. This allowed identifying the so-called bottlenecks to automation – i.e. the tasks that, given the current state of knowledge, are difficult to automate. These include: social intelligence, such as the ability to effectively negotiate complex social relationships, including caring for others or recognizing cultural sensitivities; cognitive intelligence, such as creativity and complex reasoning; and perception and manipulation, such as the ability to carry out physical tasks in an unstructured work environment. These bottlenecks were used to compute a risk of automation for occupational titles that were not included in the expert assessment and for countries outside the United States.

More recent studies, exploiting the Survey of Adult Skills (PIAAC), brought the estimates of the share of jobs at risk of automation down significantly. These studies show that there is considerable variation in the tasks involved in jobs having the same occupational title and that accounting for this variation is essential to gauge the extent of the problem. Arntz, Zierhan and Gregory (2016), for instance, put this share to 9% in the United States. While this figure is only a fraction of the estimate provided by Frey and Osborne, it translates to approximately 13 million jobs across the United States, based on 2016 employment figures. As job losses are unlikely to be distributed equally across the country, this would amount to several times the disruption in local economies caused by the 1950s decline of the car industry in Detroit where changes in technology and increased automation, among other factors, caused massive job losses.

The current study aims to go beyond providing an estimate of the share of jobs at high risk of automation by also highlighting the significant changes that jobs will undergo as a result of the adoption of new technologies. It also offers an analysis of the distribution of risk among different population groups and the role of training in helping workers transit to new career opportunities. The study builds on the work done by Arntz, Zierhan and Gregory (2016) for OECD and exploits PIAAC to account for the variation in tasks within narrowly-defined occupational groups. However, coverage is broadened to all 32 countries that have participated in the survey so far and the engineering bottlenecks identified by Frey and Osborne (2013) are more closely matched. In doing so, the current study better aligns to the original expert assessment of the potential automation deriving from the development of Machine Learning. The methodological differences also imply that this study covers a broader set of workers than the study by Arntz, Zierhan and Gregory (2016). Notably, it includes workers who lack basic computer skills and/or are in jobs that do not require using a computer. As the use of ICT correlates negatively with the risk of automation, this study yields a higher estimated share of jobs at risk of automation.

Here are the study's key findings.

- Across the 32 countries, close to one in two jobs are likely to be significantly affected by automation, based on the tasks they involve. But the degree of risk varies. About 14% of jobs in OECD countries participating in PIAAC are highly automatable (i.e., probability of automation of over 70%). Although smaller than the estimates based on occupational titles obtained applying the method of Frey and Osborne (2013) this is equivalent to over 66 million workers in the 32 countries covered by the study. In addition, another 32% of jobs have a risk of between 50 and 70% pointing to the possibility of significant change in the way these jobs are carried out as a result of automation – i.e. a significant share of tasks, but not all, could be automated, changing the skill requirements for these jobs.
- The variance in automatability across countries is large: 33% of all jobs in Slovakia are highly automatable, while this is only the case with 6% of the jobs in Norway. More generally, jobs in Anglo-Saxon, Nordic countries and the Netherlands are less automatable than jobs in Eastern European countries, South European countries, Germany, Chile and Japan. Caution is needed when interpreting the numbers related to the risk of automation: the actual risk of automation is subject to significant variation and, while country rankings at the top and the bottom of the scale are robust to methodological changes, there is more uncertainty for countries closer to the cross-country average. As a result, for instance, while the findings reliably point to jobs in Slovakia having a higher risk of automation than jobs in Norway, the specific probability of automation is harder to pin down.
- The cross-country variation in automatability, contrary to expectations, is better explained by the differences in the organisation of job tasks within economic sectors, than by the differences in the sectoral structure of economies. About 30% of the cross-country variance is explained by cross-country differences in the structure of economic sectors and 70% is explained by the fact that, within these sectors, countries employ different occupational mixes. Moreover, within the same occupations, the frequency of perception and manipulation tasks as well as cognitive and social intelligence tasks varies. Within industry and occupation differences in the task-content of jobs may reflect the extent to which automation has already taken place and jobs have adapted as a result. Countries where the adoption of labour-substituting technologies has not yet taken place would show a structure of job tasks that is more prone to automation.
- Robustness checks carried out using data for Germany and the United Kingdom yield qualitatively similar results as those obtained for these two countries when using the Survey of Adult Skills: the actual estimate of the risk of automation varies but the picture emerging in terms of who is most affected is very similar. In addition, the two national databases show how jobs have become more intensive in less automatable tasks and this had been the case both within and between occupations. In other words, bottleneck tasks such as analytical and social skills have become more common within occupations but occupations that already performed those tasks intensively have also grown in number. On the other hand, in these two countries, the decline in tasks involving physical strength has primarily happened through the reduction in the number of occupations that

were intensive in those tasks. While these results point to interesting trends in the skills content of jobs, they cannot be easily generalised to other OECD countries as the trends would have been influenced by the timing and speed of technology penetration and adoption and by the employment structure of each country.

- There are upside and downside risks to the figures obtained in this paper. On the upside, it is important to keep in mind that these estimates refer to technological possibilities, abstracting from the speed of diffusion and likelihood of adoption of such technologies. Adoption, in particular, could be influenced by several factors, including regulations on workers dismissal, unit labour costs or social preferences with regard to automation. In addition, technology will without doubt also bring about many new jobs. For instance, several analysts have found an association between automation and job growth in the service sector in parallel to job destruction primarily in manufacturing. Also, PIAAC does not include information on some key social intelligence tasks such as caring for and assisting others and this would bias the risk of automation upwards somewhat. But there are risks on the downside too. First, the estimates are based on the fact that, given the current state of knowledge, tasks related to social intelligence, cognitive intelligence and perception and manipulation cannot be automated. However, progress is being made very rapidly, particularly in the latter two categories.
- Most importantly, the risk of automation is not distributed equally among workers. Automation is found to mainly affect jobs in the manufacturing industry and agriculture, although a number of service sectors, such as postal and courier services, land transport and food services are also found to be highly automatable. The occupations with the highest estimated automatability typically only require basic to low level of education. At the other end of the spectrum, the least automatable occupations almost all require professional training and/or tertiary education.
- Overall, despite recurrent arguments that automation may start to adversely affect selected highly skilled occupations, this prediction is not supported by the Frey and Osborne (2013) framework of engineering bottlenecks used in this study. If anything, Artificial Intelligence puts more low-skilled jobs at risk than previous waves of technological progress, whereby technology replaced primarily middle-skilled jobs creating labour market polarisation – i.e. a rise in the employment share of low-skilled and high-skilled jobs and a decline in the share of middle-skilled ones. Indeed, with the exception of some relatively low-skilled jobs – notably, personal care workers – the findings in this study suggest a rather monotonic decrease in the risk of automation as a function of educational attainment and skill levels.
- A striking novel finding is that the risk of automation is the highest among teenage jobs. The relationship between automation and age is U-shaped, but the peak in automatability among youth jobs is far more pronounced than the peak among senior workers. In this sense, automation is much more likely to result in youth unemployment, than in early retirements. To some extent, this higher risk of automation may be countered by smoother transitions between jobs for young people compared to older individuals. In most countries, young people are better skilled than their older counterparts so they may find it easier to adapt to new jobs, including those created as a result of the introduction of new technologies. Furthermore, as high-risk jobs are, in many countries, associated with student jobs, schemes that facilitate internships in areas related to each student field of

study may allow practicing job-specific skills as well as facilitate the acquisition of generic skills once achieved through low-skilled summer jobs.

- This unequal distribution of the risk of automation raises the stakes involved in policies to prepare workers for the new job requirements. In this context, adult learning is a crucial policy instrument for the re-training and up-skilling of workers whose jobs are being affected by technology. Unfortunately, evidence from this study suggests that a lot needs to be done to facilitate participation by the groups most affected by automation. The odds of participating in any type of training, on-the-job and outside the job, are found to be significantly lower among workers in jobs at risk of being automated. Workers in fully automatable jobs are more than three times less likely to have participated in on-the-job training, over a 12-months period, than workers in non-automatable jobs. Differences in training participation outside work are also marked, with workers with the highest risk of automation about twice less likely to participate in formal education and 3.5 times less likely to take part in distant learning. These findings also apply to training duration: individuals in fully automatable job spend 29 hours less in job-related training annually than those in non-automatable jobs, ceteris paribus. These findings point to the importance of training provision outside the workplace, particularly for workers in jobs where most tasks are automatable.
- An analysis of German data suggests that training is used to move to jobs at lower risk of automation. Looking at the content of the subsequent training spells of German workers, the risk of automation tends to decline. This suggests that participants already use requalification – the participation in a training course that provides a new qualification – as a mechanism to transition from more to less automatable occupations. However, these transitions are gradual, meaning that workers choose to requalify to occupations that are quite closely-related in skill content to their previous training. To the extent that bolder moves may be required in the future as the distance in skills content between declining jobs and growing ones broadens, the effectiveness of existing adult learning systems may come under strain.

Overall, while job destruction figures estimated in this paper exploiting job-specific information are smaller than the higher estimates obtained based on occupational titles, it is crucial not to dismiss the important of providing retraining and social protection for the 14% of workers who may see their job being entirely restructured in terms of job tasks or significantly downsized. This is a group that receives very little retraining from their own employers and may face several barriers to participate in adult learning, notably low basic skills, time constraints or limited motivation. In parallel, the large share of workers whose jobs are likely to change quite significantly as a result of automation calls for countries to strengthen their adult learning policies to prepare their workforce for the changes in job requirements they are likely to face.

Finally, this study highlights, but does not deal with, some important issues that will be the focus of further work. First, as mentioned above, the focus is placed on technological possibilities, abstracting from technology penetration and adoption. Ongoing work is expected to shed light on the timing of the risk of automation in different industries and countries. Secondly, this study only touches on how technological progress may affect wages by highlighting the negative association between the estimated risk of automation and hourly wages. This relationship is being looked at more in-depth in the context of work on wage polarisation and inequality and will lead to a broader discussion on the potential need for income redistribution. Thirdly, the regional concentration of the risk of automation could amplify its social and economic impact, particularly in countries where geographical mobility is low. The OECD is currently working on deriving regional estimates of the risk of automation to highlight the policy implications of risk concentration.

Principaux résultats

Les conséquences sur l'emploi et les compétences des progrès de l'intelligence artificielle et de l'apprentissage automatique ont été au cœur des récents débats sur l'avenir de l'emploi et les transformations induites par les technologies numériques. Depuis que Frey et Osborne (2013) ont provoqué un choc parmi les analystes et décideurs publics du monde entier en publiant une étude selon laquelle aux États-Unis, 47 % des emplois seraient exposés à un risque élevé d'automatisation, plusieurs autres chercheurs et institutions ont apporté leur contribution au débat et tous sont parvenus à des estimations très élevées. Toutes ces études reposent sur une évaluation du risque d'automatisation d'un ensemble de professions réalisée par des experts à partir des taches que comportent ces professions. Cette évaluation a permis d'identifier des obstacles à l'automatisation ou « goulets d'étranglement », en d'autres termes des tâches qui, en l'état actuel des connaissances, sont difficilement automatisables. Il s'agit de tâches qui font appel à l'intelligence sociale, par exemple la capacité à négocier efficacement des relations sociales complexes, notamment à s'occuper d'autrui ou à percevoir les sensibilités culturelles ; à l'intelligence cognitive, en particulier la créativité et la capacité à mener un raisonnement complexe ; et à la perception et à la manipulation, par exemple la capacité à exécuter des tâches physiques dans un environnement de travail non structuré. Ces goulets d'étranglement ont été utilisés pour calculer un risque d'automatisation pour des professions non prises en compte dans l'évaluation des experts et pour d'autres pays que les États-Unis.

Des études conduites plus récemment à partir de données de l'Évaluation des compétences des adultes du Programme pour l'évaluation internationale des compétences des adultes (PIAAC) ont abouti à des estimations nettement inférieures du pourcentage d'emplois menacés d'automatisation. Ces études montrent que les tâches à exécuter varient considérablement entre des emplois appartenant à une même profession et qu'il est indispensable d'en tenir compte pour apprécier l'ampleur du phénomène d'automatisation. Notamment, en tenant compte de cette variabilité, Arntz, Zierhan et Gregory (2016) évaluent à 9 % la proportion d'emplois menacés aux États-Unis. Quoique nettement inférieur à l'estimation de Frey et Osborne, ce pourcentage représente environ 13 millions d'emplois sur l'ensemble du territoire des États-Unis d'après les statistiques sur l'emploi de 2016. Comme il est peu probable que les destructions d'emplois soient réparties de manière équilibrée sur le territoire national, les économies locales subiraient une déstabilisation plusieurs fois supérieure à celle provoquée par le déclin de l'industrie automobile à Detroit dans les années 50, durant lesquelles le progrès technologique et le développement de l'automatisation, entre autres, avaient fait disparaître une grande quantité d'emplois.

Cette étude entend non seulement fournir une estimation de la proportion d'emplois menacés d'automatisation, mais aussi apporter un éclairage sur les transformations importantes que subiront les emplois en raison de l'adoption de nouvelles technologies. Elle présente également une analyse de la répartition des risques entre différents groupes de la population, ainsi que du rôle que peut jouer la formation pour aider les travailleurs à évoluer afin d'accéder à de nouveaux débouchés professionnels. Elle s'appuie sur les travaux réalisés par Arntz, Zierhan et Gregory (2016) pour l'OCDE et exploite les données issues du PIAAC pour prendre en compte les différences de tâches au sein de professions définies de manière étroite. Elle porte cependant sur une zone géographique plus large, à savoir sur les 32 pays qui participent à ce jour à l'Évaluation des compétences des adultes, et les variables utilisées correspondent mieux aux goulets d'étranglement décrits par Frey et Osborne (2013). L'étude est ainsi plus cohérente par rapport à l'évaluation de l'automatisation susceptible de résulter des progrès de l'apprentissage automatique initialement réalisée par les experts. Du fait des différences méthodologiques, l'étude couvre en outre un éventail plus large de travailleurs que celle réalisée par Arntz, Zierhan et Gregory (2016). Sont notamment aussi inclus dans l'analyse les travailleurs qui sont dépourvus de compétences élémentaires en informatique et/ou qui occupent des emplois ne nécessitant pas l'utilisation d'un ordinateur. Comme il existe une corrélation négative entre l'utilisation des technologies de l'information et de la communication (TIC) et le risque d'automatisation, l'estimation de la proportion d'emplois menacés d'automatisation obtenue dans cette étude est plus élevée.

Les principaux résultats de l'étude sont les suivants :

- Dans les 32 pays étudiés, près d'un emploi sur deux risque d'être sensiblement affecté par l'automatisation compte tenu des tâches qu'il comporte. Toutefois, l'ampleur du risque est variable. Dans les pays de l'OCDE qui participent à l'Évaluation des compétences des adultes, environ 14 % des emplois sont fortement automatisables (caractérisés par une probabilité d'automatisation supérieure à 70 %). Ce pourcentage est inférieur à l'estimation calculée au niveau des professions en utilisant la méthode de Frey et Osborne (2013), mais n'en représente pas moins plus de 66 millions de travailleurs au total dans les 32 pays étudiés. Par ailleurs, 32 % des emplois sont exposés à un risque d'automatisation compris entre 50 et 70 %, ce qui signifie que la manière dont ils sont exercés pourrait se transformer sensiblement sous l'effet de l'automatisation – en d'autres termes, bien que toutes les tâches qu'ils comportent ne soient pas concernées, une forte proportion pourrait être automatisée, si bien qu'ils exigeront des compétences différentes.
- Le risque d'automatisation est très variable d'un pays à l'autre : alors que 33 % des emplois sont fortement automatisables en Slovaquie, ce pourcentage ne dépasse pas 6 % en Norvège. Plus généralement, les emplois se prêtent moins à une automatisation dans les pays anglo-saxons, dans les pays nordiques et aux Pays-Bas que dans les pays d'Europe de l'Est et d'Europe du Sud, ainsi qu'en Allemagne, au Chili et au Japon. Il faut cependant interpréter les chiffres relatifs au risque d'automatisation avec prudence : le risque lui-même est très variable et, si les chiffres obtenus pour les pays qui se situent aux extrémités supérieure et inférieure du classement ne sont pas sensibles aux changements de méthodologie, ceux concernant les pays proches de la moyenne sont plus incertains. En conséquence, s'il est par exemple possible d'affirmer que la proportion d'emplois menacés par l'automatisation est plus forte en Slovaquie qu'en Norvège, il est plus difficile de déterminer spécifiquement la probabilité d'automatisation dans chaque pays.
- Contrairement à ce que l'on aurait pu attendre, les écarts entre pays en matière de risque d'automatisation s'expliquent davantage par des différences au niveau de l'organisation des tâches au sein des secteurs économiques que par des

différences de structure sectorielle. Ainsi, 30% environ de ces écarts sont imputables à des différences de structure sectorielle, tandis que les 70 % restants sont dus au fait que l'éventail des professions représentées au sein de ces secteurs varie selon les pays. De surcroît, dans une même profession, la fréquence des tâches exigeant des capacités de perception et de manipulation et de celles faisant appel à l'intelligence sociale et cognitive est variable. Ces disparités observées au sein d'un même secteur et d'une même profession au niveau des tâches que comportent les emplois pourraient elles-mêmes refléter le fait qu'une plus ou moins grande automatisation a déjà eu lieu et que les emplois ont évolué en conséquence. Les pays qui n'ont pas encore adopté les technologies susceptibles de se substituer à la main-d'œuvre se caractérisent par une structure des tâches qui se prête relativement bien à l'automatisation.

- Les tests de robustesse réalisés à partir de données nationales relatives à l'Allemagne et au Royaume-Uni donnent des résultats qualitativement similaires à ceux obtenus pour ces deux pays au moyen des données issues de l'Évaluation des compétences des adultes : l'estimation du risque d'automatisation n'est pas la même, mais les conclusions relatives aux travailleurs les plus exposés au risque d'automatisation sont très proches. De plus, les deux bases de données nationales montrent que les emplois comportent désormais davantage de tâches relativement peu automatisables et que cette augmentation a eu lieu aussi bien au sein des professions qu'au niveau de la structure par profession de l'économie. En d'autres termes, les tâches difficilement automatisables comme celles qui font appel à des compétences analytiques et sociales sont devenues plus courantes au sein d'une même profession, mais le nombre de professions dans lesquelles elles étaient déjà fréquentes a lui aussi augmenté. En revanche, dans ces deux pays, le recul des tâches faisant appel à la force physique s'explique en premier lieu par une diminution du nombre de professions dans lesquelles ces tâches occupent une large place. Si ces résultats mettent en lumière des tendances intéressantes sur le plan du contenu des emplois, ils peuvent difficilement être généralisés à d'autres pays de l'OCDE parce que ces tendances peuvent être influencées par le moment où la pénétration et l'adoption des technologies ont eu lieu et la vitesse à laquelle elles se sont faites, ainsi que par la structure de l'emploi de chaque pays.
- Il est possible que les chiffres présentés ici soient surestimés ou sous-estimés. S'agissant du risque de surestimation, il faut garder à l'esprit que les calculs présentés reposent sur des possibilités technologiques et ne tiennent pas compte de la vitesse de diffusion de ces technologies et de la probabilité qu'elles soient adoptées. L'adoption, en particulier, peut être influencée par divers facteurs, par exemple la réglementation relative au licenciement, les coûts salariaux unitaires ou les préférences sociales à l'égard de l'automatisation. De plus, les technologies engendreront aussi sans nul doute de nombreux emplois nouveaux. Certains analystes ont par exemple constaté que si elle entraînait une destruction de l'emploi, principalement dans le secteur manufacturier, l'automatisation avait aussi pour corollaire une croissance de l'emploi dans le secteur des services. Enfin, l'Évaluation des compétences des adultes ne fournit pas d'informations sur certaines tâches importantes faisant appel à l'intelligence sociale comme les activités d'aide à la personne, ce qui pourrait être à l'origine d'une surestimation du risque d'automatisation. Néanmoins, il est aussi possible que les chiffres soient sous-estimés. Premièrement, les estimations reposent sur l'hypothèse selon laquelle, en l'état actuel des connaissances, les tâches qui mobilisent l'intelligence sociale, l'intelligence cognitive et les capacités de perception et de manipulation

ne sont pas automatisables. Or, les progrès sont très rapides, en particulier dans les deux derniers domaines cités.

- Autre point particulièrement important : le risque d'automatisation n'est pas réparti de manière égale entre les travailleurs. L'automatisation touche principalement des emplois des secteurs manufacturier et agricole, même si certaines activités de service, comme les activités de poste et de courrier, de transport terrestre et les services de restauration sont également très facilement automatisables. En règle générale, les professions les plus exposées au risque d'automatisation exigent un niveau d'études très faible à faible. À l'inverse, la quasi-totalité des professions qui se prêtent le moins à une automatisation requièrent une formation professionnelle et/ou un diplôme de l'enseignement supérieur.
- Dans l'ensemble, la thèse régulièrement avancée selon laquelle l'automatisation pourrait commencer à avoir des conséquences négatives sur certaines professions très qualifiées n'est pas corroborée par le cadre d'évaluation des goulets d'étranglement défini par Frey et Osborne (2013) et utilisé dans cette étude. En fait, l'intelligence artificielle menace sans doute davantage les emplois non qualifiés que les précédentes vagues de progrès technologique, qui s'étaient essentiellement traduites par une substitution de la technologie aux emplois moyennement qualifiés et avaient entraîné une polarisation du marché du travail – une augmentation de la proportion d'emplois peu et très qualifiés et une diminution de la part des emplois moyennement qualifiés. La présente étude montre en effet que si l'on exclut certains emplois relativement peu qualifiés – comme les services à la personne –, le risque d'automatisation diminue de manière relativement monotone en fonction du niveau d'études et de compétences.
- Une conclusion inédite et surprenante se dégage de l'étude, à savoir que le risque d'automatisation le plus élevé concerne les emplois occupés par les adolescents. Le lien entre automatisation et âge prend en effet la forme d'une courbe en U, mais le sommet atteint par la probabilité d'automatisation est beaucoup plus élevé pour les emplois occupés par les jeunes que pour ceux occupés par les travailleurs âgés. L'automatisation risque donc nettement plus de se traduire par du chômage parmi les jeunes que par des départs en préretraite. Ce risque plus élevé peut être en partie contrebalancé par le fait que les jeunes passent plus facilement d'un emploi à un autre que leurs aînés. Dans la plupart des pays, ils sont plus qualifiés que les travailleurs âgés, ce qui peut faciliter l'adaptation à des emplois nouveaux, dont ceux engendrés par l'introduction de nouvelles technologies. De surcroît, étant donné que dans bon nombre de pays, les emplois très exposés au risque d'automatisation sont souvent occupés par des étudiants, des dispositifs leur permettant d'effectuer des stages dans la discipline où ils suivent leurs études pourraient leur permettre de mettre en pratique des compétences spécifiques à un emploi donné et faciliteraient l'acquisition de compétences génériques auparavant acquises dans le cadre d'emplois d'été peu qualifiés.
- Cette inégale répartition du risque d'automatisation ne fait qu'accroître l'enjeu des politiques visant à préparer les travailleurs à satisfaire aux nouvelles exigences du marché du travail. Dans ce contexte, la formation des adultes est un instrument primordial pour permettre à ceux dont les emplois sont touchés par le progrès technologique de se reconvertir ou d'améliorer leurs qualifications. Malheureusement, l'étude laisse penser qu'il reste un long chemin à parcourir pour faciliter l'accès à la formation des catégories les plus concernées par

l’automatisation. La probabilité de participer à une formation, en cours d’emploi ou non, est en effet nettement plus faible parmi les travailleurs dont les emplois sont menacés d’automatisation. Ainsi, sur une période de 12 mois, les travailleurs qui occupent un emploi automatisable ont une probabilité plus de trois fois plus faible d’avoir suivi une formation en cours d’emploi que leurs homologues occupant un emploi non automatisable. Les différences sont également fortes s’agissant de la participation à la formation en dehors du cadre professionnel, les travailleurs les plus menacés par l’automatisation ayant une probabilité environ deux fois plus faible de suivre une formation formelle et 3.5 fois plus faible de suivre une formation à distance. Les constatations sont les mêmes en ce qui concerne la durée de la formation : toutes choses égales par ailleurs, les personnes qui occupent un emploi totalement automatisable consacrent 29 heures de moins par an à la formation professionnelle que celles qui exercent une activité non automatisable. Ces conclusions montrent à quel point il est important d’offrir des formations en dehors du cadre professionnel, en particulier aux travailleurs qui occupent un emploi comportant essentiellement des tâches automatisables.

- Il ressort de l’analyse des données nationales allemandes que la formation est utilisée pour accéder à des emplois moins exposés au risque d’automatisation. L’étude du contenu des formations désormais suivies par les travailleurs allemands révèle une diminution du risque d’automatisation. Il est permis d’en déduire que les participants aux formations utilisent déjà la reconversion – la participation à une formation qui permet d’acquérir une nouvelle qualification – pour accéder à des emplois moins automatisables. Toutefois, ces transitions entre emplois se font progressivement, en ce sens que les travailleurs choisissent de se reconvertir dans des professions étroitement liées en termes de qualifications requises à celle correspondant à leur formation antérieure. À l’avenir, des transitions plus radicales pourraient se révéler nécessaires à mesure que l’écart de qualification entre les emplois en déclin et les emplois en croissance se creusera, si bien que l’efficacité des systèmes de formation pour adultes pourrait être insuffisante.

Dans l’ensemble, le fait que les chiffres relatifs à la destruction d’emplois obtenus dans cette étude à partir de données relatives aux tâches spécifiques à chaque emploi soient inférieurs à ceux calculés sur la base des professions ne doit pas faire oublier combien il est essentiel que les 14 % de travailleurs dont l’emploi risque de se transformer radicalement ou de disparaître aient accès à une protection sociale et à une formation pour se reconvertir. Ces travailleurs bénéficient très rarement d’une formation proposée par leur employeur. En outre, divers facteurs peuvent les empêcher de participer à la formation des adultes, notamment le manque de connaissances de base, de temps et de motivation. Parallèlement, comme une forte proportion de travailleurs occupe des emplois qui risquent d’évoluer sensiblement sous l’effet de l’automatisation, il faudrait que les pays améliorent leurs politiques de formation des adultes afin de préparer la population active dans la perspective de l’évolution des compétences requises.

Enfin, cette étude met en évidence, sans toutefois les traiter, certains aspects importants qui feront l’objet de travaux ultérieurs. Premièrement, comme souligné précédemment, elle aborde l’automatisation sous l’angle des possibilités technologiques, indépendamment de la pénétration et de l’adoption des technologies. Des travaux en cours devraient apporter un éclairage sur la probabilité concrète d’automatisation et son échéance dans différents secteurs d’activité et pays. Deuxièmement, l’étude ne fait qu’aborder les effets négatifs que le progrès technologique peut avoir sur les salaires, en mettant en évidence la corrélation négative entre le risque d'automatisation estimé et le salaire horaire. Ce lien est analysé de manière plus approfondie dans le cadre de travaux sur l'inégalité et la polarisation des salaires qui donneront lieu à une réflexion plus large sur la nécessité éventuelle d'une redistribution des revenus. Troisièmement, il est possible que la concentration régionale du risque d'automatisation amplifie ses retombées sociales et économiques, en particulier dans les pays où la mobilité géographique est limitée. L'OCDE a engagé des travaux pour effectuer des estimations régionales du risque d'automatisation afin de mettre en évidence les implications de la concentration de ce risque pour l'action publique.

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1. Introduction

1. How new technologies transform work has always been a fascinating topic for analysts. Whenever there is a new potentially impactful technology, the media and academia become busy predicting its potential impact on people's jobs and lives. The timing of technological breakthroughs is often surprising and poorly predicted. Less than 15 years ago, Autor, Levy and Murnane (Autor, Levy and Murnane, 2003[1]) (ALM hereafter) suggested that computers were good at performing repetitive routine cognitive and manual tasks, but poor at performing non-routine tasks, which are tacit in nature, or which require "flexibility, creativity, generalised problem-solving, and complex communications." (p. 1280). Less than 10 years after ALM wrote their influential work on the skill content of the recent technological change, many of the tasks they identified as non-routine, and hence non-automatable, were found well within the reach of cutting-edge technologies. Advances in machine vision and simultaneous localisation and mapping have brought the long-standing dream of automated vehicles closer to commercialisation than ever in the past. In 2016, IBM Watson showed that it can combine big data and artificial intelligence (AI) to outperform oncologists in complex cognitive tasks such as cancer diagnosis and treatment recommendations. In fact, the scope of what digital technologies can do expanded so much that more recent work on job automation found it easier to ask "what is that computers cannot do" than to keep asking "what is that computers can do."

2. The debate on how many jobs might be destroyed by technology advances was reignited, in 2013, by Carl Frey and Michael Osborne who collected expert views about the likelihood of automation in a selected set of 70 occupations. In the exercise run by the two researchers, experts were asked to assess whether "the tasks in these occupations are sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer equipment". This allowed identifying the so-called bottlenecks to automation – i.e. the tasks that, given the current state of knowledge, are difficult to automate. These include: social intelligence, such as the ability to effectively negotiate complex social relationships, including caring for others or recognizing cultural sensitivities; cognitive intelligence, such as creativity and complex reasoning; and perception and manipulation, such as the ability to carry out physical tasks in an unstructured work environment. This information was used to obtain a risk of automation for each occupational title, including about 630 occupations outside the initial 70. In the United States, Frey and Osborne (2013) estimated that 47% of jobs are at high risk of being automated.

3. A set of more recent studies have challenged these extremely high figures. These studies build on evidence from the Survey of Adult Skills (PIAAC) that there is considerable variation in tasks within occupational groups and show how accounting for this variation is essential to gauge the extent of the problem and brings the estimates of jobs threatened by automation down significantly. Arntz, Zierhan and Gregory (2016), for instance, put this share to 9% in the United States.

4. This study builds on the work done by Arntz, Zierhan and Gregory (2016) for OECD and exploits PIAAC to account for the variation in tasks within narrowly-defined occupational groups. Compared to the previous study, coverage is broadened to the 32 countries that have participated in the PIAAC survey so far and the engineering bottlenecks identified by Frey and Osborne (2013) are more clearly identified. In doing so, the current study closely aligns in spirit to the assessment of the potential automation deriving from the development of Machine Learning. The methodological differences also imply that this study covers a broader set of workers than the study by Arntz, Zierhan and Gregory (2016). Notably, it includes workers who lack basic computer skills and/or are in jobs that do not require using a computer. As the use of ICT correlates negatively with the risk of automation, this results in a higher estimated share of jobs at risk of automation.

5. However, these improvements come with a caveat. In order to identify the same 70 occupations used in Frey and Osborne (2013) in PIAAC, ISCO at the 4-digit level is needed. This level of disaggregation is available for Canada where sample size in PIAAC is particularly large. Hence, the relationship between the engineering bottlenecks and the risk of automation is estimated using Canadian data and then the estimation coefficients are applied to calculate the risk of automation of jobs beyond the original 70 occupations and outside Canada. This is a major improvement over previous work which exploited occupational titles at the 2-digit level only, preventing the exact identification in PIAAC of the 70 occupations used by Frey and Osborne. However, while there is no specific reason to believe that the way bottlenecks relate to the risk of automation differs across countries, it is possible that Canada's specific industrial structure and its position in global value chain may influence the coefficients. Overall, the pros of conducting the estimation on better defined occupations and the larger sample size outweigh the cons which should nevertheless be kept in mind.

6. The PIAAC-based analysis is complemented by evidence from job-task surveys in the United Kingdom and Germany. This allows checking the robustness of the PIAAC results for these two countries against national sources. It also allows exploring the changes over time in the task composition of jobs as time series are available for both countries, with the caveat that trends in these two countries cannot be generalised to other PIAAC participants as they may depend on factors such as the penetration and adoption of technology, the productive structure, and the position of the countries in global value chains.

7. In addition to estimating the share of workers whose jobs are at very high risk of being automated using the methodology briefly described above, this study sheds light on a number of other crucial issues. First, it brings attention to the bigger group of workers whose job tasks would likely change significantly as a result of the current wave of technological innovations. Second, it looks at the characteristics of jobs at risk of automation and the characteristics of workers in these jobs. Finally, it offers an assessment of the risk of automation against the use of ICT at work and the role of training in helping workers transit to new career opportunities.

8. The study is organised as follows. Section 2 summarises the past and near-future trends in the supply of and the demand for skills. Section 3 reviews the key literature on the effects of digitalisation on the labour market. Section 4 introduces the estimates of the risk of automation in 32 OECD countries, provides cross-country comparisons and studies the characteristics of workers in jobs at risk of automation. Section 5 tests how predictive the measure of job automation used in the paper is when it comes to actual

labour market developments. Section 6 studies the changes of skill demands over time in Germany and the United Kingdom. Section 7 analyses the relationship between skills and ICT. Section 8 checks the robustness of PIAAC-based findings for Germany and the United Kingdom against results obtained with country-specific surveys. Section 9 discussed the role of training, on-the-job and outside the job, in preparing workers affected by automation to transition to other career paths. Section 10 concludes and highlights the potential for further work.

2. Past and future trends in the supply of and the demand for skills

9. Before starting to dwell on the relationships between automation, employment, wages and work content, it is useful to gain an understanding of the general labour market trends, past and projected, in OECD countries. As discussed in more than one instance in this study, automation has proven much more likely to redistribute the demand for various skills and jobs than to eliminate work altogether. Therefore, the degree to which OECD countries experience technological unemployment depends not only on the disruptiveness of the technological change, but also on the readiness of the educational systems and the industries themselves to meet the demand for changing skill profiles with relevant education, training and re-training.

2.1. Long-term trends in skill demand

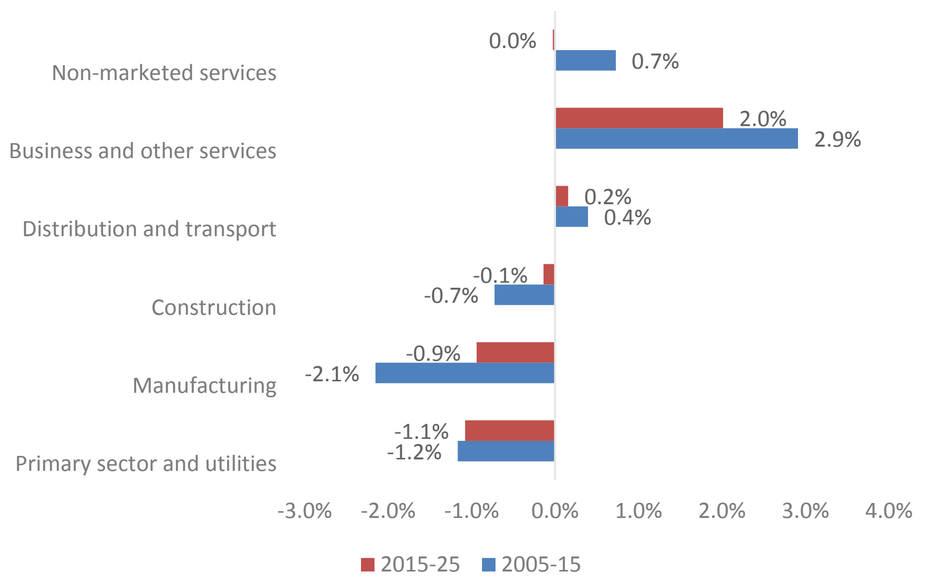
10. The actual demand for jobs and skills is difficult to measure. However, employment levels and shares of occupational groups are considered good proxies (Handel 2012, p. 11). Focusing on occupations has become more and more common in this literature, following the findings that much of our skills are occupation-specific (Kambourov and Manovskii 2009; Gathmann and Schoenberg 2010). However, some of the skills we use at work are also industry-specific (Neal 1995; Parent 2000), so in addition to occupations, industry employment patterns are also informative. Focusing on employment *shares* (as opposed to employment levels) is intentional. By shedding light on the relative changes in groups' employment instead of the absolute changes, employment shares are more informative about the *biases* in employment creation and destruction. As discussed later, such biases typically originate in organisational and technological changes in the production process.

11. Handel (2012) shows that most OECD countries saw their manufacturing jobs rise as a share of total employment between the 1950s and the 1970s, and decline afterwards. Starting in the 1950s, countries with a sizeable share of agricultural employment saw this share decline sharply in parallel to the rise in manufacturing employment. The share of agricultural employment remained stable in countries where it was low to start with. In parallel, throughout the whole period, Handel evidenced a steady growth of the employment shares of professionals, managers and service jobs. Interestingly, clerical jobs first grew, until the 1980s or 1990s depending on the country, and then started to decline.

12. For more recent trends and forecasts of occupational and industry-specific job demand in OECD countries, it is helpful to highlight the findings by Cedefop (2016a and 2016b). The Cedefop Skills Forecast program offers occupation-level and industry-level 10-year employment estimates and forecasts for the 28 member countries of the European Union (EU-28). According to Cedefop (2016a), between 2005 and 2015, the economy of EU 28 grew by 3%, but growth rates differed significantly across economic sectors (Figure 2.1). The employment share of the primary sector and utilities shrank 1.2%age points (pp), the one of the manufacturing sector shrank 2.1 pp, and the one of

construction shrank by 0.7 pp. At the same time, services expanded their shares in total employment: non-market services by 0.7, business and other services by 2.9 and distribution and transport by 0.4 pp. In the next 10 years (2015-2025), Cedefop expects that the primary sector and the manufacturing sector will each reduce their shares in total employment by about 1 pp, while business and other services will increase their share by 2 pp. At the same time, the employment shares of construction, distribution and transport, and non-market services are not expected to change significantly.

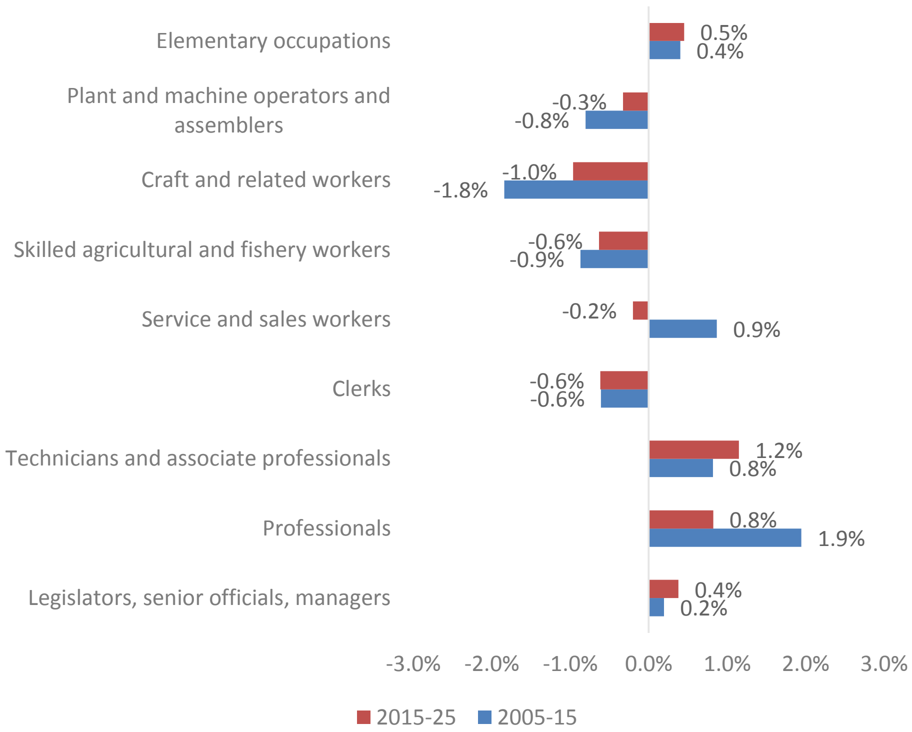
Figure 2.1. Changes in employment shares, past and projected by economic sector



Source: Cedefop skills forecast 2016, as published in Cedefop (2016a) and Cedefop (2016b)

13. In terms of occupations (Figure 2.2), highly skilled occupations (managers, professionals, associate professionals and technicians) experienced sizeable expansions in their shares between 2005 and 2015, continuing the trends observed in Handel (2012). The share of service and sales workers also grew 1 pp, and the one of elementary occupations grew 0.4 pp. At the same time, production workers, crafts workers, agricultural workers and clerks all saw their employment shares decline (by 0.8, 1.8, 0.9 and 0.6 pp respectively). These growth trends for all but service and sales workers are expected to continue until 2025. In the case of service and sales workers Cedefop expects a trend reversal – their employment share is expected to slightly shrink this coming decade.

Figure 2.2. Changes in employment shares, past and projected by occupation, 2005-2025



Note: All occupations include also armed forces (not presented in the chart).
Source: Cedefop skills forecast 2016, as published in Cedefop (2016b).

14. Unlike the EU, the United States haves been experiencing somewhat different developments when it comes to the jobs for highly educated since the turn of the 21st century. Acemoglu and Autor (2011) and Beaudry, Green and Sand (2016) showed that, in the United States, employment growth among the highly skilled occupations has slowed down drastically since 2000. Beaudry, Green and Sand (2016) associate this decline with the 2000 bust of the *dotcom* bubble. They suggest that the IT industry in the United States reached maturity around the turn of the century. The period of innovation and cognitive investment in the industry was completed at about that time and the industry started routinising, shedding employment among the managers and other cognitive workers. These conclusions are somewhat at odds with the Bureau of Labour Statistics (BLS) 2014-2024 projections for jobs in the United States IT sector and at odds with the expectations that other scholars have for the future of the IT sector (Brynjolfsson and McAfee 2014). While jobs as IT managers are projected to grow slower than the average, most other IT jobs (system managers, IT engineers, software developers etc.) are projected to grow faster than the average employment growth (Bureau of Labour Statistics 2016).

15. The pattern of change shown in Figure 2.2 sheds light on the widely-observed job polarisation in developed economies (Goos and Manning 2007; Goos, Manning and Salomons 2009 and 2014). Job polarisation refers to the phenomenon of hollowing out of the middle-paid, middle-skilled jobs in developed countries. Workers in the declining occupations in Figure 2.2 used to constitute the middle-paid group in the 1970s and the 1980s, while the workers in growing occupations were either the high (managers,

professionals, technicians and associate professionals) or the low-wage earners (elementary occupations, sales and other service jobs).

16. The occupation and industry-specific trends tell us little about what happens to the skill demands *within* occupations and industries. If the job content of occupations and industries changes over time, we would understate the degree to which the skill demands in the economy change. ALM documented that, in the United States, within the same industries, the demand for routine cognitive and routine manual tasks at work has been decreasing since the 1980s, while non-routine manual tasks have been declining at least since the 1960s (Table 2.1). On the other hand, within the same industries, non-routine cognitive and non-routine interactive tasks have been increasing since the 1960s. Spitz-Oener (2006) showed that West Germany experienced similar within-occupational trends between 1979 and 1999. Throughout the whole period, routine cognitive and routine manual tasks declined within occupations, while non-routine cognitive, non-routine interactive and non-routine manual tasks grew (Table 2.2). Handel (2012) shows that these trends continued in the new century. Analysing changes in the occupational skill requirements of countries around the world, he concludes that the educational, cognitive and interpersonal skill requirements have been gradually increasing, while craft skills, physical demands and the repetitive physical tasks have declined. He also finds that these changes were more rapid in European countries than in the United States, and that the reason for this is that the United States de-routinised earlier than Europe.

Table 2.1. Decomposition of task shifts into between and within industry components

	Non-routine cognitive		Non-routine interactive		Routine cognitive		Routine manual		Non-routine manual	
	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn
1960-70	1.74	0.83	-0.34	1.49	1.14	1.06	2.39	1.62	-2.28	-0.74
1970-80	1.54	1.48	0.26	4.42	0.33	-0.47	0.79	0.84	-1	-1.25
1980-90	0.92	2.05	0.52	4.79	-1.42	-2.07	-0.16	-1.31	-1.27	-1.31
1990-98	0.67	2.45	0.54	3.94	-1.31	-3.57	-0.38	-3.5	-0.31	-0.31

Note: Values expressed as 10 x annual changes in mean task percentile
Source: Reproduced based on Autor, Levy and Murnane (2003), Table IIb

Table 2.2. Decomposition of task shifts into between and within occupation components

	Non-routine cognitive		Non-routine interactive		Routine cognitive		Routine manual		Non-routine manual	
	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn	Btwn	Wthn
197985	-0.27	9.1	0.15	3.21	-1.4	-7.03	-1.26	-6.57	0.77	8.75
198591	0.44	1.68	0.1	10.02	0.87	-8.92	0	-4.5	0.34	-0.55
199199	2.67	1.55	5.24	19.39	0.06	-7	-6.04	-2.94	-0.97	9.91
197999	0.77	4.24	1.7	11.64	-0.06	-7.7	-0.98	-6.22	0.12	6.11

Source: Spitz-Oener (2006), Table 5

17. The between and within occupational and industry shifts away from routine and towards non-routine tasks are tightly related to the trends in educational upgrading in OECD countries. Using data for 11 OECD-member countries, Michaels, Natraj and van Reenen (2014) show that the wage share of jobs typically requiring tertiary education increased by an average of 10 pp between 1980 and 2004. The largest expansion

happened in the UK (16.5 pp), Finland (15.2 pp), the United States (13.9 pp) and the Netherlands (13.1 pp). Interestingly, in three out of four of these countries (United States, Finland, and the Netherlands), the wage share of tertiary educated was already far above the estimated mean across the 11 countries in 1980. The smallest expansion in the wage bill of the highly educated was observed in Denmark (4.1 pp), Italy (5.3 pp), Austria (5.4 pp) and Germany (6.3 pp). These happen to also be countries where the wage share of tertiary educated was below the estimated cross-country mean in 1980. The wage share of the medium skilled also expanded in all countries, except for the United States and the Netherlands, where it declined by 5.1 and 2.9 pp respectively. Finally, the wage share of the low skilled declined across the board, losing 18.7 pp on average. Michaels, Natraj and van Reenen (2014) also show that already in the 1980s, highly skilled Americans specialised in non-routine cognitive tasks, middle-skilled specialised in routine cognitive and routine manual tasks and low-skilled Americans specialised in routine cognitive and non-routine manual. Hence, as the demand for non-routine tasks increased, so did the demand for tertiary education.

2.2. Supply Trends

18. On the supply side, educational attainment has been increasing across all OECD member countries. Between 1971 and 2014, the average tertiary school enrolment ratio[1] in OECD countries increased by a spectacular 46.3 pp, from 23.7% in 1971 to 70% in 2014 (Table 2.3).

19. Moreover, the changes in the choice of occupational training in developed economies show that educational upgrading is a mechanism through which economies move away from learning routine cognitive tasks and manual tasks and towards learning non-routine cognitive and interactive tasks. Data for Germany shows this very clearly (Figure 2.3). Germans who enrolled in occupational training (vocational training, applied sciences college or university education) in the 1960s and the 1970s opted for occupations that typically have higher frequency of routine cognitive tasks and manual tasks (both routine and non-routine) than did Germans who started occupational training in the most recent decades.[2]

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[1] Total enrolment in tertiary education (ISCED 5 to 8), regardless of age, expressed as a%age of the total population of the five-year age group following on from secondary school leaving.

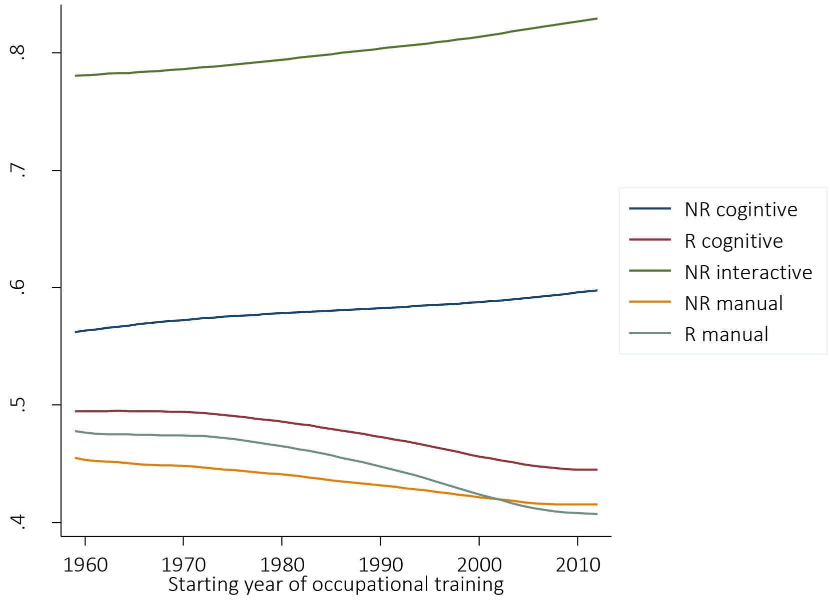
[2] These estimates measure the typical occupational task content as of 2012, meaning that they ignore the within-occupational task changes. Moreover, the data comes from a survey of working Germans in 2012 and not from separate representative surveys in each decade. These two facts imply that the actual trends in job task changes are steeper than the ones reported here.

Table 2.3. Gross tertiary school enrolment in OECD countries

	Gross tertiary school enrolment (%)	Δ Gross tertiary school enrolment
	1971	1971-2014
Australia*	19.5	70.8
Austria**	15.14	66.4
Belgium	16.86	56.45
Chile	11.16	75.47
Czech Republic	8.92	57.09
Denmark	18.86	62.66
Finland	13.13	75.54
France	18.54	45.85
Hungary	10.02	43.17
Iceland	9.91	71.35
Ireland	10.59	67.04
Israel	19.41	46.77
Italy	16.88	46.22
Japan	17.64	45.72
Korea	7.25	88.1
Luxembourg*	1.59	17.82
Mexico	5.29	24.65
Netherlands*	19.73	58.77
New Zealand	16.91	63.97
Norway	15.79	60.99
Poland	13.36	57.8
Portugal	7.27	58.33
Spain	8.67	80.4
Sweden	21.73	40.62
Switzerland	10.04	47.19
Turkey	5.1	81.21
United Kingdom	14.57	41.91
United States	47.32	39.34
OECD members	23.71	46.3

Note: Data is not available for Canada, Latvia, Estonia, Slovenia, Slovakia. The estimates for Germany and Greece are unreliable, hence not shown here. * Last available year is 2012. ** Last available year is 2013.
Source: UNESCO Institute for Statistics, as reported in the World Bank's World Development Indicators. Data as of May 2017

Figure 2.3. Task Content of Occupational Training in Germany 1960-2012



Note: The graph plots the average task intensity in the occupations for which training was obtained in the year indicated on the axis. Task intensity is the share of people in each two-digit ISCO88 occupation reporting frequent or very frequent use of a task in 2012. Since these estimates measure the occupational task content as reported in 2012, they ignore the within-occupational task changes discussed earlier. Moreover, the data comes from a survey of working Germans in 2012 and not from separate representative surveys of Germans in each decade. These two facts imply that the actual trends in job tasks must be steeper than the ones reported here.
Source: BIBB/BAuA Employment Survey 2012, own estimates.

2.3. Supply meets demand

20. The demand for skills is driven by technological changes, but also by institutional factors (e.g., level of unionization and employment protection) and the patterns of international trade, and with that, the international division of labour. The supply side is driven by the decisions of educational institutions, the provision of employer training and on-the-job learning, and for many countries, migration. In their work on “the race between education and technology,” Goldin and Katz (2007, 2009) analyse how the supply of and demand for people with different levels of education determined their groups’ wage premia in the United States between 1915 and 2005. Throughout most of the century, the college premium increased when relative demand for college graduates outstripped relative supply and it declined when relative supply surpassed relative demand. Since the 1980s, they find, technology has been racing in front of education, driving up the college premium.

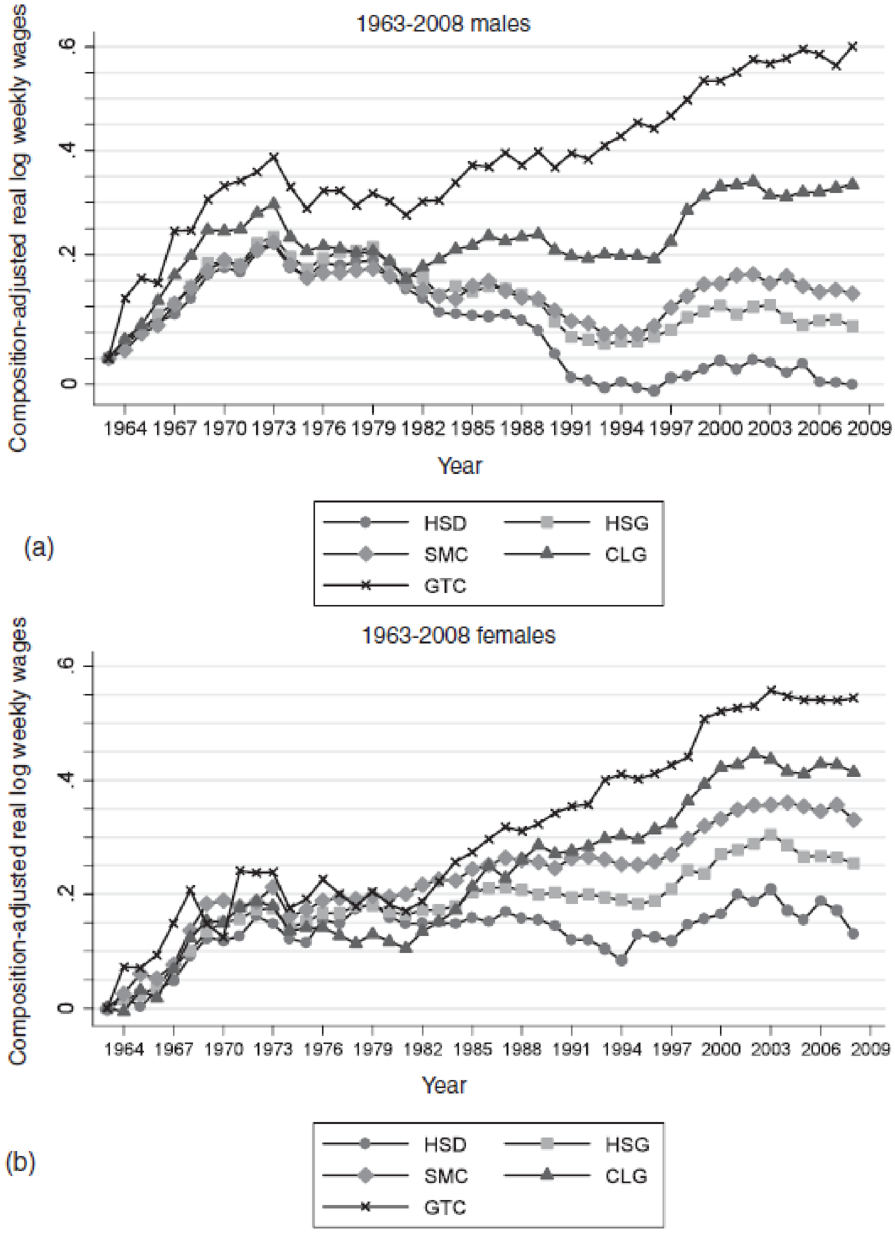
21. Educational and occupational wage premia and real wage developments are excellent indicators of over or undersupply of certain workers. The premia are typically estimated against a reference group, e.g., the premium to college degree against only having a high school degree and are hence informative of the relative wage developments. The developments in real wages by occupation or education, i.e., these wages adjusted for inflation, however show how different groups fare in real terms, i.e., whether their standard of living is improving or worsening. Education-specific real wages

in the United States have changed dramatically since the 1960s. Figure 2.4 plots the development of real log earnings by gender and education level for samples of full-time, full-year workers in the United States. Each series is normalised at zero in the starting year of 1963, and the subsequent values correspond to the log change in earnings for each group relative to its 1963 level. There are three distinct periods in terms of wage trends in the figure. The first period is the first decade (1963-1973), where real wages rose for males and females and for all educational groups. The second period started with the 1973 oil shock and lasted for a decade. During this period, male wages either fell or stagnated and female wages mainly stagnated. The third period started in the mid-1980s with a sharp divergence in wage rates across educational attainment groups. This development has been most pronounced in the case of male workers. Real wages of male post-graduates and college graduates have risen, while the wages of all other educational groups have declined. In the case of female workers wages have grown across all educational groups but at different rates. Raising wage inequality is evident for both genders.

22. Summing up, while remaining agnostic about the drivers of demand and supply for now, starting in the mid-1980s demand for college and post-college graduates has increased relative to other educational groups. In line with the conclusions by Goldin and Katz (2007, 2009), demand has outpaced supply for these educational group bringing about real wage increases. At the same time, the lack of demand for the other, less educated groups, relative to their supply levels, has resulted in a real wage decline. If educational institutions had been quick to realize this trend and adjust the supply accordingly, the developments might have looked very different today. Hence, from a policy perspective, it is critical to understand that the effects of technological change on the employment and wage outcomes of citizens are deeply dependent on how well educational and training institutions can anticipate demand shifts and how quickly and substantively they can respond to them. While it may be difficult to control the diffusion of technologies, it is certainly possible to mitigate their “dark side”[3] by designing timely and adequate institutional responses.

[3] Goldin and Katz (2007), p. 26.

Figure 2.4. Real, composition-adjusted log weekly wages for full-time full-year workers in the United States



Note: HSD-high school dropout; HSG-high school graduate; SMC-some college; CLG-college graduate; GTC-greater than college.
Source: Acemoglu and Autor (2011)

3. The effects of digitalisation on jobs and skills

23. For most of the 20th century, technological innovations were considered to be skill-biased, i.e. they increased the demand for the educated relative to the demand for the less-educated (Nelson and Phelps 1966; Katz and Murphy 1992; Goldin and Katz 1998; Bekman, Bound and Machin 1998; Violante 2008). Nelson and Phelps (1966) explained that “education enhances one’s ability to receive, decode, and understand information.” This ability of workers is particularly important in jobs where technological improvements are common and where workers need to keep up with technology by learning new things (p. 69). Renowned economists of the 20th century repeatedly predicted that new technologies would directly replace labour[4], but these predictions proved erroneous or premature: in spite of structural sectoral and occupational shifts, aggregate employment kept growing. The case of digital technologies, and computers in particular was no different. The research work on this topic focused on the aspect of capital-labour complementarities (Krueger 1993; Autor, Katz and Krueger 1998, Machin and Van Reenen 1998; Bresnahan, Brynjolfsson, and Hitt 2002) and less on the substitution of labour by capital. The changes in the employment structure along the skill dimension could be explained by labour movements from less skilled to more skilled jobs, and the jobs created by growing sectors (first manufacturing, then services) more than compensated the job destruction in declining sectors (first agriculture, then manufacturing) in developed economies.

24. In 2003, ALM published an analysis that looked into the task content of jobs that use computers and explicitly argued that computer capital is both task-complementing and task-substituting. They put forward that computer capital “substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules; and complements workers in performing non-routine problem-solving and complex communications tasks” (p. 1279). What computers can do well, the authors argued, is follow exact procedures designed by programmers. That means that computers can only be made to perform tasks that humans have thoroughly understood and meticulously codified. Moreover, these need to be tasks that can technically be executed by technology. Tasks with high tacit content, and tasks requiring situational adaptability, visual and language recognition, and in-person interaction, i.e. non-routine manual and interactive tasks, are out of reach for computers. This also holds for tasks that require creativity, problem-solving and persuasion (abstract tasks). This seminal empirical work, employing what is now referred to as “the task-based approach,” fundamentally changed the course of research on this topic. The basic mechanism behind the computer-skill interaction is quite straightforward. The price of computers fell dramatically[5] between its

[4] Acemoglu and Restrepo (2016) nicely summarise the grand statements by some of the most prominent 20th century, among which Keynes and Leontief, on how new machines create widespread technological unemployment.

[5] A key assumption is that this fall was exogenous to firms’ human resource decisions.

introduction and the time when this study was conducted, leading to wide-spread adoption across industries. Jobs specialised in routine tasks started competing directly with computers. As computers became cheaper and more prevalent, employers opted for computer-performed routine tasks rather than human-performed routine tasks. However, routine tasks and non-routine tasks are complements. As a consequence, the increased supply of (computer-performed) routine tasks increased the demand for non-routine tasks, driving the wages and employment of non-routine jobs up. This analytical and empirical framework proved extremely predictive of the developments of the relative demands for labour and job polarisation (Goos and Manning 2007; Autor, Katz and Kearney 2006; Antonczyk, DeLeire and Fitzenberger 2010; Goos, Manning and Salomons 2009 and 2014), educational upgrading (ALM, Spitz-Oener 2006), and wage inequality (Dustmann, Ludsteck and Schoenberg 2009; Autor, Katz and Kearney 2008; Acemoglu and Autor 2011) until recently.

25. Less than ten years after the ALM study was published, digital technology advanced so much that the ALM categorization of tasks seemed partially outdated. Brynjolfsson and McAfee (2014) and Frey and Osborne (2013 and 2017), among others, argued that digital innovations, and in particular in machine learning, have made many tasks that ALM considered out of reach for computers for many more years achievable. The self-driving car has become a plausible threat to driving jobs, ranging from taxis, Uber and Lyft to bus and truck drivers and drivers of construction machinery. Language translation, including simultaneous translation is widely available to everyone with internet access through technologies such as Google Translate and Skype Translation. In 2016, IBM’s Watson and DeepMind Health proved to be better at diagnosing rare cancers than human doctors. Journalistic text writing, at least simple ones, can now be partially automated, as can personal financial advice (Frey and Osborne 2017; Mims, 2010). According to Frey and Osborne (2017) (FO) these innovations expand the list of potentially automatable jobs to drivers, translators, tax analysts, medical diagnostics, legal assistants, security guards, law enforcement officers, teachers, HR workers, financial analysts, and even software programmers.[6]

3.1. Labour Market Implications

26. The labour market implications of a strictly skill-biased technological change (SBTC) are different from the ones of a task-biased technological change (TBTC). SBTC would increase the relative employment and wages of the more skilled. It could also increase the real wages and employment levels of the most skilled if certain conditions are met: elastic output demand and inelastic skilled labour supply (Autor 2015). As technologies make certain work that complements highly skilled workers cheaper, we can reasonably expect that the demand for this output would grow. On the labour supply side, education takes time to acquire and even if schools are able to quickly react to changing labour demands and quickly absorb new applicants, the time it takes to educate a labour force cohort will induce a lag between demand and supply.

27. ALM-type TBTC would have similar implications as SBTC on real and relative wages, as well as employment levels and relative employment, but the important

[6] In contrast, the ALM framework typically categorizes clerical, administrative support workers, sales workers, production, crafts, repair, and operative occupations among those that can be automated.

dimension would not be the level of education, but the task content of jobs/occupation, i.e. the degree to which a job/occupation is routinisable. Non-routinisable jobs would see an increase in relative employment and wages, as well as an increase in real wages,[7] at least in the short run, and a higher employment level. Moreover, TBTC would erode the real wages and employment of those in routinisable jobs/occupations. In the 1970s and the 1980s routinisable jobs were concentrated in the middle of the wage distribution in OECD countries. Many clerical and blue collar manufacturing workers occupied these middle-paying jobs. Hence, TBTC has distinctively different empirical predictions than SBTC: it predicts that the most adversely affected occupations will be middle-paid ones.

3.1.1. Wage developments

28. In the United States, starting in the 1980s, real wages rose for highly educated workers, particularly those with a post-college education, and fell steeply for the least educated. For male workers in particular, the real hourly wage in 2009 was significantly lower for those with less than 14 years of education than what similar workers would have earned in 1973 or 1989. For instance, a male worker with only 7 years of education earned 18% lower hourly wages in 2009 than a similar worker in the 1970s or the 1980s. At the same time, a worker with 18 years of education, earned 22% more in 2009 than in the 1970s and the 1980s (Acemoglu and Autor 2011). These wage dynamics translated in the widely-observed rising wage inequality in the United States (Bound and Johnson 1995; Levy and Murnane 1992; Murphy and Welch 1992; Juhn, Murphy, and Pierce 1993; Katz and Murphy 1992; Acemoglu 2002; Autor, Katz, and Kearney 2008).

29. This pattern was not unique to the United States. Rising income inequality since the 1980s was observed in other OECD countries, such as the United Kingdom (Gosling, Machin, and Meghir 2000), Canada (Boudarbat, Lemieux, and Riddell 2006) and Germany (Dustmann, Ludsteck and Schoenberg 2009; Antonczyk et al. 2010). In addition to OECD countries, Piketty (2014) documented rising inequality in emerging economies.

30. While the rise in wage inequality was found to coincide with wage polarisation in the United States in the 1990s, when lower tail inequality increased and upper tail inequality decreased, this was not the case in later decades or in other countries. Rather, most countries have seen an increase in the gap between top and median wages, and either a stable or increasing gap between median and bottom wages (OECD, 2017).

3.1.2. Employment

31. Goos and Manning (2007) were among the first ones to notice that the changes in the employment structure of OECD countries followed a pattern that is difficult to reconcile with SBTC. For the UK, they found that since the mid-1970s, the employment shares of the lowest and the highest paid occupations have been growing at the account of those in the middle. They termed this phenomenon job polarisation. Autor, Katz and Kearney (2006) documented a similar pattern for the United States. Goos, Manning and Salomons (2009 and 2014) and OECD (2017) documented that job polarisation has been prevalent across 16 OECD countries. All these studies argue that TBTC is the driving force behind job polarisation. What are these middle-paying jobs? They are mainly the skilled blue-collar jobs, unskilled labourers, the clerical and the sales occupations whose

[7] This assumes that there are at least some frictions or costs to workers who would switch from routine to non-routine jobs. If there is sufficient supply of workers in non-routine jobs, wages will, of course, not increase.

job tasks fall in the categories of routine manual and routine cognitive work (Acemoglu and Autor 2011; Autor 2015). The clerical and some of the sales jobs typically require high school and some college. The production jobs typically require some form of vocational training. Hence, at least to a degree, the middle paying jobs fall within the category of middle-skilled jobs.

3.1.3. Declining labour-capital ratio and premature industrialisation

32. Berger and Frey (2016) review the cumulating evidence of declining labour share in income, and related to this, premature deindustrialisation of countries. Karabarbounis and Neiman (2014) document that the share of global corporate gross value added paid to labour across 59 countries declined 5 pp over the past 35 years. Among these 59 countries, 42 experienced a decline in the labour share. At the industry level, 6 of the 10 major industries experienced significant labour share declines (mining, manufacturing, transport, utilities, wholesale and retail, and public services) and 2 experienced significant growth (agriculture, financial services and business services). They find that most of the global decline in the labour share can be attributed to within-industry changes and not to changes in industrial composition of countries. They consider several factors that might have caused this decline, but conclude that the most likely factor is the decline in the price of investment goods, which incentivised companies to shift the production function from employing labour to utilising technology. Rodrik (2015) describes that peak manufacturing employment has steadily declined among emerging economies over the course of the twentieth century, leading to what is often termed as the middle-income trap. The employment share of manufacturing in the world's first industrial nation, the United Kingdom, peaked at about 45%, while manufacturing employment in today's emerging economies typically peaked at below 15%.

3.1.4. Educational upgrading and skill mismatch

33. As technology changes the character of job tasks, how do people adapt to new ones? SBTC would suggest that technology prefers highly educated workers and that adaptation to new technologies takes place through selection and matching between skilled workers and technologically innovative jobs (Nelson and Phelps 1966). There is probably a lot of truth in this because the skill supply has been a strong predictor of skill-specific wage premia (Katz and Murphy 1992; Goldin and Katz 2007 and 2009) and skill upgrading has been the mark of the 20th and the 21st centuries. However, skills are multidimensional, and not single-dimensional as depicted by most economists. A degree in biology has a fundamentally different quality than a degree in law. These two fields may require the same years of schooling, but the skills obtained in each one of them are not interchangeable. Probably the only way a lawyer could become a decent biologist is to attend the full length of education that biologists undertook. And although both types of occupational education teach high-level of analytical and interactive skills, the nature of these differs in each training. This means as well that making one of these occupations obsolete would not translate into frictionless employment transition from the obsolete occupation to the growing one.

34. Given the gravity of the technological transformation we are undergoing, there is astonishingly little research effort in understanding the subsequent response through skill adjustment. Autor, Dorn and Hanson (2015) find that Americans that were displaced as a result of automation opt for non-participation rather than unemployment, suggesting that they become discouraged to search for jobs. However, for Germany, Nedelkoska (2013) finds that the workers displaced from routinised jobs are more likely to switch

occupations than to become unemployed.[8] Fujita (2014) analyses the causes for the increasing non-participation in the American labour market and finds that, along with retirement, non-participation due to schooling and disability explain most of its increase. This means that to some extent non-participation masks the increases in re-qualification also in the American labour market. However, it is important to note that in absence of regional re-qualification opportunities, the skill gap between the obsolete routinised occupations and the growing non-routine ones may discourage workers to search for jobs – this may be one reason why many opt to claim disability benefits rather than retrain. Nedelkoska, Neffke and Wiederhold (2015) analysed the job transitions of displaced workers in Germany between 1975 and 2010 and found that workers who after being displaced from their jobs moved to occupations requiring skill upgrades (relative to their pre-displacement job), did not experience the typically observed long-term earnings losses (Jacobson, La Londe, and Sullivan 1993; Neal 1995; Fallick 1996; Schmieder, von Wachter and Bender 2010), but workers who after job displacement moved to occupations where they were down-skilled compared to their pre-displacement jobs, experienced large long-term earnings losses. This suggests that re-qualification and upskilling play a key role in mitigating the difficult transitions awaiting workers whose skills have been rendered obsolete by technological progress.

35. Finally, while re-qualification and the educational choices of the young are highly important, one should not oversee the skill-shifts that happen at the workplace. A great deal of skill upgrading happens at the job. ALM and Spitz-Oener (2006) for instance find that the intensity of non-routine analytic and interactive tasks increased within the same educational groups and the intensity of routine manual and cognitive tasks decreased within the same educational groups in the course of the 1980s and the 1990s. ALM also show that computer adoption can explain large share of the variance in task changes, and in the case of high school graduates, the full variance. Hence, adaptation does not only happen through requalification, but also through the change in the work content of jobs.

3.2. Innovation, Diffusion, and Market Responses

36. The ALM framework is accompanied by a large number of studies which, as elabourated earlier, show that the automation of routinised jobs had wide-spread implications on the labour markets of OECD countries since the 1980s. The more recent hypothesis that automation has a reach beyond routine tasks put forward by Brynjolfsson, McAfee, Frey and Osborne and others has been less tested. One of the reasons for this is that many of their predictions apply to events that may unfold in the future, e.g., self-driving cars or large-scale computerised medical diagnosis, while ALM's hypotheses were formulated to capture what automation was already doing. Moreover, specifically for the United States, for which FO's study was designed, the Bureau of Labour Statistics projects that many of the occupations that FO categorize as being at a high risk of automation – translators and interpreters, marketing specialists, technical writers, medical and clinical labouratory technologists and others – will grow significantly faster than the average employment growth between 2014 and 2024 (Bureau of Labour Statistics, 2016).

37. In 2014 Brynjolfsson and McAfee found that the jobless recovery following the 2008 Great Recession could be attributed to automation. Indeed, Jaimovich and Siu

[8] National statistics show that the participation rate in the USA has been declining since the mid-1990s, while the opposite is the case for Germany.

(2014) found that about 80% of the jobless recovery in the last two recessions can be attributed to the loss of routine employment, resulting in job polarisation. In line with a pattern suggested by Brynjolfsson and McAfee (2014), Autor (2015) showed that, for the United States, polarisation changed in nature over the most recent decade. While the general pattern is still polarising, the growth of jobs in the lowest skill percentiles accelerated, while the growth of jobs above the median skill percentile decelerated (p. 20). However, Autor also argues that the root cause of this changing aggregate behaviour is probably not automation. Private fixed investment in information processing equipment and software has been declining since the 2000 tech bust and currently stands at 1995 levels. A more plausible hypothesis, Beaudry, Green and Sand (2016) argue, is that the pattern is driven by the fact that the IT industry reached maturity around the 2000. Industry maturity typically means that process innovation has reached its peak and that there is less need for problem-solving and creative tasks (Klepper, 1996 and 1997). The maturity of the IT industry dampened innovative activity and reduced the demand for high-skilled workers more broadly, Beaudry and colleagues conclude.

38. If current technology can replace 47% of the jobs in the United States, as FO conclude[9], why aren't all jobs for which we have readily available technological substitutes disappearing? There are several reasons for this.

3.2.1. Technologies help create new jobs

39. Declining sectors free up human resources for other sectors of the economy. The automation of agriculture in the 1960s gave its way to manufacturing and the automation of manufacturing gave a way to services. As Bessen (2016) put it "Innovative technology is displacing workers to new jobs rather than replacing them entirely." He finds that only manufacturing jobs are being eliminated persistently in developed economies, and that these losses are offset by growth in other occupations. Bessen's finding is corroborated by the observation that despite the massive sectoral transformations within a single century, OECD countries have been adding, not losing jobs in net terms. His conclusion is in line with the trends in aggregate employment in developed economies. For instance, the number of employees in the United States in February 2017 reached 145.8 million. This is 6% more employees than in February 2007 before the start of the Great recession, 205% more employees than in 1970, before the spread of commercial computers, and 487% more employees than in 1939, before the advent of the service economy (Bureau of Labour Statistics, 2017a). Automation also frees up human resources within the same jobs. Scientists are more productive today than they were three decades ago precisely because computing software performs the time-consuming calculations that data analysis requires: data organisation, cleaning, tabulation, and high-level mathematical and statistical computation such as regression analysis, network analysis and machine learning. The automation of the computational part of our work freed up resources that were reallocated to hypothesis formulation, method development, increasing the robustness of our tests, interpretation, writing and communication.

[9] Applying a method similar to the one of FO, but using individual-level job task data, Arntz, Gregory, Zierahn (2016) come to an estimate that is significantly more optimistic – they conclude that about 9% of jobs in OECD countries are at a high risk of automation.

3.2.2. Demand elasticity

40. As ALM argued, what makes automation attractive is its cost-saving feature. Cost-saving technologies can reduce the final price of a product or a service. In the case of goods and services with high demand elasticity, lower final price will result in more purchases. Cases in point are ATMs, as described by Bessen (2016). Between the 1980s and today, 400 000 ATMs were installed in the United States. The number of bank tellers in the same period increased from 500 000 to almost 600 000. Bessen argues that ATMs increased the demand for tellers precisely because they reduced the cost of operating a bank branch. While the average number of tellers required to operate a branch office in urban areas fell by 35%, the number of bank branches in these areas increased by 43%.

3.2.3. Innovation vs. diffusion

41. The path between commercial introduction of a product and its wide-spread use is long and uncertain. Gort and Klepper (1982) estimated that the average time between the first commercial application and take off in the sales of 46 commercially successful inventions of the 19th and the 20th centuries was 14.4 years. However, most innovations with potentially commercial value never reach the stage of wide-spread application. The fact that a technology has commercial value does not guarantee its diffusion and it certainly does not guarantee that it will diffuse to a degree which disrupts the way people work. The electric car, for instance, was invented towards the end of the 19th century, but it soon lost the battle against the cheaper, gasoline-fuelled car once the internal combustion engines were perfected and mass production of gasoline-based vehicles was enabled. The diffusion of modern-day electric cars is aided by generous government subsidies in countries like Norway and the Netherlands. Moreover, making electric vehicles mobile at long distances requires investment in new infrastructure - charging stations – that are not yet readily available in all places and countries. Their commercialisation does not only require perfecting the vehicles, but also changing the environment in which the vehicles operate. This is no different from the case of the self-driving car, and if anything, the environment control here is an even more pronounced obstacle to the diffusion of the self-driving car.[10]

[10] "Computer scientists sometimes remark that the Google car does not drive on roads, but rather on maps. A Google car navigates through the road network primarily by comparing its real-time audio-visual sensor data against painstakingly hand-curated maps that specify the exact locations of all roads, signals, signage, and obstacles. The Google car adapts in real time to obstacles, such as cars, pedestrians, and road hazards, by braking, turning, and stopping. But if the car's software determines that the environment in which it is operating differs from the environment that has been pre-processed by its human engineers - when it encounters an unexpected detour or a crossing guard instead of a traffic signal - the car requires its human operator to take control. Thus, while the Google car appears outwardly to be adaptive and flexible, it is somewhat akin to a train running on invisible tracks" (Autor, 2015, p. 24).

4. Who is at risk of job automation?

42. In 2003 ALM asked a simple but fundamental question about the relationship between computers and humans: “what do computers do – that is, the tasks they are best suited to accomplish – and how do these capabilities complement or substitute for human skills in workplace settings?” (p. 1280). By 2013, advances in machine learning (ML) and mobile robotics (MR) extended the list of job tasks that can be performed by machines by a degree that made the question “what is that machines cannot do” easier to answer than ALM’s question asked just ten years before. This change in perspective is reflected in FO’s approach to measuring the degree to which jobs are automatable (automatability). At the core of FO’s approach is identifying the current engineering bottlenecks that ML and MR developers are facing. To understand these, in 2013 FO interviewed ML scientists at a workshop held at the Oxford University Engineering Sciences Department. They showed the scientists a list of 70 occupations and their O*NET[11] job tasks descriptions and asked “Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?”. Those occupations for which the scientists agreed that all tasks can be automated were labelled 1 and occupations that could only be partially automated were labelled 0. The second source of data in FO’s approach is O*NET (www.onetonline.org). For each occupation (702 in total) O*NET provides detailed descriptions of job tasks. FO focused on 9 such descriptions (variables) that correspond to 3 distinct engineering bottlenecks identified through the interviews with ML scientists (Table 4.1).

[11] The Occupational Information Network (O*NET) is the primary source of occupational information for the USA. Its’ data is publically available online at www.onetcentre.org.

Table 4.1. O*NET variables corresponding to identified engineering bottlenecks

	Variable	Definition
Perception manipulation	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped work space, awkward positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social intelligence	Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behaviour.
	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients.

Source: Frey and Osborne (2017), Table 1.

43. In FO's notation, the list of O*NET variables is a feature vector denoted as $\boldsymbol{x}\ \mathbb{R}^9$. The feature vector is available for all 702 occupations in O*NET. The dataset constructed with the scientists' answers – the so-called "training dataset" – is denoted as $D = (\boldsymbol{X}, \boldsymbol{y})$, where $\boldsymbol{X} \in \mathbb{R}^{70\times 9}$ is the matrix of O*NET variables for the subset of 70 occupations and $\boldsymbol{y} \in \{0,1\}^{70}$ has the occupational labels of automatability. Using the training data, FO estimate the underlying latent probability of automation, $P(y_* = 1|f_*)$. This "true" probability of becoming automated as a function of the feature vector can be modelled in various ways. FO assume that the latent probability distribution is logistic:

$$P(y_* = 1|f_*) = \frac{1}{1 + \exp(-f_*)'}$$

and explore two broad statistical approaches when modelling it: (a) modelling f_* parametrically as a logistic regression, and (b) modelling it non-parametrically using Gaussian process (GP) classifiers, a machine learning technique. The logistic regression implies a simple monotonic relationship between the probability of automation and the feature vector, while the GP approach is non-parametric and more flexible in terms of functional forms. They try three different covariances of the GP: exponentiated quadratic, rational quadratic and linear covariances. Judging by conventional measures of model fit and in particular the area under the curve (AUC) criterion, the exponentiated quadratic model fitted the data best. Estimating these models for the subset of training data then allows for an out-of-sample prediction across all 702 occupations, since the feature vector is available for all of them.

44. Using this approach, FO found that 47% of all 2010 employees in the United States were at a high risk (i.e. over 70% risk) of automation in near future, while only 33% of the employees were at less than 30% risk of being automated. A few other studies translated FO's study at the occupational level for other countries and found, not

surprisingly, correspondingly high risks of automation (Brzeski and Burk 2015; Pajarinen and Rouvinen (2014). Arntz, Gregory and Zierahn (2016) (AGZ) designed a study similar to the one by Frey and Osborne, however with two advantages: (a) they use PIAAC data for 22 countries and (b) they have access to individual-level data on job content. Contrary to FO, AGZ find that, on average, only 9% of jobs across the considered OECD countries are have a probability of automation equal of higher than 70%.

4.1. Estimating the probability of automation using PIAAC data

45. This study follows the FO approach very closely in order to analyse the risk of automation in 32 OECD countries. The individual-level data were collected through the first two rounds of the PIAAC study in 2011/2012 and 2014/2015 (OECD, 2013; OECD, 2016; Quintini, 2016). In order to replicate FO as closely as possible for OECD countries, two empirical challenges needed to be met. First, a correspondence between the 70 hand labelled occupations in FO's training data and a subset of the 440 ISCO-08 occupational classes in the PIAAC data was needed. This was done by manually comparing the 70 O*NET occupations with the available ISCO data. The second challenge was to find job task variables in PIAAC that correspond to the engineering bottlenecks identified in FO. Table 4.2 shows the PIAAC variables that correspond to the three types of engineering bottlenecks: perception and manipulation, creative intelligence and social intelligence. While PIAAC contains variables that adequately match these areas, there is no perfect overlap with the O*NET variables selected in FO. Most importantly, there are no questions in PIAAC about job aspects which have to do with caring for and assisting others. This affects a large population working in healthcare and services. A potential consequence of missing this part of social intelligence is that automatability of jobs that involve care and assisting others will be overstated.[12]

[12] In a replication of the FO approach using data from Germany (BIBB/BAuA Employment Survey), we find that caring for others is one of the most predictive variables of automatability. They are, of course, negatively correlated. However, we also find that caring for others correlates with advising ($\rho = 0.19$) and teaching ($\rho = 0.28$), hence we expect that some of its variance will be picked up by the other variables of social intelligence.

Table 4.2. PIAAC variables corresponding to FO-identified engineering bottlenecks

Engineering bottlenecks	Variable in PIAAC	Variable code	Variable description
Perception manipulation	Fingers, (dexterity)	F_Q06C	How often - using skill or accuracy with your hands or fingers?
Creative intelligence	Problem-solving, simple	F_Q05A	How often - relatively simple problems that take no more than 5 minutes to find a good solution?
	Problem-solving, complex	F_Q05B	Problem solving - complex problems that take at least 30 minutes thinking time to find a good solution?
Social intelligence	Teaching	F_Q02B	How often - instructing, training or teaching people, individually or in groups?
	Advise	F_Q02E	How often - advising people?
	Plan for others	F_Q03B	How often - planning the activities of others?
	Communication	F_Q02A	How often - sharing work-related information with co-workers?
	Negotiate	F_Q04B	How often - negotiating with people either inside or outside your firm or organisation?
	Influence	F_Q04A	How often - persuading or influencing people?
	Sell	F_Q02D	How often - selling a product or selling a service?

Source: Survey of Adult Skills (PIAAC) 2012, 2015

46. An important difference between the approach using PIAAC data and the approach using O*NET data is that PIAAC offers individual-level data on job tasks. Taking advantage of this feature the latent variable function for the subset of training data is estimated at the individual level. A logistic regression is used, as done in one of the variants of the FO's approach. Also, the training data is limited to Canada, because Canada has a substantially larger sample than any other country in PIAAC allowing a better identification of the 70 FO occupations.[13] This is a major improvement over previous work which exploited occupational titles at the 2-digit level only, preventing the exact identification in PIAAC of many of the 70 occupations used by Frey and Osborne. However, while there is no specific reason to believe that the way bottlenecks relate to the risk of automation differs across countries, it is possible that Canada's specific industrial structure and its position in global value chain may influence the coefficients. Arntz, Zierhan and Gregory (2016) provide the opportunity for a simple robustness test. In fact, they estimate the coefficients on a sample that pools all countries and includes country dummies. With the exception of the frequency of solving simple problems, the sign and significance of the estimated coefficients are the same between the two studies. Overall, the pros of conducting the estimation on better defined occupations and the larger sample size probably outweigh the cons which should nevertheless be kept in mind.

47. The coefficients estimated on Canadian data are then applied to all other individuals across 32 countries in PIAAC to obtain an out-of-sample prediction of the individual risk of automation. Table 4.3 summarises the results of the logistic regression estimation.

[13] Seven occupations could not be identified in ISCO-08: dishwashers; parking lot attendants; technical writers; paralegals and legal assistants; gaming dealers; farm labour contractors; claim adjusters, examiners and investigators. Additionally, the same ISCO-08 code – credit and loan officers – is used for two of the 70 FO occupations: credit authorisers, checkers and clerks; and loan officers. See Table A A.1 in Annex A for the whole correspondence.

Table 4.3. Automatability as a function of engineering bottlenecks. PIAAC Canadian data

Logistic regression results

	Logit coefficients	Robust standard errors
Dexterity	0.105***	0.022
Simple problems	0.0573*	0.0309
Complex problems	-0.0691**	0.0297
Teach	-0.0691***	0.0255
Plan work of others	-0.308***	0.0234
Influence others	-0.235***	0.0267
Negotiate	0.0463*	0.0255
Sell	0.160***	0.0206
Advise	-0.199***	0.027
Communicate	0.214***	0.026
Constant	0.363**	0.152
Observations	4,656	
Pseudo R-squared	0.137	
Log Likelihood	-2769	
Area under ROC curve	0.743	
AIC	1.194	
BIC	-33693.5	

Note: Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: Canadian Sample, Survey of Adult Skills (PIAAC) 2012.

48. As one can see in Table 4.3, while all variables are predictive of automatability, not all of them are predictive in the expected way. Finger dexterity, selling and communicating are positively, not negatively associated with automatability. Even solving simple problems and negotiating are positively, although only marginally statistically significantly associated with automatability.[14] Table 4.4 shows the analysis of the variance (ANOVA) decomposition. The ANOVA shows that the variables that explain the largest share of the variance in automatability are planning for others, selling, influencing, communicating and advising, while negotiating, and problem-solving explain small, insignificant part of the variance.

[14] In FO's 2017 publication, Figure 2, one can also see that the variables of finger dexterity, manual dexterity and cramped workspace are all positively correlated with the probability of computerisation.

Table 4.4. Automatability as a function of engineering bottlenecks – ANOVA analysis, PIAAC Canadian data

	Partial SS	df	MS	F	Prob<F
Model	227.25	40	5.68	28.29	-
Plan work of others	33.85	4	8.46	42.14	-
Sell	18.07	4	4.52	22.49	-
Influence	17.74	4	4.44	22.09	-
Communicate	14.5	4	3.63	18.05	-
Advise	12.41	4	3.1	15.45	-
Dexterity	10.93	4	2.73	13.6	-
Teach	4.1	4	1.03	5.1	0
Negotiate	1.6	4	0.4	1.99	0.09
Simple problems	1.5	4	0.38	1.87	0.11
Complex problems	1.06	4	0.27	1.32	0.26
Residual	926.82	4,615	0.2		
Observations	4,656				
Root MSE	0.45				
R-squared	0.2				
Adj. R-squared	0.19				

Source: Canadian sample, Survey of Adult Skills (PIAAC) 2012.

4.2. Main findings and cross-country variation

49. For the overall sample of 32 countries, the median job is estimated to have 48% probability of being automated (Table 4.5). However, there is a large variation in the degree of automatability across countries. In New Zealand and Norway, for instance, the median worker has 39 and 40% probability of being automated, respectively. This is about half a standard deviation less than the median automatability for all 32 countries. At the other extreme, the median worker in Slovakia has 62% probability of being automated and in Greece and Lithuania the median worker has 57% chance of being automated. These values are at least half a standard deviation above the median for the full sample. To illustrate what these differences mean in terms of distributional properties, Figure 4.1 plots the distributions of automatability for Canada, the reference country, and for the four countries at the two extreme ends of automatability. It exemplifies the wide distributional differences observed across countries. The modes for New Zealand and Norway are found to be less the 30%, Slovakia's mode is about 70% and Lithuania's mode is around 60% of automatability. It appears that the countries that score lowest on the probability of being automated are countries located in the North of Europe (Norway, Finland, UK, Sweden, the Netherlands and Denmark), in Northern America (United States and Canada) and New Zealand. New Zealand is an interesting case. Ethnically it is dominated by Europeans, especially Europeans of British origin (74% according to the 2013 Census), and it trades intensively with other countries of Anglo-Saxon origin (Australia, United States, UK), and with Asian countries (China, Japan, Singapore). These relations may drive the similarities that we see with other Anglo-Saxon countries. Another interesting observation (documented by Handel 2012) that may explain this pattern is that New Zealand, more than other OECD countries, experienced a sharp rise in occupations that specialise in cognitive jobs: professionals since the early 1990s and managerial occupations since 2010. At the other end of

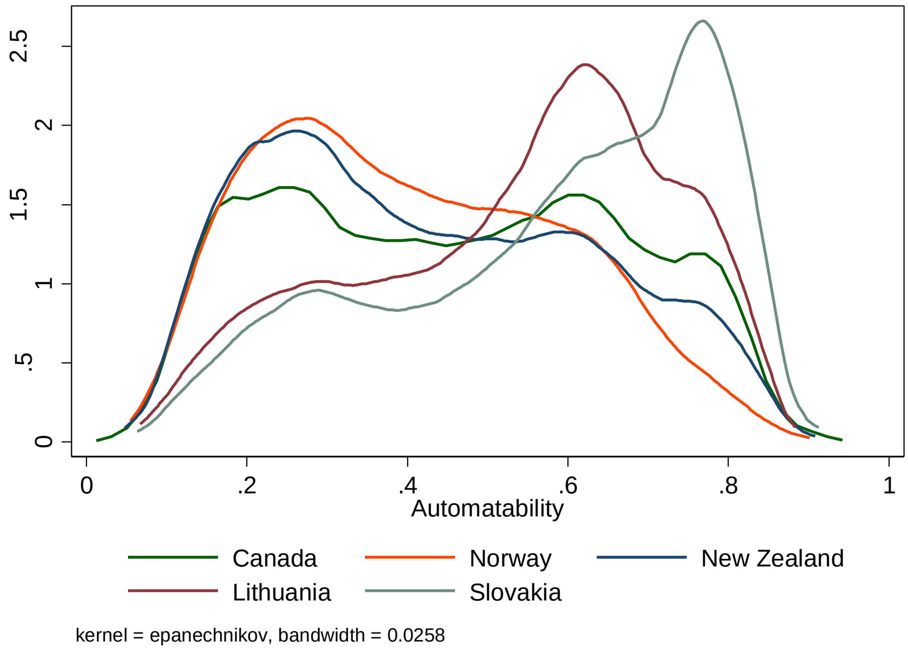
the automatability distribution are the countries of South and Eastern Europe, but also Slovakia, Germany and Japan. The higher risk of automatability does not only arise from the fact that these countries have relatively larger share of manufacturing jobs, but also from differences in the job content within nominally similar industries and occupations (see below).

Table 4.5. Cross-country variation in job automatability

Country	Median	Mean	S.D.
New Zealand	0.39	0.42	0.20
Norway	0.40	0.41	0.18
Finland	0.41	0.43	0.18
United States	0.41	0.43	0.20
Northern Ireland (UK)	0.42	0.43	0.21
England (UK)	0.42	0.43	0.20
Sweden	0.43	0.44	0.19
Netherlands	0.44	0.45	0.19
Denmark	0.44	0.45	0.19
Canada	0.45	0.45	0.21
Ireland	0.45	0.46	0.22
Singapore	0.45	0.46	0.20
Belgium	0.46	0.46	0.20
Israel	0.46	0.47	0.21
Estonia	0.47	0.46	0.19
Korea	0.47	0.46	0.19
Austria	0.49	0.48	0.20
Russian Federation	0.49	0.47	0.19
Czech Republic	0.49	0.48	0.20
France	0.51	0.49	0.20
Italy	0.52	0.49	0.20
Cyprus	0.52	0.51	0.21
Poland	0.52	0.50	0.21
Japan	0.53	0.51	0.18
Slovenia	0.53	0.51	0.21
Spain	0.54	0.51	0.21
Germany	0.54	0.52	0.18
Chile	0.55	0.52	0.20
Turkey	0.55	0.52	0.18
Greece	0.57	0.54	0.19
Lithuania	0.57	0.54	0.19
Slovak Republic	0.62	0.57	0.20
All countries	**0.48**	**0.47**	**0.20**

Note: all observations are weighted using the final survey weights; for the median and mean columns, the colours in each row draw a heat map, with green corresponding to lowest risk and red to highest risk; standard deviations values are shown along a bar chart, with higher bars corresponding to higher standard deviations
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 4.1. Automatablity distribution for selected countries



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

50. Another way to present these findings is akin to the FO and AGZ studies (Figure 4.2), looking at the share of workers at high and low risk of automation. Across all countries in our sample, 14% of jobs have a probability of being automated higher than 70% (as opposed to the 47% estimated by FO and 9% estimated by AGZ).[15] Another 32% have a chance of automation between 50 and 70%. This is a group at risk of significant change. Put in other words, these are jobs that presumably include several automatable tasks – which will ultimately disappear from the job description – but also some of the bottleneck tasks listed above which will presumably become more prominent or be complemented by similarly non-automatable tasks. At the opposite end of the automatability spectrum, about 26% of jobs have less than 30% chance of automation (as opposed to 33% in FO). Hence, the results of this study are more similar to those estimated by AGZ (2016), and less similar to the results derived by FO. As noted above, there are large differences across countries. In Norway, for instance, only 6% of all jobs have a risk of automation higher than 70%. Similarly, the share of jobs at high risk is just 7% in Finland and 8% in Sweden. However, 33% of all jobs in Slovakia are at high risk and so are 25% of the jobs in Slovenia and 23% of the jobs in Greece.

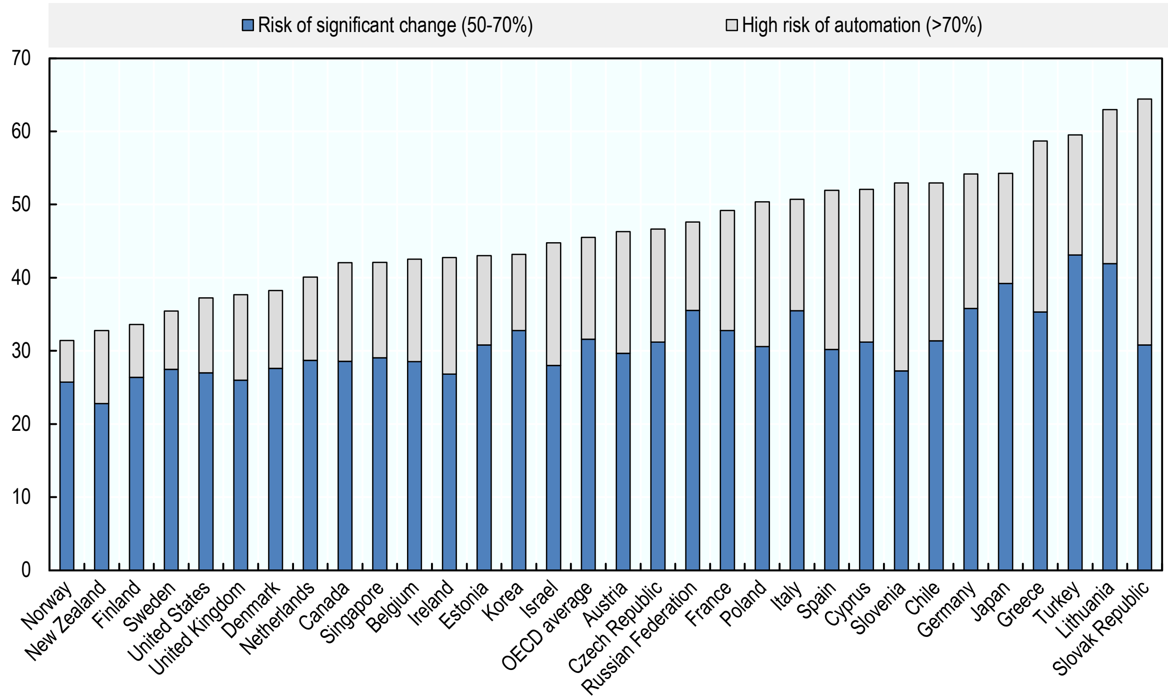
51. Several facts can explain the large differences in the share of jobs at high risk of automation estimated by FO – 47% of jobs in the United States – and that calculated in

[15] This figure refers to the share of all (job) observations in the OECD countries that participated in PIAAC whose risk of automation is higher than 70%, after applying sampling weights. In other words, cross-country averages reported in this paper are weighted averages.

this study – just 10% of jobs in the United States. While the distribution of the risk of automation appears to be informative about the relative risk of automation, estimates of its absolute risk are more dependent on estimation methods. This finding will be further corroborated in Section 8, using country-specific data for Germany and the United Kingdom compared to PIAAC-based results for these two countries. A major difference between the two studies is the level of aggregation. The latent function in FO was fitted on 70 observations (corresponding to 70 occupations in the training data). In the current study, the latent function was fitted using 4,656 individual-level observations.[16] As a result, the degrees of freedom in our study are far larger than in the case of the FO. Replications of our study at higher level of occupational aggregation show that the level of aggregation affects the kurtosis of the latent variable distribution. As we aggregate the data, the kurtosis increases and the bimodality of the distribution becomes more pronounced. Hence, most occupations are categorized either as highly susceptible or as not susceptible to automation at higher levels of aggregation, similarly to the outcomes of the FO study. At low levels of aggregation, the distribution becomes unimodal with lower kurtosis. In other words, as jobs differ significantly within occupations in the tasks they involve, valuable information is lost when the risk of automation is calculated based on the skill requirements of broad occupational categories.

[16] While the Canadian sample includes 26 880 observations, only workers employed in one of the ISCO-08 occupations identified in Table A A.1 and for which valid answers on the engineering bottlenecks variables are available are used to estimate the latent function.

Figure 4.2. Cross-country variation in job automatability,%age of jobs at risk by degree of risk



Note: High risk – more than 70% probability of automation; risk of significant change – between 50 and 70% probability.
Source: PIAAC 2012.

4.3. Characteristics of jobs at risk of automation

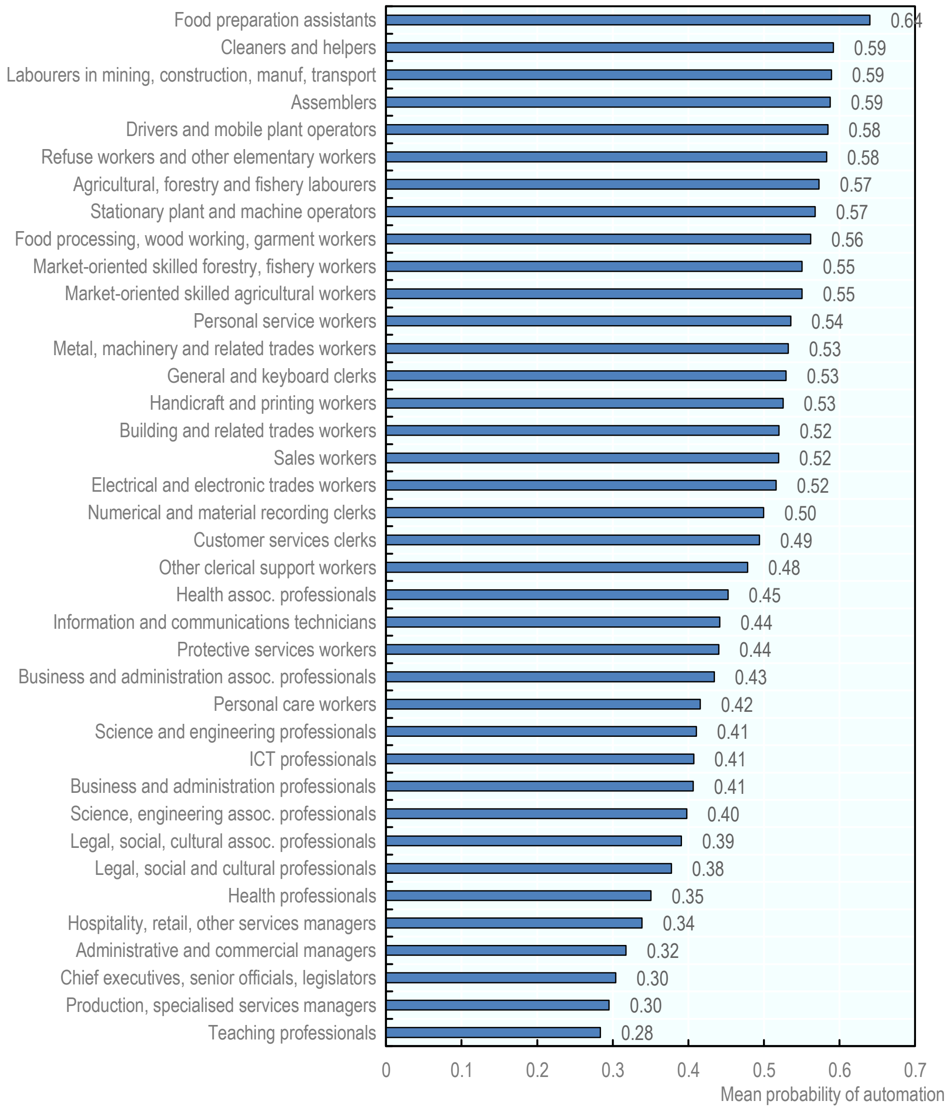
52. This section discusses what kind of occupation-specific and industry-specific human capital is being automated and analyses the socio-demographic characteristics of workers in jobs at high risk of automation.

53. Figure 4.3 and Figure 4.4 show the mean probability of automation by occupation and industry. Although for at least part of the countries a more detailed occupational classification is available, the results are presented at 2-digit ISCO-08 occupational categories, which are available for all 32 countries. The occupational groups that have the highest probability of becoming automated typically do not require specific skills or training: food preparation assistants, assemblers, labourers, refuse workers, cleaners and helpers. The next category are however workers with at least some training, and what they have in common is that large part of their job content is interacting with machines, mainly in the manufacturing sector: machine operators, drivers and mobile plant operators, workers in the processing industry, skilled agricultural workers, metal and machine workers etc. At the other end of the spectrum are occupations that require high level of education and training and which involve high degree of social interaction, creativity, problem-solving and caring for others. This end is populated by all sorts of professionals and managers, but also by personal care workers. Overall, despite recurrent arguments that the current wave of automation will adversely affect selected highly skilled occupations, this prediction is not supported by the FO-type framework of

engineering bottlenecks. Indeed, with the exception of some relatively low-skilled jobs – notably, personal care workers – the findings here suggest a rather monotonic decrease in the risk of automation as a function of skill level. Section 7 confirms that these results hold true when the same measurement approach is applied to data in Germany and the UK, suggesting that the pattern is rather a result of how engineering bottlenecks are defined and less a result of data specificities.

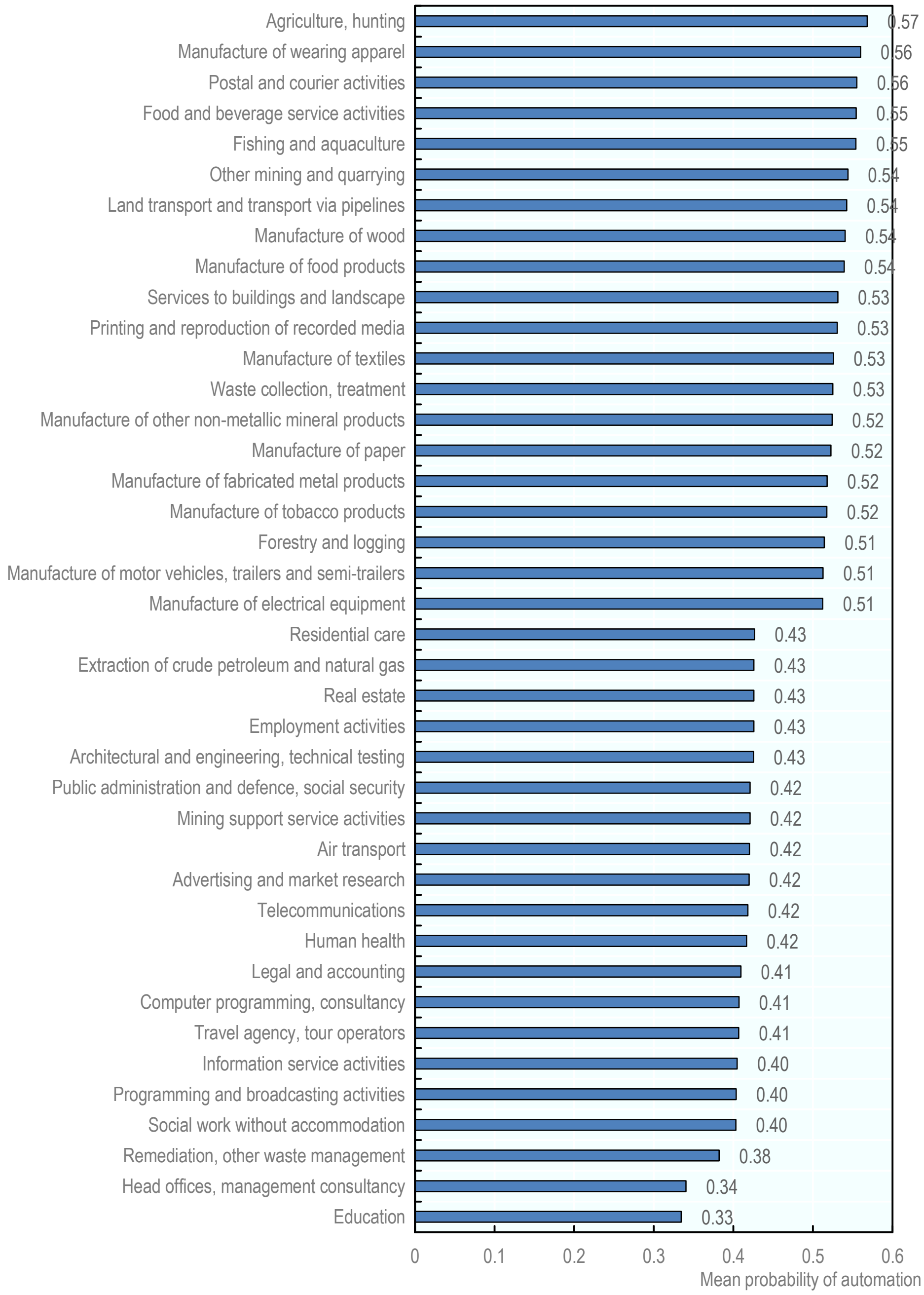
54. As far as industries are concerned, there are 88 2-digit ISIC Rev. 4 industries. Figure 4.4 shows the 20 industries at highest average risk of automation and the 20 industries at lowest. The industries with high risk of automation belong mostly to the primary and the secondary sector. Few service industries – notably, postal and courier services, food and beverage services, land transport, waste collection and treatment, and services to buildings and landscape – face a high risk of automation. At the opposite end of the ranking, the industries with low average probability of being automated are all part of the service sector, with the exception of oil extraction. Most of these industries belong to the category of Knowledge Intensive Business Services (KIBS).

Figure 4.3. Mean probability of automation by occupation



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 4.4. Mean probability of automation by industry



Note: The figure only includes the 20 industries with highest average risk of automation and the 20 industries with lowest average risk of automation. The classification is ISIC Rev. 4, 2-digit.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

4.4. Characteristics of workers whose jobs are at risk of automation

55. To further understand the question of what kind of human capital is being automated and identify which groups of employees deserve most policy attention, this section focuses on educational attainment as well as socio-demographic characteristics of workers at risk of automation.

56. A simple OLS regression is estimated to explain the probability of automation as a function of: 9 categories of educational attainment, age, gender, and PIAAC's numeracy scores and country fixed effects; with the addition of occupation and industry dummies in a second model[17],[18] (Table 4.6). These variables together only explain 27% of the variation in job automatability which is astonishingly low given the attention that has been given to the role of skills in technology-labour relationships (Table 4.7).

57. Educational attainment shows a very clear pattern in relation to automatability: a higher educational attainment translates into a lower risk of automation (Figure 4.5). There is no indication that the risk of automation brought about by AI and ML is particularly high for the medium skilled jobs, as observed in the polarisation literature based on the routine content of jobs. Numeracy and being male correlate negatively with the probability of automation, but the economic significance of their coefficients is not high. Being male is associated with a lower risk of 1.6%, and one standard deviation higher numeracy is associated with 1.7% lower risk. The inclusion of occupation and industry controls does not change the results fundamentally. Notably, these controls reduce differences between groups with different educational attainment, the relationship between educational attainment and the risk of automation remains negative and monotonic. They do not seem to affect differences by age and actually reinforce the disadvantage of female workers over their male counterparts. In essence, while sorting into occupations and sectors plays a role in some cases, differences between socio-demographic groups appear to be driven by differences in the task composition of individual jobs. This is particularly striking for women when controlling for industry and occupation actually increases the likelihood of automation relative to men, suggesting that women tend to sort into occupations that have a lower risk of automation but within these occupations, they are often carrying out more automatable tasks than their male counterparts.

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[17] Please note that including controls such as occupational dummies in addition to education creates a "bad control" problem (Angrist and Pischke 2009). As a result the inclusion should be seen as a robustness check to reassure readers that the results are not driven by the sorting of different groups into specific occupations. However, only the first specification gives a meaningful read of the coefficients of education and numeracy, and neither of the two regressions is meant to suggest causal relationship between automatability and the right hand side variables.

[18] As the inclusion of occupation and industry controls in Model 2 implies a significant reduction in sample size due to missing values in these two variables, a third model is presented. Model 3 uses the same specification as Model 1, applied to the smaller sample used for Module 2.

Table 4.6. The risk of automation and socio-demographic characteristics

OLS regression results

	Model 1		Model 2		Model 3	
	OLS coefficient	Robust standard errors	OLS coefficient	Robust standard errors	OLS coefficients	Robust standard errors
Numeracy	-0.017***	0.002	-0.008***	0.002	0.018***	0.002
Female	0.016***	0.003	0.035***	0.003	0.015***	0.003
Age	-0.008***	0.001	-0.007***	0.001	-0.008***	0.001
Age squared	0.0001***	0.000	0.0001***	0.000	0.0001***	0.000
Lower secondary education (ISCED 2, 3c)	-0.025***	0.005	-0.013**	0.006	0.020***	0.006
Upper secondary (ISCED 3A-B, C long)	-0.061***	0.005	-0.029***	0.006	-0.057***	0.006
Post-secondary, non-tertiary (ISCED 4A-B-C)	-0.083***	0.008	-0.041***	0.008	-0.081***	0.009
Tertiary/professional degree (ISCED 5B)	-0.108***	0.006	-0.041***	0.007	-0.101***	0.007
Tertiary/bachelor degree (ISCED 5A)	-0.151***	0.006	-0.055***	0.007	-0.147***	0.007
Tertiary/master degree (ISCED 5A)	-0.204***	0.007	-0.083***	0.007	-0.198***	0.007
Tertiary/research degree (ISCED 6)	-0.233***	0.011	-0.087***	0.010	-0.225***	0.011
Tertiary-bachelor/master/research degree (ISCED 5A, 6)	-0.161***	0.009	-0.066***	0.009	-0.153***	0.009
Country effects (32 countries)	Yes		Yes		Yes	
Occupation dummies (ISCO 08; 2-digits)			Yes			
Industry dummies (ISIC rev 3, 2-digits)			Yes			
Observations	145 294		127 970		127 970	
Adj. R-square	0.15		0.27		0.15	

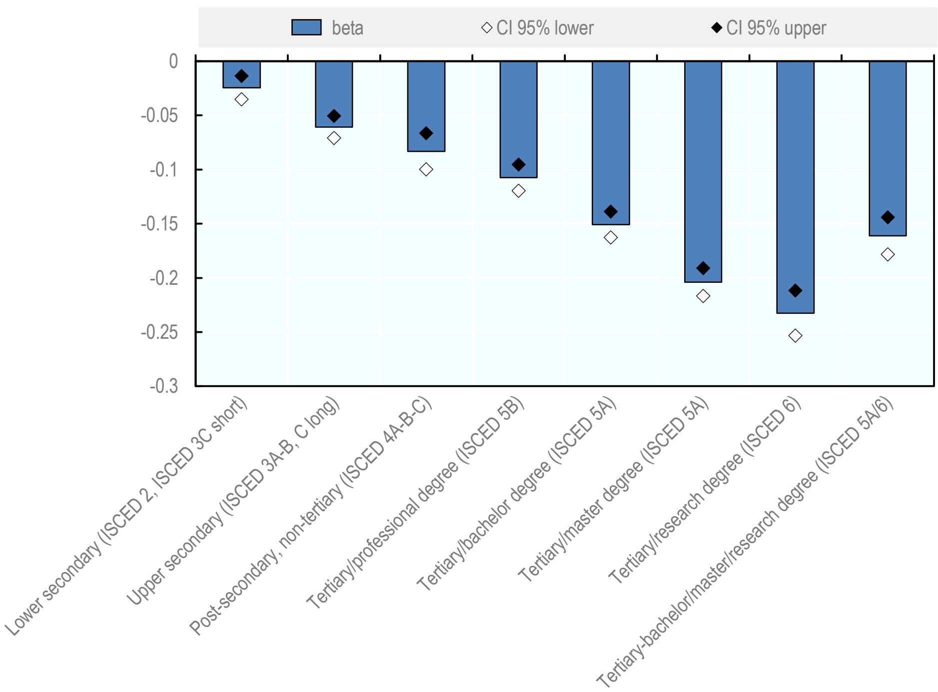
Note: OLS regression over the pooled sample of countries participating in PIAAC. Significant at: *** p<0.01, ** p<0.05, * p<0.1
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Table 4.7. Automatability as a function of individual characteristics – ANOVA

Source	Partial SS	df	MS	F	Prob>F
Numeracy	46.22	1	46.22	1 341.56	0
Female	5.77	1	5.77	167.51	0
Age	63.55	1	63.55	1 844.61	0
Educational achievement (9 categories)	397.24	8	49.65	1 441.20	0
Country effects (32 countries)	153.13	31	4.94	143.37	0
Model	988.12	42	23.53	682.85	0
Residual	5 004.44	145 251	0.03		0
Total	5 992.56	145 293	0.04		0
Observations	145 294				
Adj. R-square	0.1646				

Source: Survey of Adult Skills (PIAAC) 2012, 2015.

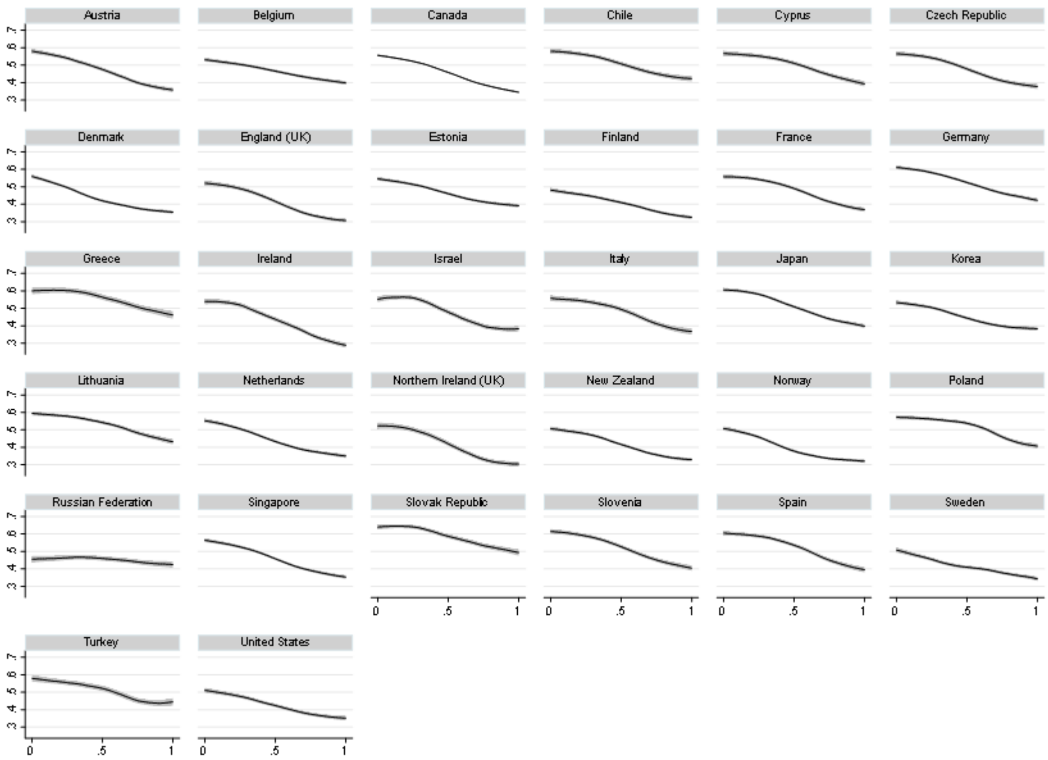
Figure 4.5. Partial correlations – automatability and educational attainment



Note: Results from an OLS regression including all 32 PIAAC countries for which we could estimate the probability of automation. They refer to model 1 of Table 4.6. The confidence intervals are based on robust standard errors. The observations (145,294) are weighted using survey design weights.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

58. Just like in the case of education, the risk of automation falls monotonically as a function of earnings. This is the case in all 32 countries, except for Russia where the risk does not differ among wage earners (Figure 4.6). There is no indication that the wave of near future automation will be wage polarising, i.e. affecting middle-income jobs in a more pronounced way, or that it will start affecting high-income, highly-educated professionals.

Figure 4.6. Automatability and earnings

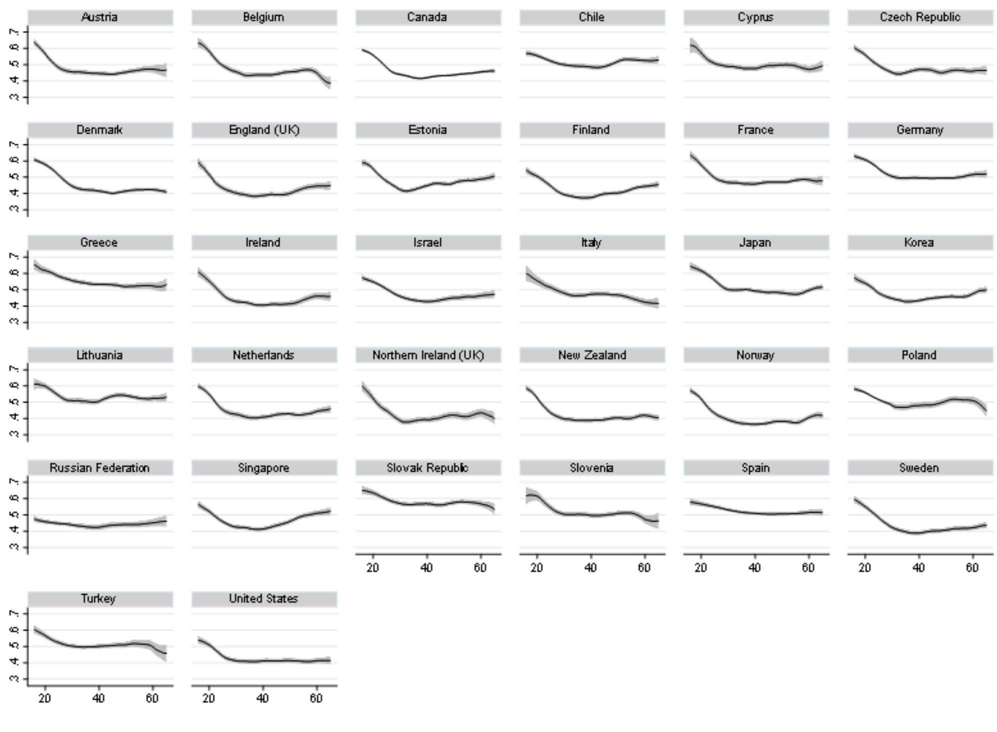


Note: Earnings percentile on the x-axis and probability of automation on the y-axis. Earnings are only defined for wage and salary earners and include bonuses. For cross-country comparability, we express earnings in percentiles and rank all workers by their standing in the wage distribution.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

59. The relationship between age and automatability is U-shaped for most countries and for the weighted sample of OECD individuals PIAAC (Figure 4.7). There are exceptions though. In Cyprus, the Czech Republic, Denmark, Greece, Lithuania, New Zealand and the United States, the risk of automation does not increase significantly with age after peaking in the teens. In Italy, Slovakia, Slovenia the risk even declines with age. What is surprising is that the risk of automation in all countries, except in Russia, peaks at the earliest working age. This is contrary to the intuition that automation is more likely to affect older workers who employ technologically outdated skills and are least likely to participate in lifelong learning (Autor and Dorn 2009). What causes this pattern is the occupational choice of young workers. Almost 20% of those aged 20 or younger work in elementary occupations (labourers, cleaners and helpers, agricultural jobs, food preparation and refuse jobs), while only 7% of those older than 20 work in such jobs. As shown above, these elementary jobs have the highest estimated probability of

automation. Another 34% of teen jobs are in sales and personal services, another occupational group with a rather high risk of automation. Only 13% of older workers hold such jobs. Not only are these figures informative of what might happen in the near future, they also match ongoing trends in teenage jobs, particularly in the United States. Pew Research Centre (Desilver 2015) has documented a sharp decline in the share of teens that hold jobs in the United States in the past few decades, from about 42% in the 1970s, 1980s and 1990s, to 28% in 2014. This is not only a consequence of the teenagers opting more often for formal education instead of taking jobs. Summer jobs which teens used to take during summer vacations have also become less likely: from 57% in the 1970s and 1980s to 34% in 2014. These changes call for ways to ensure that youth have access to jobs at lower risk of automation, either as new labour market entrants or working students. On the other hand, it is also important to acknowledge that while the risk of automation faced by older workers might be smaller, this age group may face more difficult transitions: adult learning participation tends to be lower for older workers making it harder to pursue upskilling and re-training for this age group.

Figure 4.7. Automatability and age

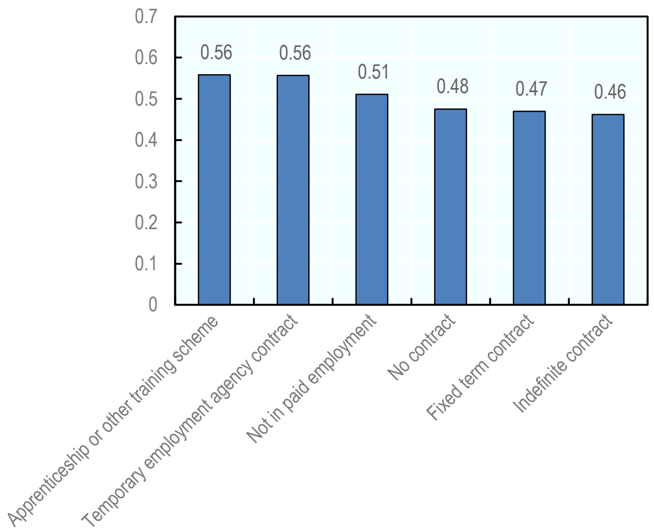


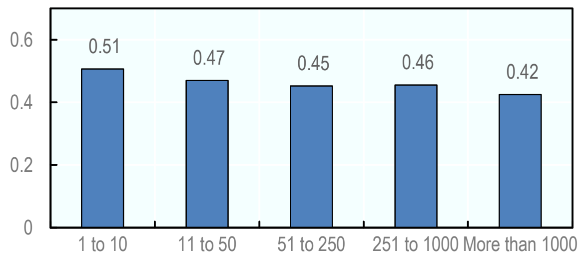
Note: Age on the x-axis and probability of automation on the y-axis.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

60. Finally, Figure 4.8 illustrates the risk of automation by type of work contract and firm size. Employees on work-based VET programmes or in apprenticeships, as well as those hired through employment agencies on temporary contracts have the highest risk of automation, while those with indefinite and fixed term contracts have the lowest risk. The elevated risk among those in apprenticeships may reflect the over-representation of traditional trades as many countries have only recently started to encourage the creation

of apprenticeship programmes in new emerging occupations. Looking at firm size, the risk of automation declines with the size of the firm although this could be due to compositional effects relating to industry and occupation. On the other hand, larger firms may be better prepared to adopt new technologies and job descriptions may change more rapidly to reflect these choices.

Figure 4.8. Automatability and contract type (left) and firm size (right)





Note: All differences across groups are statistically significant at 99% level or better.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

4.4.1. Differences across countries in the between and within task variation of industries and occupations

61. As shown above, countries differ significantly in the extent to which they are susceptible to automation. There are typically two broad reasons for this. First, the economic structures of countries differ a lot. Second, the way work is organised within the same industry could differ a great deal too. Economists strongly believe that what makes some countries richer is that their production of goods and services is organised in a more efficient way (Bloom and Van Reenen 2011; Bloom, Sadun and Van Reenen 2012). To study this, a shift-share analysis is conducted whereby all PIAAC countries are compared to Canada, the reference country, and the difference in the risk of automation is decomposed into differences in the structure of industries (between variance) and differences in the job content within industries (within variance). This calculation is typically called shift-share analysis. The methodology is similar to that used in ALM, p. 1299, except it is applied to cross-country instead of over-time differences:

$$\Delta A_c = \sum_i(\Delta E_{ic\neq CAN} A_{iCAN}) + \sum_i(E_{iCAN}\Delta A_{ic\neq CAN})$$ [19]

The total difference in automatability (ΔA_c) between any country different from Canada ($c \neq CAN$) and Canada can be decomposed into a between industry component: $\sum_i(\Delta E_{ic\neq CAN} A_{iCAN})$, and a within-industry component: $\sum_i(E_{iCAN}\Delta A_{ic\neq CAN})$. Here, E_i is industry-specific employment share and A_i is the industry-specific level of automation; i is an industry (occupation) index. E_i and A_i take values between 0 and 1. Figure 4.9 shows the results of this decomposition using industries as dimension along which the variance is decomposed. Figure 4.10 shows the results of this decomposition using occupations instead of industries.

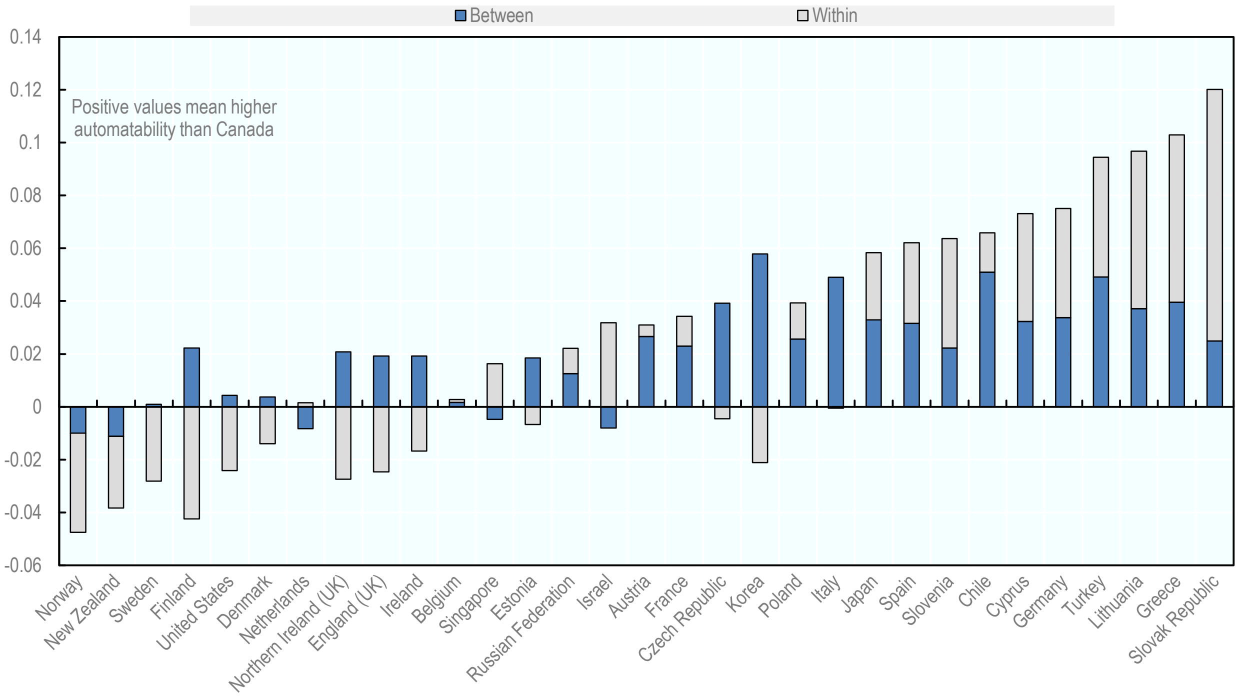
62. The first striking finding in the industry-based shift share analysis is that the within-industry differences explain the bulk of the variation (71%), while the between-industry differences only explain 29% of the variation. This is somewhat surprising – it is easier to think of the differences in job content between sectors (e.g., agriculture vs. manufacturing vs. service) while it is more difficult to think of the differences between countries in way work is organised in a given sector. One could argue that this is an artifact of working with only 85 different industries, but a robustness check shows that using the 4-digit ISIC Rev. 4 classification instead (containing 737 industries) results in between-variance of only 39%.

63. In the case of occupations, the between variance explains 47% of the total variance. This is already significantly higher than in the case of industries, although the 2-digit ISCO-08 classification used in this exercise only distinguishes among 38 classes.

64. It seems that within nominally similar industries, different countries organise their work content very differently. They use different combinations of occupations and even within these occupations they embrace variations in the job content. To develop an intuition of what is happening, it is helpful to look at some examples. For instance, jobs in the Republic of Korea are at higher risk of automation than in Canada (positive total variance in Figure 4.9 and Figure 4.10). The main reason for this is that Korea has different industry and occupational structure than Canada (positive between-variance). Over 30% of Korean jobs are in manufacturing, while this is the case with only 22% of Canadian jobs (Handel 2012). However, within the same industries, Korean jobs are organised in a way that makes them less susceptible to automation (negative within-variance). Korea might be ahead of Canada in automating routine jobs or it might be combining social and creative tasks together with routine tasks more frequently than Canada. The jobs in Slovakia, Greece and Lithuania, on the other hand are on average more susceptible to automation than the jobs in Canada, but this is less a result of different industry and even occupational structure, and more a result of differences in job content within nominally same industries and occupations. Slovakia, Greece and Lithuania are simply lagging behind Canada when it comes to the automatability of tasks accomplished in the workplace, for similar kinds of jobs in terms of industry and occupational groupings.

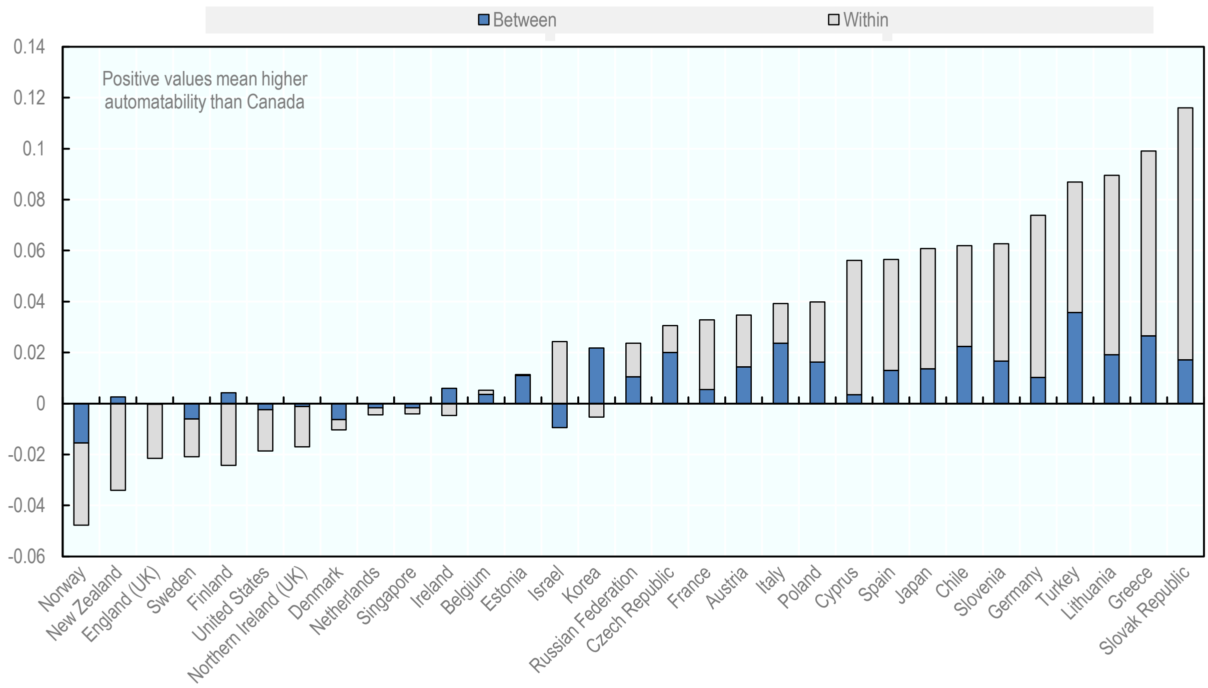
[19] A typical shift-share analysis has a third component which in this context would reflect the size difference in the pairs of countries. We are however not interested in this component.

Figure 4.9. Decomposition of cross-country differences in the level of automatability along the industry dimension



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 4.10. Decomposition of cross-country differences in the level of automatability along the occupation dimension



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

5. Are the estimates of automatability predictive of labour market outcomes?

65. To our knowledge, none of the studies that have used FO's engineering bottlenecks to estimate the risk of automation have tested how it relates to labour market outcomes of potentially affected workers. One could argue that at the time FO formulated their arguments about the engineering bottlenecks it was difficult to say what the future may bring. The prediction pertains to technologies that may be developed in the future as much as it does to commercially available technologies today.[20] However, according to FO, already now (i.e., at the time of their study) one should see a growing breadth of the impact of computerization on the labour market than what ALM predicted in 2003. This prediction is certainly testable. Section 3 discussed the theoretical predictions of how computerization should affect the employment and wages of people with different skills and job task content. Over time, as new computer technologies spread, the employment in more automatable occupations relative to the employment in less automatable ones should decline. The same should hold for relative wages. The absolute level of employment in automatable occupations should also decline. Wages in these occupations could also decline, but Autor (2015) argues that this depends on the conditions of task complementarity, output demand elasticity and the reactions of the labour supply.

66. In this section, PIAAC is used to show how employability and wages correlate with the degree of automatability in order to establish basic generalizable facts for the 32 OECD countries. Then, the German BIBB/IAB BIBB/BAuA Surveys are used to compare the FO-based estimates of automatability and its relationship with employment and wages with those using ALM-based estimates. The categorization of routine and non-routine tasks in the German skills survey is based on the rich literature on this topic (Spitz-Oener 2006; Antonczyk et al. 2008; Rohrbach-Schmidt and Tiemann 2013).

5.1. Automatability, job security and earnings

67. To get a sense of whether declining occupations or industries correspond to those with the highest risk of automation, occupation-specific and industry-specific unemployment rates are calculated for the 32 PIAAC countries. PIAAC includes detailed occupational data (4-digit ISCO-08) and detailed industry data (4-digit ISIC Rev. 4) for all interviewed working individuals. Those individuals, that at the time of the survey were not employed, were instead asked to report the occupation and the industry of their last job. This allows calculating occupation-specific and industry-specific unemployment rates: for each group we know the number of people currently working and the number of people that used to work there, but are now unemployed. The share of unemployed individuals in occupation *o* in the total pool of individuals in this occupation (employed

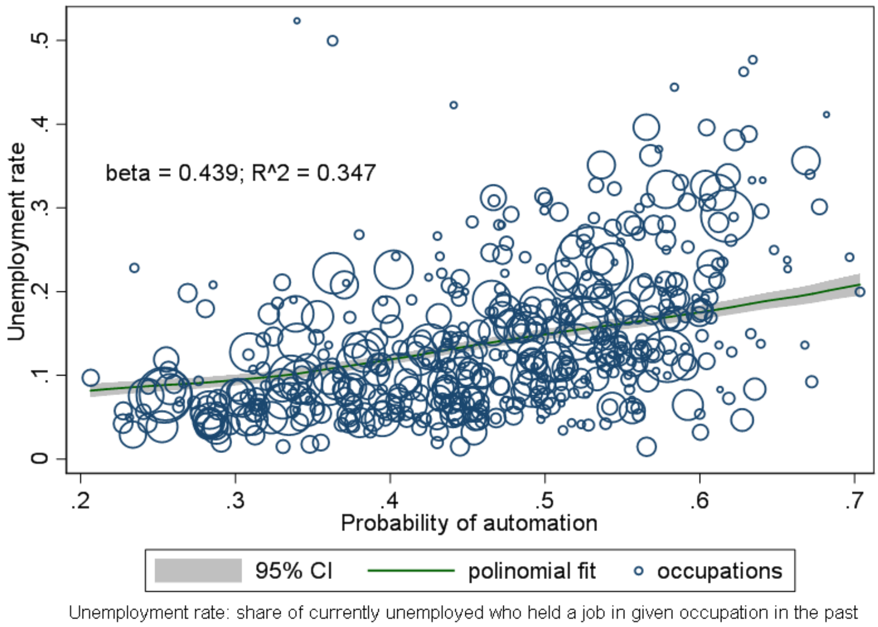
[20] This reveals potential weakness in this futuristic approach to measuring automatability. The approach is based on technical feasibly and ignores how the markets may react to the adoption of these technologies.

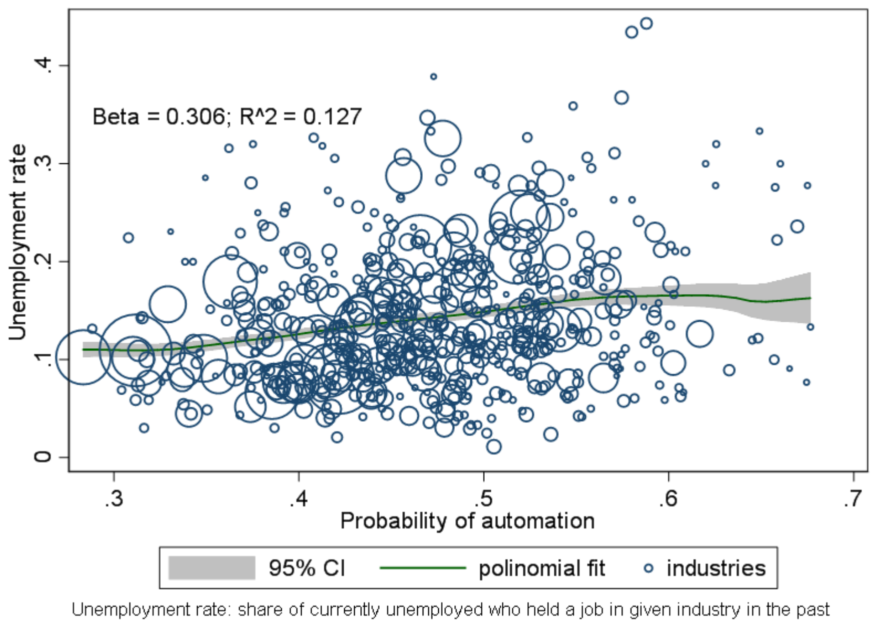
and unemployed) gives the unemployment rate for that specific occupation. The resulting indicators effectively capture which occupations/industries have been declining recently. Figure 5.1 shows that occupations that have higher average risk of being automated today or in the future have higher unemployment rates. Similar correlations are found between industry automatability and industry unemployment rates, but the relationship is somewhat weaker.[21] The strength of this simple relationship is astonishing. The difference in the unemployment rate between the least and the most automatable occupation is 44 pp (31 pp in the case of industries). Over a third of the variance in the occupational unemployment rate can be attributed automatability, when not controlling for other factors.

68. To study the relationship further, notably by accounting for other factors affecting occupational and industry unemployment rates beyond automatability, individual level data on hours worked are used. The supply of working hours is a choice variable to an extent. Higher hourly rates increase the supply of hours, men choose to work more hours than women and better educated people work more hours than less educated ones. It is also country specific: different countries have different regulations about the official working week and overtime. Once these factors are controlled for, it is expected that jobs that are at higher risk of automation will have fewer working hours. As these jobs are being phased out, the number of hours that employers are willing to offer in these jobs, will decline.

[21] The most likely reason why automatability and job risk are more correlated at the occupational level is because job tasks are more occupation and less industry specific (Poletaev and Robinson 2008; Gathmann and Schoenberg 2010; Kambourov and Manovskii 2009).

Figure 5.1. Occupation-specific and industry-specific unemployment rates and automatability





Note: 499 occupations in the left chart and 582 industries in the chart to the right. We only include occupations (industries) with at least 10 observations and the overall sample only includes prime-age people (age 25-54). The size of the circles is proportional to the size of the occupation (industry). The fitted polynomials are weighted by the final survey design weights. The reported coefficients and R-squared approximate the relationship by a linear OLS model, where the unemployment rate is explained only by the probability of automation. Each cell is weighted by the number of occupation (industry) – specific observations.
Source: PIAAC 2011/2012.

69. The number of weekly working hours is modelled as a function of automatability, age, gender, the hourly wage, education and country-specific effects using OLS. Across the 32 countries, the difference in working hours between the least and the most automatable job is 8 hours per week (Table 5.1). These results are not affected by the inclusion of occupation and industry controls (Model 2 in Table 5.1).[22] Workers in the most automatable jobs work about a day less than workers in the safest jobs ceteris paribus.[23] Figure 5.2 shows these estimates, country by country. The relationship is strongest in New Zealand, England (UK) and Germany. The relationship is not statistically different from zero in seven countries: Chile, the Czech Republic, Korea, Lithuania, Poland, the Russian Federation and Turkey.

[22] See footnote 17.

[23] It is important to note that full identification of the impact of automatability on employment and wages in OECD countries is beyond the scope of this study. Unobserved individual characteristics (e.g., intelligence or personality traits) may correlate with the choice of job (and hence automatability), biasing the findings away from zero. In spite of these limitations, the analysis should be able to indicate whether the basic theoretically expected patterns hold in the data.

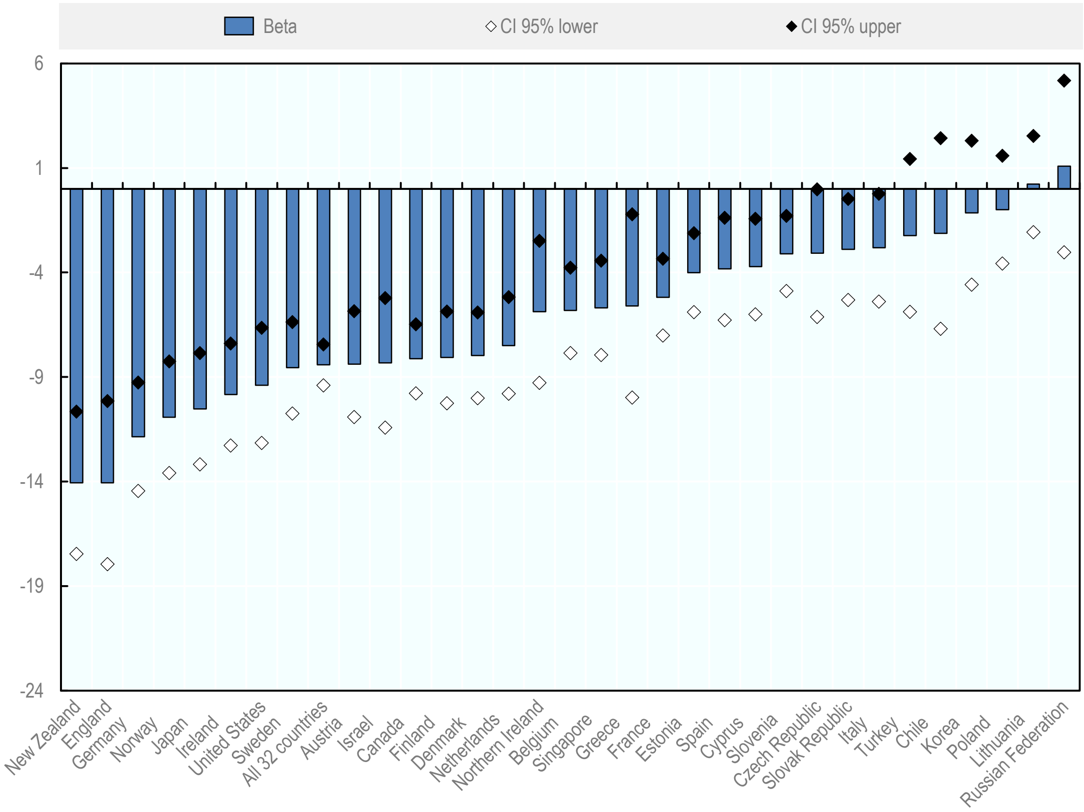
Table 5.1. Partial correlations between individual weekly working hours and the risk of automation

	Model 1		Model 2	
	OLS coefficient	Robust standard errors	OLS coefficient	Robust standard errors
Automatability	-8.42***	0.498	-8.12***	0.51
Age	0.276**	0.113	0.17*	0.11
Age^2	-0.003**	0.001	-0.002	0.00
Female	-7.042***	0.198	-4.91***	0.22
ln(hourly wages)	-1.463***	0.262	-2.49***	0.31
Lower secondary education (ISCED 2, 3c)	0.451	0.578	0.131	0.579
Upper secondary (ISCED 3A-B, C long)	0.514	0.558	-0.149	0.570
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.822	0.743	0.122	0.746
Tertiary/professional degree (ISCED 5B)	0.0939	0.600	0.0037	0.615
Tertiary/bachelor degree (ISCED 5A)	1.491***	0.607	0.502	0.632
Tertiary/master degree (ISCED 5A)	2.732***	0.645	1.754**	0.671
Tertiary/research degree (ISCED 6)	1.980*	1.052	2.054*	1.056
Occupation dummies			Yes	
Industry dummies			Yes	
Country fixed effects	Yes		Yes	
Constant	49.22***	2.317	58.02***	3.00
Observations	66 671		66 671	
R-squared	0.178		0.25	

Note: All observations weighted using survey weights. Significant at: *** p<0.01, ** p<0.05, * p<0.1. The sample includes prime-age workers from 32 OECD countries.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 5.2. Country-specific partial correlations between working hours and automatability

OLS coefficients and confidence intervals



Note: Results from country-specific OLS regressions including controls for age, age squared, gender, hourly wages and educational attainment (Model 1 of Table 5.1). 95% confidence intervals are estimated using robust standard errors. All observations are weighted using survey weights. The samples include prime-age workers only.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

70. Turning to the relationship between wages and the risk of automation, PIAAC includes information on hourly wages including bonuses. In the regression analysis, the natural log of hourly wages is used as a dependent variable; hence the coefficients can be interpreted as semi-elasticities. For the full sample, the difference in hourly wages between the least and the most automatable job is 43% (Table 5.2). In other words, 10 percentage points higher automatability corresponds with 4.3% lower hourly earnings ceteris paribus. Including occupation and industry controls does not change the correlation between wages and the risk of automation substantially. To check for cross-country differences, the relationship is estimated country-by-country (Figure 5.3). The relationship is significant and economically large in all countries but the United States and the Russian Federation. The relationship is most pronounced in the three Asian countries surveyed in PIAAC: Japan, Singapore and Korea.

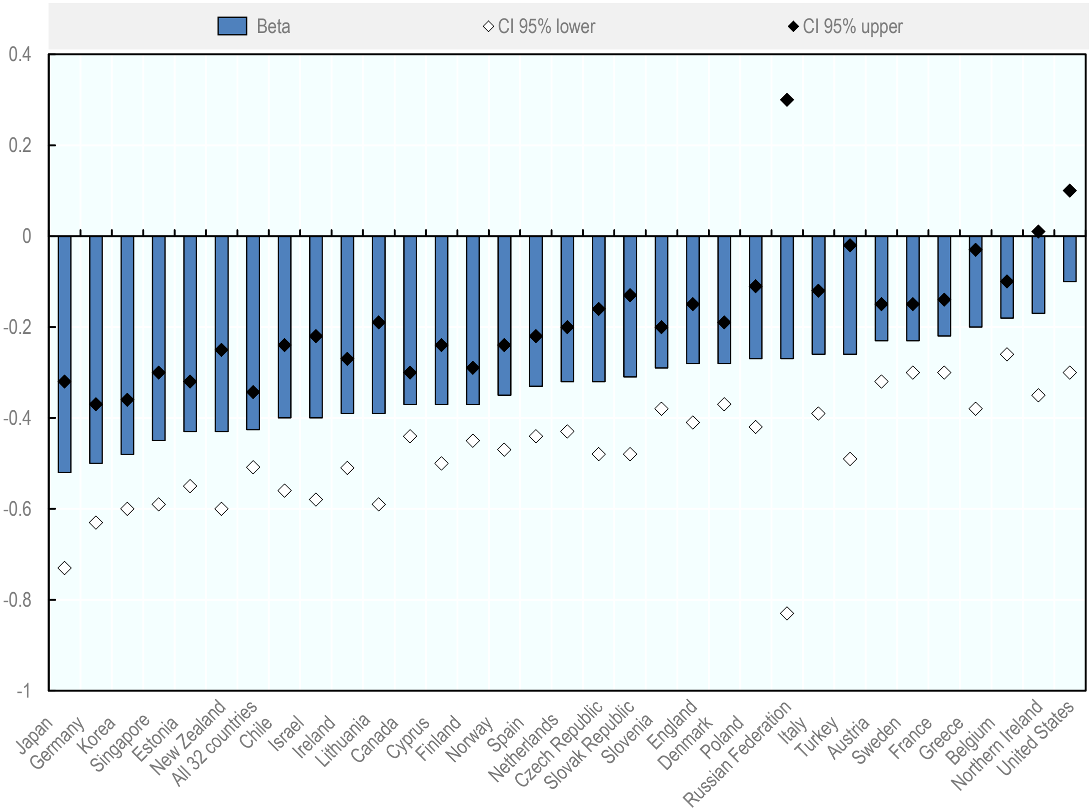
Table 5.2. Partial correlations between individual wages and risk of automation

	Model 1		Model 2	
	OLS coefficients	Robust standard errors	OLS coefficient	Robust standard errors
Automatability	-0.426***	0.042	-0.32***	0.04
Age	0.0681***	0.009	0.05***	0.08
Age^2	-0.001***	0.0001	-0.001***	0.00
Female	-0.271***	0.0152	-0.18***	0.02
Working hours	-0.00538***	0.001	-0.009***	0.00
Lower secondary education (ISCED 2, 3c)	0.209***	0.0471	0.169***	0.041
Upper secondary (ISCED 3A-B, C long)	0.328***	0.0268	0.223***	0.026
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.425***	0.0384	0.297***	0.038
Tertiary/professional degree (ISCED 5B)	0.506***	0.0316	0.324***	0.029
Tertiary/bachelor degree (ISCED 5A)	0.723***	0.0288	0.463***	0.032
Tertiary/master degree (ISCED 5A)	0.826***	0.0323	0.541***	0.039
Tertiary/research degree (ISCED 6)	0.846***	0.078	0.588***	0.077
Occupation dummies			Yes	
Industry dummies			Yes	
Country fixed effects	Yes		Yes	
Constant	1.642***	0.193	2.35	0.24
Observations	66 671		66 671	
R-squared	0.92		0.93	

Note: Results from OLS regression. All observations weighted using survey weights. Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 5.3. Country-specific partial correlations between wages and automatability

OLS coefficients and confidence intervals



Note: Results from country-specific OLS regressions including controls for age, age squared, gender, working hours and educational attainment (Model 1 of Table 5.2). 95% confidence intervals are estimated using robust standard errors. All observations are weighted using survey weights. The samples include prime-age workers only.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

5.2. FO automatability vs. ALM automatability

71. The validity of the FO's engineering bottlenecks as a predictor of labour market trends compared to older measures based on the distinction among routine, non-routine and interactive tasks is tested in this section using the BIBB/IAB and BIBB/BAuA Surveys 2006 and 2012. Section 3. explains how the FO measure of automatability is constructed. For a concept of automatability in line with that developed by ALM, routine and non-routine tasks are identified following Antonczyk et al. (2008). These are then used in place of the variables corresponding to FO's engineering bottlenecks in the logit model. The logit regression models the probability of automation as a function of job tasks. Annex B has the details of the estimations.

72. In a second step, working hours are modelled as a function of automatability, hourly wages, age, gender and education, once for FO and once for ALM automatability

in each survey wave.[24] The results for the case of working hours are presented in Table 5.3. In 2006, ALM and FO automatability both render similar estimated coefficients: 10 pp higher FO automatability corresponds to 0.18 fewer hours worked and 10 pp higher ALM automatability corresponds to 0.16 fewer hours worked. The differences between the two coefficients are not statistically significant. In 2012, the differences seem greater: 10 pp higher FO automatability corresponds to 0.2 fewer hours a week, while 10 pp higher ALM automatability corresponds to 0.09 fewer hours a week.[25] However, these coefficients are also not statistically significantly different from each other. The difference in the R-squared (0.218 vs. 0.216 in 2012) furthermore suggests that there is only a marginal improvement in the model fit when FO is used instead of the ALM tasks in 2012 (and no improvement in 2006).

73. Differences between the FO and the ALM estimates in the case of hourly wages are also found not to be statistically significant (Table 5.4): 10 pp higher automatability corresponds with 25-27% lower gross hourly wages in the case of FO automatability and with 23 to 30% lower wages in the case of ALM automatability. Judging by the R-squared, the ALM model is marginally preferred in 2006 (0.272 for ALM vs. 0.268 for FO), and the FO model is marginally preferred in 2012 (0.254 for FO vs. 0.252 for ALM).

74. To summarise, when applied to German data between 2006 and 2012, the more recent approach to measuring the risk of automation through identifying engineering bottlenecks developed by FO yields similar predictions of labour market outcomes to the routine-based approach of ALM. Both approaches show that higher estimated automatability is associated with fewer working hours and lower hourly wages at the individual level, ceteris paribus. A slight shift in predictive power is observed over time, with the routine-based approach fitting the data better in 2006 and the bottlenecks approach providing a better fit in 2012, but the difference is only marginal.

[24] These estimates probability suffer from the typical omitted variable biases such as potential correlations between unobserved individual characteristics and our measures of automatability. However, since both estimates (FO and ALM) are probability equally affected by these, the difference between two should still be informative.

[25] It is striking that the coefficients of automatability with respect to working hours are substantially smaller than the ones estimated using the PIAAC. We are not sure what causes this difference, but most likely this is due to the differences in the automatability variables between PIAAC and BIBB. The coefficients of “female” and “education” have comparable magnitudes between the BIBB and the PIAAC, suggesting that the discrepancy is not due to differences in the definition of working hours.

Table 5.3. Comparing the relationships between individual working hours, FO and ALM automatability

	(1)	(2)	(3)	(4)
VARIABLES	2006	2012	2006	2012
Automatability (FO)	-1.771***	-1.950***		
	(0.336)	(0.367)		
Automatability (ALM)			-1.574***	-0.945***
			(0.326)	(0.353)
Age	-0.785***	-0.695***	-0.783***	-0.700***
	(0.103)	(0.118)	(0.103)	(0.118)
Age^2	0.00955***	0.00837***	0.00953***	0.00841***
	-0.00127	-0.00142	-0.00127	(0.00143)
Female	-8.324***	-8.261***	-8.357***	-8.294***
	(0.161)	(0.168)	(0.162)	(0.169)
ln(gross hourly wages)	0.396*	-0.771**	0.386*	-0.680**
	(0.231)	(0.308)	(0.232)	(0.309)
Vocational qualification	2.301***	2.214***	2.331***	2.268***
	(0.377)	(0.438)	(0.377)	(0.439)
Technical college	3.227***	3.589***	3.252***	3.660***
	(0.431)	(0.484)	(0.431)	(0.485)
University	2.734***	3.292***	2.743***	3.410***
	(0.409)	(0.485)	(0.411)	(0.487)
Constant	59.57***	61.36***	59.49***	60.70***
	(2.154)	(2.494)	(2.151)	(2.501)
Observations	13,769	12,192	13,769	12,192
R-squared	0.231	0.218	0.231	0.216

Note: Results from OLS regressions. Robust standard errors in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Table 5.4. Comparing the relationships between individual hourly wages, FO and ALM automatability

	(1)	(2)	(3)	(4)
VARIABLES	2006	2012	2006	2012
Automatability (FO)	-0.267***	-0.251***		
	(0.0171)	(0.0175)		
Automatability (ALM)			-0.300***	-0.230***
			(0.0163)	(0.0173)
Age	0.0462***	0.0350***	0.0467***	0.0347***
	(0.00496)	(0.00555)	(0.00495)	(0.00555)
Age^2	-0.000464***	-0.000330***	-0.000469***	-0.000327***
	(6.23E-05)	(6.86E-05)	(6.21E-05)	(6.86E-05)
Female	-0.216***	-0.214***	-0.222***	-0.220***
	(0.0094)	(0.0103)	(0.00937)	(0.0103)
Working hours	0.00108*	-0.00195**	0.00105*	-0.00172**
	(0.00063)	(0.00079)	(0.00063)	(0.00079)
Vocational qualification	0.179***	0.140***	0.180***	0.142***
	(0.0173)	(0.0223)	(0.0173)	(0.0223)
Technical college	0.352***	0.360***	0.347***	0.361***
	(0.0218)	(0.0248)	(0.0218)	(0.0249)
University	0.564***	0.542***	0.552***	0.541***
	(0.0184)	(0.0235)	(0.0185)	(0.0236)
Constant	1.776***	2.193***	1.797***	2.191***
	(0.105)	(0.125)	(0.105)	(0.125)
Observations	13,769	12,192	13,769	12,192
R-squared	0.268	0.254	0.274	0.252

Notes: Results from OLS regressions. Robust standard errors in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

6. Changes in the task content of jobs over time: evidence from Germany and the United Kingdom

75. PIAAC is the first international survey to include a comprehensive assessment of the tasks that employees perform in their jobs and the skills required for these tasks. Its predecessors, IALS and ALL do not include sufficient information to identify time trends in the risk of automation. To fill this gap, country-specific sources exist for the UK and Germany dating back to the 1970s (Germany) and the 1980s (UK). This Section analyses the changes in task-content of jobs in these two countries over a more recent period 1997-2012 in UK and 1999-2012 in Germany. These are the periods for which comparable skill survey data can be identified in three broad skill domains: manual, social and analytical. Nevertheless, trends in these two countries cannot be generalised to other PIAAC participants as they may depend on factors such as the penetration and adoption of technology, the productive structure, and the position of the countries in global value chains.

6.1. Skill trends in the United Kingdom 1997-2012

76. The UK Skills Survey (Felstead, Gallie and Green 2014) offers a rich description of the content of jobs held by British employees in the most recent decade and a half. Table 6.1 describes the variables that broadly correspond to manual, analytical and social skills at the job.

77. Table 6.2 shows the correlations among the skills and tasks covered by the survey. Manual skills correlate positively with other manual skills and negatively with social skills (e.g., dealing with people and influencing). This means that people who specialise in manual skills are less likely to use social interaction skills at the job. These skills also correlate negatively with literacy, numeracy and self-planning. However, manual workers do perform problem-solving in their jobs, and in particular the part of problem-solving that has to do with detection of a problem/fault and detection of the cause that triggered the problem. At the same time, manual workers are less likely to engage in problem-solving that works out a solution for the problem. One could say that manual workers spend more time on diagnosing problems and less time on actual problem-solving. They spend more time in interacting with objects than with people. Finally, they have less influence over the work content of their jobs than do people that specialise in social and analytical skills.

78. Social skills coincide with other social skills and also with analytical skills. This is important to emphasize: jobs that require analytical work, also require significant amount of social interaction and vice versa. Let’s take as an example the skill of influencing, which we broadly categorized as a social skill. Employees, who report that this skill is important for their job, also report a fair deal of teamwork, dealing with people, advising, communicating, but also complex problem-solving, thinking ahead, detecting problems, identifying the cause of problems and figuring out a solution to

a problem. All these co-occurrences are measured at the individual level and this suggests that social and analytical tasks are complements in day-to-day work.

79. Turning to the trends in the demand for manual, analytical and social skills in the UK between 1997 and 2012, three binary variables are created for the purpose of the analysis[26]:

- Manual skills equals 1 if at least one of these variables was indicated as very important or essential: physical stamina, physical strength or accurate working with fingers/hands. Otherwise it equals 0.
- Analytical skills equals 1 if at least one of these variables was indicated as very important or essential: problem-solving, complex problem solving or thinking ahead. Otherwise it equals 0.
- Social skills equals 1 if at least one of these variables was indicated as very important or essential: team work, dealing with people or counselling/advising/caring for others. Otherwise it equals 0.

80. Skill demands in the three skill domains are then estimated as a function of time. The reference year is taken to be 1997 and skill demand in 2001, 2006 and 2012 is expressed as difference relative to the reference year. Logit models are estimated since the three general skills are defined as binary variables. The variables of interest are the year dummies (2001, 2006 and 2012), while 1997 is the reference year against which the trend is estimated.

81. Table 6.3 shows the results of estimating these skill requirements as a function of time, while controlling for changes in the age structure and the gender structure of the working population. In the case of manual skills, an increase is observed in 2001, but the trend reverses in 2006 and becomes significantly negative in 2012. In the case of analytical skills, a strong positive increase can be seen throughout the whole period. Finally, in the case of social skills, an increase is found in 2006 and 2012, while the difference between 1997 and 2001 is not significant. Overall, it seems that there is a trend towards higher incidence of analytical, but also social tasks, and a weaker trend away from the use of manual tasks.

82. Table 6.4, Table 6.5 and Table 6.6 give a more detailed view on the skill trends by domain. The variables of interest are again the year dummies. Table 6.4 shows that the trends in the use of manual skills are more nuanced when looking at sub-categories of manual skills. For instance, there is no trend in the importance of physical strength and physical stamina, but the importance of hands and finger dexterity first increased significantly between 1997 and 2001 and then declined somewhat as of 2012. The trends are more straightforward in the case of social skills (Table 6.5). Here, all indicators of social skills show positive trends either throughout the whole period or in the last two periods (2006 and 2012) except for selling of goods and services, where the trend is not straightforward and is less economically and statistically significant. Similar to the case of social skills, analytical skills show positive trends across the board, either throughout

[26] We chose only three variables for each binary construct in order to stay consistent in the measurement across the three domains. We also chose the three variables that could be consider most general for each domain and we avoided using variables within domains that carry the same type of information (e.g., categorical variable problem-solving and its derived continuous variable problem-solving skills).

the whole period, or staring in 2006. One exception are the skills of diagnosing problems (problem/fault spotting and problem/fault cause detection). Here we see no change between 1997, 2001 and 2006 and a notable negative change in 2012.

83. Finally, these changes are decomposed using a shift share analysis into between-occupational and within-occupational changes (

84. Table 6.7). We find that the observed decline in the use of manual skills is mainly a result of the changes in the occupational structure of the economy, which has been shifting away from occupations that specialise in manual tasks throughout the observed period. Within occupations, the manual skill demands first increased between 1997 and 2001 and then declined. Overall, these dynamics translate into an average increase and then decline in the use of manual skills at the job. The use of analytical skills increased mainly because analytical tasks gained in importance within the same occupations. In addition to this, there is a trend towards expanding the occupations that specialise in analytical tasks (between changes). Social skills became more prevalent mainly by increasing the within-occupational importance of these tasks.

Table 6.1. Manual, social and analytical tasks and skills in the UK Skills Survey

Variable	Description	Unique values	Mean	Min	Max	Obs
Manual skills						
Physical strength	Importance: physical strength	5	2.67	1	5	16,841
Physical stamina	Importance: physical stamina	5	2.92	1	5	16,841
Using hands/fingers	Importance: skill or accuracy in using hands/fingers	5	3.02	1	5	16,841
Physical skills	Physical skills	17	1.98	0	4	16,841
Social skills						
Teamwork	Importance: working with a team	5	4.07	1	5	16,841
People work	Importance: dealing with people	5	4.44	1	5	16,841
Teaching	Importance: teaching people (individuals or groups)	5	3.45	1	5	16,841
Persuading/influencing	Importance: persuading or influencing others	5	3.25	1	5	16,841
Selling	Importance: selling a product or service	5	2.73	1	5	16,841
Counselling/advising/caring	Importance: counselling, advising, caring for customers	5	3.56	1	5	16,841
Influence skills	Influence skills	21	2.19	0	4	16,841
Communication skills	Client communication skills	17	2.64	0	4	16,841
Analytical skills						
Problem/fault-spotting	Importance: spotting problems or faults	5	4.13	1	5	16,841
Problem/fault-cause detect	Importance: working out cause of problems/ faults	5	3.89	1	5	16840
Problem-solving	Importance: thinking of solutions to problems	5	3.94	1	5	16,841
Complex problem-solving	Importance: analyzing complex problems in depth	5	3.25	1	5	16,841
Planning	Importance: planning the activities of others	5	2.84	1	5	16,841
Thinking ahead	Importance: thinking ahead	5	4.13	1	5	16,841
Literacy	Literacy	25	2.54	0	4	16,841
Numeracy	Numeracy	14	1.88	0	4	16,841
Self-planning skills	Self-planning skills	13	3.02	0	4	16,841
Problem-solving skills	Problem-solving skills	17	2.8	0	4	16,841

Source: UK Skills Survey 1997, 2001, 2006, 2012

Table 6.2. Correlations among manual, analytical and social skills in the UK Skills Survey

Variable	Var No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Physical strength	1																					
Physical stamina	2	0.75																				
Using hands/fingers	3	0.51	0.48																			
Physical skills	4	0.82	0.80	0.82																		
Teamwork	5	(0.01)	0.03	0.01	0.03																	
People work	6	(0.11)	(0.04)	(0.12)	(0.12)	0.26																
Teaching	7	0.01	0.07	0.03	0.06	0.42	0.33															
Persuading/influencing	8	(0.13)	(0.04)	(0.11)	(0.11)	0.32	0.40	0.48														
Selling	9	(0.00)	0.02	0.02	0.01	0.07	0.30	0.16	0.33													
Counselling/advising/caring	10	(0.06)	0.02	(0.05)	(0.04)	0.25	0.52	0.35	0.41	0.37												
Influence skills	11	(0.10)	(0.00)	(0.06)	(0.06)	0.52	0.44	0.78	0.79	0.28	0.46											
Communication skills	12	(0.02)	0.03	0.03	0.03	0.25	0.64	0.35	0.47	0.78	0.76	0.49										
Problems/fault-spotting	13	0.07	0.09	0.21	0.21	0.23	0.12	0.27	0.23	0.10	0.14	0.30	0.23									
Problems/fault-cause detection	14	0.05	0.07	0.22	0.19	0.22	0.14	0.31	0.29	0.14	0.17	0.37	0.27	0.75								
Problem-solving	15	(0.03)	0.03	0.13	0.10	0.24	0.23	0.35	0.41	0.18	0.24	0.47	0.34	0.63	0.75							
Complex problem-solving	16	(0.13)	(0.06)	0.03	(0.03)	0.25	0.25	0.37	0.47	0.18	0.28	0.54	0.35	0.41	0.51	0.62						
Planning	17	0.00	0.07	0.00	0.03	0.36	0.28	0.51	0.50	0.19	0.31	0.77	0.33	0.24	0.31	0.37	0.40					
Thinking ahead	18	(0.01)	0.06	0.03	0.04	0.23	0.35	0.33	0.43	0.16	0.29	0.51	0.35	0.31	0.35	0.46	0.43	0.44				
Literacy	19	(0.21)	(0.13)	(0.09)	(0.14)	0.33	0.36	0.40	0.50	0.16	0.38	0.61	0.39	0.34	0.37	0.48	0.58	0.44	0.50			
Numeracy	20	(0.15)	(0.11)	0.01	(0.05)	0.14	0.15	0.22	0.31	0.23	0.15	0.36	0.29	0.28	0.32	0.37	0.43	0.29	0.30	0.44		
Self-planning skills	21	(0.09)	(0.00)	(0.03)	(0.04)	0.21	0.37	0.33	0.47	0.19	0.32	0.55	0.38	0.30	0.36	0.48	0.47	0.50	0.84	0.55	0.33	
Problem-solving skills	22	(0.02)	0.03	0.17	0.13	0.28	0.23	0.39	0.43	0.18	0.25	0.51	0.36	0.80	0.89	0.89	0.78	0.40	0.47	0.54	0.42	0.49

Note: Correlations are measured across all years and are weighted using final survey probability weights.
Source: UK Skills Survey 1997, 2001, 2006, 2012.

Table 6.3. Skill trends in the UK 1997-2012

	(1)	(2)	(3)
VARIABLES	Manual	Analytical	Social
2001 dummy	0.145***	0.369***	0.0648
	(0.0484)	(0.0887)	(0.129)
2006 dummy	-0.046	0.465***	0.379***
	(0.06)	(0.059)	(0.102)
2012 dummy	-0.188**	0.486***	0.505***
	(0.0955)	(0.143)	(0.168)
Female	-0.295***	-0.474***	0.532***
	(0.0425)	(0.0762)	(0.0866)
Age	0.00577**	0.00543	-0.00021
	(0.00236)	(0.00345)	(0.00483)
Constant	0.21	1.616***	2.421***
	(0.136)	(0.174)	(0.211)
Observations	16,249	16,249	16,249
Wald chi2	98.8	202.4	55.56
Pseudo R2	0.00687	0.0128	0.0127
Log pseudolikelihood	-11 025	-6 025	-3 363

Note: The sample includes employees between 20 and 65 years old. Results from logit models. Standard errors clustered by region in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: UK Skills Survey 1997, 2001, 2006, 2012

Table 6.4. Manual skills trends in the UK 1997-2012

	(1)	(2)	(3)	(4)
VARIABLES	Physical strength	Physical stamina	Using hands/fingers	Physical skills
Model	O. logit	O. logit	O. logit	OLS
2001 dummy	0.0106	0.00183	0.243***	0.0596**
	(0.0436)	(0.0578)	(0.0368)	(0.0249)
2006 dummy	0.0461	0.027	0.04	-0.0186
	(0.061)	(0.0599)	(0.0531)	(0.034)
2012 dummy	0.0383	-0.0438	-0.0906**	-0.0736**
	(0.0417)	(0.0575)	(0.0371)	(0.0247)
Female	-0.421***	-0.322***	-0.473***	-0.381***
	(0.0498)	(0.0435)	(0.0422)	(0.0335)
Age	0.00132	0.00735***	0.00442**	0.00297*
	(0.00237)	(0.002)	(0.00204)	(0.00145)
Constant cut1	-1.036***	-1.087***	-1.121***	
	(0.181)	(0.112)	(0.161)	
Constant cut2	-0.0843	-0.199**	-0.243	
	(0.156)	(0.101)	(0.156)	
Constant cut3	0.734***	0.704***	0.351**	
	(0.147)	(0.101)	(0.146)	
Constant cut4	1.628***	1.744***	1.084***	
	(0.157)	(0.1)	(0.135)	
Constant				2.018***
				(0.103)
Observations	16,249	16,249	16,249	16,249
R-squared				0.028
Wald chi2	195.5	104.9	471.7	
Pseudo R2	0.00445	0.00329	0.00715	
Log pseudo likelihood	-25,545	-25,990	-25,555	
F				69.95
Adj. R2				0.0278

Note: The sample includes employees between 20 and 65 years old. Standard errors clustered by region in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. Final survey weights are used as probability weights.
Source: UK Skills Survey 1997, 2001, 2006, 2012

Table 6.5. Social skills trends in the UK 1997-2012

	-1	-2	-3	-4	-5	-6	-7	-8
VARIABLES	Teamwork	People work	Teaching	Persuading influencing	Selling	Counselling caring	Influence skills	Communication skills
Model	O. logit	O. logit	O. logit	O. logit	O. logit	O. logit	OLS	OLS
2001 dummy	0.0692**	-0.0304	0.103	0.0262	-0.0904**	0.118***	0.0739*	0.0232
	(0.0335)	(0.0491)	(0.0646)	(0.0539)	(0.0374)	(0.0234)	(0.0341)	(0.0205)
2006 dummy	0.301***	0.203***	0.248***	0.288***	0.000336	0.161***	0.204***	0.102***
	(0.0352)	(0.0616)	(0.0758)	(0.0565)	(0.0402)	(0.0366)	(0.0306)	(0.0175)
2012 dummy	0.298***	0.487***	0.401***	0.309***	0.0994*	0.199***	0.239***	0.163***
	(0.0589)	(0.0881)	(0.0745)	(0.054)	(0.0578)	(0.0454)	(0.031)	(0.0243)
Female	0.316***	0.627***	0.181***	-0.200***	-0.152***	0.631***	-0.0313	0.0771***
	(0.0355)	(0.0439)	(0.0368)	(0.0527)	(0.0363)	(0.0341)	(0.0203)	(0.0169)
Age	-0.0116***	0.000137	0.00026	0.00201	-0.00292	0.00490***	-0.00017	8.72E-05
	(0.00149)	(0.00236)	(0.00177)	(0.00192)	(0.00217)	(0.00157)	(0.00107)	(0.00098)
Constant							2.089***	2.533***
							(0.0607)	(0.0511)
Observations	16,249	16,249	16,249	16,249	16,249	16,249	16,249	16,249
R-squared							0.008	0.005
Wald chi2	227	1336	162	68.44	29.9	864.9		
Pseudo R2	0.00636	0.0149	0.00256	0.00292	0.00108	0.0107		
Log pseudo likelihood	-20,741	-16,241	-25,158	-25,410	-24,370	-23,845		
F							42.21	13.74
Adj. R2							0.00806	0.00497

Note: The sample includes employees between 20 and 65 years old. Standard errors clustered by region in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. Final survey weights are used as probability weights

Source: UK Skills Survey 1997, 2001, 2006, 2012

Table 6.6. Analytical skills trends in the UK 1997-2012

	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
VARIABLES	Problems / fault-spotting	Problems/ fault-cause detection	Problem-solving	Complex problem-solving	Planning	Thinking ahead	Literacy	Numerac y	Self-planning skills	Problem -solving skills
Model	O. logit	O. logit	O. logit	O. logit	O. logit	O. logit	OLS	OLS	OLS	OLS
2001 dummy	0.0434	0.0822	0.129*	0.0337	0.0506	0.119***	0.0990***	0.0971*	0.0996***	0.0702*
	(0.0626)	(0.0691)	(0.0751)	(0.0581)	(0.0576)	(0.0413)	(0.0303)	(0.0452)	(0.0261)	(0.0364)
2006 dummy	-0.0484	-0.00136	0.205***	0.390***	0.157***	0.279***	0.224***	0.130***	0.177***	0.115***
	(0.0573)	(0.0625)	(0.0568)	(0.0524)	(0.0469)	(0.0338)	(0.0193)	(0.0344)	(0.0265)	(0.0326)
2012 dummy	-0.207***	-0.203***	0.118**	0.400***	0.137***	0.317***	0.203***	0.186***	0.176***	0.0505
	(0.0794)	(0.0707)	(0.0571)	(0.0534)	(0.0439)	(0.0739)	(0.0484)	(0.0385)	(0.0371)	(0.0395)
Female	-0.288***	-0.434***	-0.439***	-0.506***	-0.148***	-0.0573	0.025	-0.394***	-0.0349	-0.284***
	(0.0239)	(0.0326)	(0.0444)	(0.0298)	(0.0431)	(0.0437)	(0.0266)	(0.0224)	(0.0272)	(0.0167)
Age	0.00406	0.00559** *	0.00354* *	0.00040 3	0.00772** *	0.00549** *	0.00312** *	-0.00123	0.00424** *	0.00142
	(0.0026)	(0.0017)	(0.0017)	(0.0018)	(0.0022)	(0.0015)	(0.0008)	(0.001)	(0.0008)	(0.0012)
Constant							2.260***	2.035***	2.740***	2.811***
							(0.0601)	(0.0555)	(0.0541)	(0.0555)
Observation s	16,249	16,248	16,249	16,249	16,249	16,249	16,249	16,249	16,249	16,249
R-squared							0.007	0.024	0.007	0.023
Wald chi2	803.9	230.7	199.5	460.9	46.81	196.8				
Pseudo R2	0.00345	0.00648	0.00595	0.00945	0.00164	0.00205				
Log pseudolik.	-20,226	-22,366	-21,781	-25,547	-25,997	-20,265				
F							56.91	69.76	51.05	163.9
Adj. R2							0.00634	0.0242	0.00716	0.0227

Note: The sample includes employees between 20 and 65 years old. Standard errors clustered by region in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. Final survey weights are used as probability weights.
Source: UK Skills Survey 1997, 2001, 2006, 2012

Table 6.7. Shift-share analysis of skill use in the UK 1997-2012

	Manual			Analytical			Social		
	Between	Within	Total	Between	Within	Total	Between	Within	Total
1997-2001	-0.01	0.05	0.04	0.01	0.03	0.04	0	0	0.01
1997-2006	-0.02	0	-0.02	0.01	0.04	0.04	0	0.01	0.02
1997-2012	-0.02	-0.04	-0.06	0.01	0.04	0.05	0.01	0.02	0.03

Note: The variance is decomposed between and within 2-digit ISCO-88 occupations (26 occupational groups)
Source: UK Skills Survey 1997, 2001, 2006, 2012

6.2. Skill trends in Germany 1999-2012

85. While there are no perfectly comparable variables between the German and the UK Skill Surveys, variables that broadly fall within the domains of manual, analytical and social skills can be identified in the German BIBB/IAB BIBB/BAuA Surveys (Table 6.8). In addition to this, in order to refine measurements, two variables are added which are expected to be perfectly negatively correlated with the use of analytical skills at work : performing repetitive tasks and performing tasks that are fully prescribed and performed by following strict manuals (explicit tasks).

Table 6.8. Manual, social and analytical tasks and skills in the German Skills Survey

Variable	Description	Unique values	Mean	Min	Max	Obs
Manual skills						
Heavy-lifting	Frequency: Lifting heavy objects	2	0.22	0	1	70,758
Repair	Frequency: Repair	2	0.16	0	1	70,758
Manufacture	Frequency: Manufacture, produce goods	2	0.15	0	1	70,758
Analytical skills						
Repetitive tasks (negatively linked to analytical skills)	Frequency: Repetitive work processes	2	0.46	0	1	70,758
Explicit tasks (negatively linked to analytical skills)	Frequency: Work process is prescribed in all possible details	2	0.26	0	1	70,758
Immerse	Frequency: Immerse yourself in a task/problem to accomplish it	2	0.39	0	1	70,758
Process improvement	Frequency: Improve existing processes, invent new things	2	0.27	0	1	70,758
Information assessment	Frequency: Collect, research, document information	2	0.44	0	1	70,758
Development	Frequency: Develop, research, construct	2	0.09	0	1	70,758
Social skills						
Advise	Frequency: Consult and inform	2	0.58	0	1	70,758
Teach	Frequency: Educate, teach, upbring	2	0.2	0	1	70,758
Procure, sell	Frequency: Procure, sell	2	0.24	0	1	70,758
Organise	Frequency: Organise, plan work processes	2	0.39	0	1	70,758

Note: All variables are transformed to be binary in order to ensure comparability between survey waves. 1 means that a task is performed frequently, very frequently or always, 0 means that a task is performed sometimes, seldom or never
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

86. Table 6.9 shows the correlations among the variables. Similar to what was found in the case of the UK, manual skills are positively correlated among each other, but they are negatively correlated with analytical and social skills. The German data does not make the distinction between diagnosing a problem and acting upon it, so here we cannot observe such more nuanced co-occurrences. Analytical skills are correlated with other analytical skills and they are negatively correlated with repetitive and explicit tasks. They also correlate with social skills (advising, teaching and organizing), but less with sales and procurement.

Table 6.9. Correlations among manual, analytical and social skills in the German Skills Survey

Variable	Var No.	1	2	3	4	5	6	7	8	9	10	11	12
Heavy-lifting	1												
Repair	2	0.21											
Manufacture	3	0.14	0.17										
Repetitive tasks	4	0.13	(0.02)	0.09									
Explicit tasks	5	0.13	0.03	0.11	0.38								
Immerse	6	(0.04)	0.06	0.00	(0.17)	(0.07)							
Process improvement	7	(0.02)	0.04	0.04	(0.12)	(0.08)	0.41						
Information assessment	8	(0.16)	(0.09)	(0.11)	(0.17)	(0.15)	0.27	0.25					
Development	9	(0.08)	0.02	0.06	(0.14)	(0.10)	0.21	0.26	0.22				
Advise	10	(0.14)	(0.08)	(0.14)	(0.15)	(0.16)	0.21	0.20	0.37	0.11			
Teach	11	(0.03)	(0.01)	(0.04)	(0.11)	(0.10)	0.15	0.22	0.23	0.12	0.27		
Procure, sell	12	0.02	0.02	0.02	(0.00)	(0.08)	(0.00)	0.04	0.05	(0.01)	0.23	0.02	
Organize	13	(0.05)	(0.00)	(0.01)	(0.14)	(0.14)	0.22	0.26	0.33	0.14	0.31	0.27	0.19

Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

87. Following the same approach as for the UK Skills Survey, three binary variables corresponding with the domains of manual, analytical and social skills are created:

- Manual skills takes a value of 1 if one of these skills/tasks was reported to be used frequently: heavy-lifting, repair or manufacturing. Otherwise it takes a value of 0.
- Analytical skills takes a value of 1 if one of these variables was reported to be used frequently: development, information assessment or process improvement. Otherwise it takes a value of 0.
- Social skills takes a value of 1 if one of these variables was reported to be used frequently: teaching, advising or organizing. Otherwise it takes a value of 0.

Table 6.10 shows the results of estimating logit regressions that model the requirements of manual, analytical and social skills as a function of time. Here as well, knowing that the workforce has been changing in terms of gender and age structure, the impact of gender and age is controlled for. The variables of interest are the 2006 and 2012 time dummies. They show the average changes in the frequency of skill use compared to 1999, the reference year. In the case of manual skills, we observe a decline in 2006, and no significant additional change in 2012. In the case of analytical skills, we observe very rapid growth, both in 2006 and in 2012. Among the social skills, notable increase in their frequency is observed in both periods. A more nuanced version of the manual task trends (Table 6.11) shows that the general negative trend is driven by the lower frequency of heavy-lifting over time. Repair has not experienced any changes, while, surprisingly, the frequency of tasks related to the manufacturing of goods has intensified between 1999 and 2012. The more detailed estimates of trends among social skills (Table 6.12) show consistent increase of all social skills (advising, teaching and organizing), except for sales and procurement, which show a negative trend. Finally, we see strong positive trends across all analytical tasks: immersing, process improvement, information assessment and development (Table 6.13). Among the “anti-analytical” tasks, we see a decline in the explicit tasks, but an increase in the reporting of repetitive work.

88. To summerise, in Germany, strong unambiguous trends towards more analytical and more social skills at the workplace are found. The trends of manual skills, however, are mixed. Job tasks involving heavy-lifting have been consistently declining between 1999 and 2012, but production tasks more generally, having increased, not declined.

89. Lastly, the observed trends are decomposed into between and within-occupational changes using shift-share analysis (Table 6.14). Similar to the case of the UK, manual skills mainly declined by shifting away from occupations that specialise in these skills, while within occupations, the use of manual skills even increased somewhat. Analytical skills, on the other hand, mainly increased as a result of changes in skill requirements within occupations. This as well is similar to what was observed in the case of the UK. In addition to within-occupational changes, shifts towards occupations that employ analytical skills also contributed to the overall increase. Finally, social skills increased significantly both within and between occupations.

Table 6.10. Skill trends in Germany 1999-2012

	(1)	(2)	(3)
VARIABLES	Manual	Analytical	Social
2006 dummy	-0.0762***	0.893***	0.416***
	(0.0166)	(0.0437)	(0.0382)
2012 dummy	-0.039	0.990***	0.476***
	(0.0246)	(0.043)	(0.0359)
Female	-0.922***	-0.252***	0.125***
	(0.0229)	(0.0385)	(0.035)
Age	-0.0142***	0.00453***	0.00464***
	(0.00119)	(0.00141)	(0.00154)
Constant	0.654***	-0.487***	0.224***
	(0.0454)	(0.0632)	(0.0724)
Observations	70,806	70,806	70,806
Wald chi2	4108	1321	205.3
Pseudo R2	0.0408	0.0405	0.0109
Log likelihood	-45748	-46962	-44337

Note: The sample includes employees between 20 and 65 years old. Results from logit regressions. Standard errors clustered by 16 states in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. All observations are weighted using final survey probability weights.
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

Table 6.11. Manual skills trends in Germany 1999-2012

	(1)	-2	-3
VARIABLES	Manual	Analytical	Social
2006 dummy	-0.0762***	0.893***	0.416***
	(0.0166)	(0.0437)	(0.0382)
2012 dummy	-0.039	0.990***	0.476***
	(0.0246)	(0.043)	(0.0359)
Female	-0.922***	-0.252***	0.125***
	(0.0229)	(0.0385)	(0.035)
Age	-0.0142***	0.00453***	0.00464***
	(0.00119)	(0.00141)	(0.00154)
Constant	0.654***	-0.487***	0.224***
	(0.0454)	(0.0632)	(0.0724)
Observations	70,806	70,806	70,806
Wald chi2	4108	1321	205.3
Pseudo R2	0.0408	0.0405	0.0109
Log likelihood	-45748	-46962	-44337

Note: A The sample includes employees between 20 and 65 years old. Results from logit regressions. Standard errors clustered by 16 states in parentheses. Significant at: *** p.
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

Table 6.12. Social skills trends in Germany 1999-2012

	-1	-2	-3	-4
VARIABLES	Advise	Teach	Procure, sell	Organise
2006 dummy	0.322***	0.348***	-0.154***	0.0176
	(0.035)	(0.054)	(0.0265)	(0.0361)
2012 dummy	0.314***	0.350***	-0.181***	0.151***
	(0.0308)	(0.0454)	(0.027)	(0.0415)
Female	0.229***	0.0860**	0.239***	-0.230***
	(0.0278)	(0.0368)	(0.0223)	(0.0188)
Age	0.00651***	0.00976***	0.000342	0.00740***
	(0.00141)	(0.00181)	(0.00053)	(0.00123)
Constant	-0.290***	-2.058***	-1.213***	-0.763***
	(0.0628)	(0.0876)	(0.0215)	(0.0674)
Observations	70,758	70,758	70,758	70,758
Wald chi2	173.3	289	163.9	340.2
Pseudo R2	0.00891	0.00775	0.00313	0.00423
Log likelihood	-47945	-34904	-38538	-46583

Note: Results from logit regressions. Standard errors clustered by 16 states in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. All observations are weighted using final survey probability weights.
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

Table 6.13. Analytical skills trends in Germany 1999-2012

	-1	-2	-3	-4	-5	-6
VARIABLES	Immerse	Process improvement	Information assessment	Development	Repetitive tasks	Explicit tasks
2006 dummy	0.333***	0.351***	0.993***	1.009***	0.158***	-0.508***
	(0.0525)	(0.0535)	(0.051)	(0.0477)	(0.0354)	(0.0266)
2012 dummy	0.326***	0.299***	1.102***	1.108***	0.0815*	-0.343***
	(0.0505)	(0.0553)	(0.0473)	(0.0483)	(0.049)	(0.0386)
Female	-0.530***	-0.328***	-0.112***	-0.688***	0.460***	0.00186
	(0.0224)	(0.0282)	(0.034)	(0.0592)	(0.0166)	(0.0167)
Age	-0.00369***	-0.00214**	0.0101***	-0.00240**	-0.00024	-0.00974***
	(0.00143)	(0.00105)	(0.00142)	(0.00119)	(0.00179)	(0.00199)
Constant	-0.296***	-1.001***	-1.307***	-2.685***	-0.376***	-0.373***
	(0.0525)	(0.0611)	(0.0684)	(0.0947)	(0.065)	(0.0915)
Observations	70,758	70,758	70,758	70,758	70,758	70,758
Wald chi2	832.6	270.8	1432	719.8	1275	605.1
Pseudo R2	0.0151	0.00782	0.0506	0.0422	0.0107	0.0107
Log likelihood	-46028	-39992	-45571	-19443	-48362	-40668

Note: Results from logit regressions. Standard errors clustered by 16 states in parentheses. Significant at: *** p<0.01, ** p<0.05, * p<0.1. All observations are weighted using final survey probability weights.
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

Table 6.14. Shift-share analysis of skill use in Germany 1999-2012

	Manual			Analytical			Social		
Year	Between	Within	Total	Between	Within	Total	Between	Within	Total
2006	-0.05	0.01	-0.04	0.04	0.16	0.19	0.03	0.05	0.08
2012	-0.07	0.01	-0.06	0.04	0.18	0.22	0.04	0.07	0.11

Note: The variance is decomposed between and within 2-digit KldB-92 occupations (86 occupational groups).
Source: BIBB/IAB and BIBB-BAuA Employment Surveys 1999, 2006, 2012

7. How skills use varies across jobs with different degrees of ICT penetration

90. As elabourated in Section 3, skills and technology have historically been considered complements. Better skilled workers adopt technology faster and make better use of it. Technology, on the other hand, requires that workers keep abreast of its developments and updates. Hence, this is not a one-way causation. Skills and technology are mutually reinforcing: skills beget technology and technology begets skills. Although this is not the case with all technologies, e.g., industrial robots directly substitute labour, many current technologies such as laptops and PCs, software, printers, and phones, are complement to skilled workers. This section sheds light on the skills that are complemented by ICT and those that are not.

91. This section uses data from PIAAC, which asked the participants about the use of ICT at home and at work. More specifically, the survey asked: Do you use a computer[27] in your current job? Those who responded affirmatively were then asked about the frequency of e-mail, internet, spreadsheet, Word processor, computer coding and online conversations. The survey also asked respondents about the level of computer use: straightforward, moderate or complex.[28] Identical questions were asked for the use of computers in everyday life. Based on these original questions, a composite ICT variable for the use of ICT at work and in everyday life was derived by the OECD summing individual scales and using Cronbach's alpha to test the consistency of the variables included. [29]The final index constructed this way ranges between 1 and 5 and higher values indicate higher frequency of ICT use. This is variable used in the analysis below.

7.1. Computers and education

92. Figure 7.1 shows the relationship between computer use and the level of education. The figure plots the distributions of the shares of computer users by occupation, by educational requirements of the occupation. Only 23% of the workers in occupations that typically require lower secondary education or less say they use computers at work. This share rapidly increases with required education and it reaches

27 This includes cell-phones and other hand-held electronic devices that are used to connect to the internet, check e-mails etc. Computer can be a mainframe, desktop or laptop computer, or any other device that can be used to do such things as sending or receiving e-mail messages, processing data or text, or finding things on the internet.

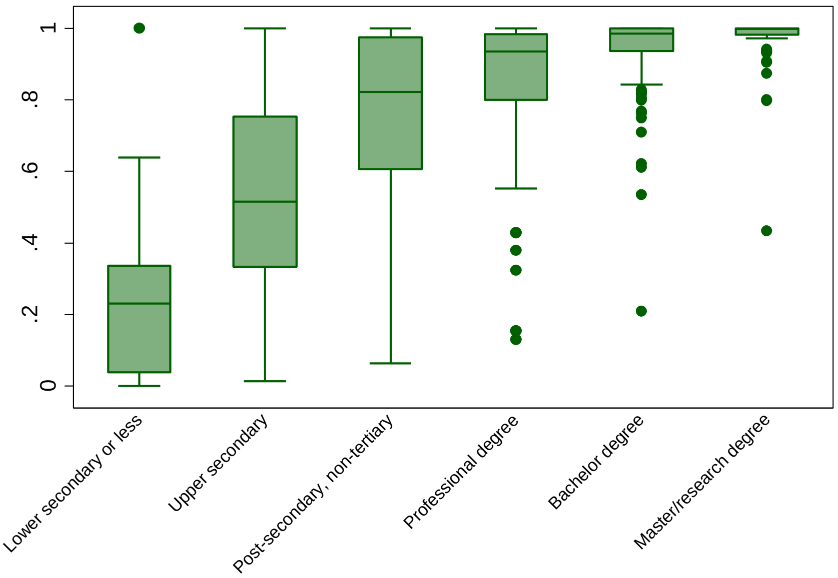
28 Straightforward: for example, using a computer for straightforward routine tasks such as data entry or sending and receiving e-mails; Moderate: for example, word-processing, spreadsheets or database management; Complex: for example, developing software or modifying computer games, programming using languages like java, sql, php or perl, or maintaining a computer network.

29 Cronbach's alpha uses the average correlation among the ICT items (emails, information, transactions, spreadsheets, word and real-time conversations) to assess their consistency when building an index. See Kankaraš et al (2016, p. 98) for more details.

over 98% in occupations that require a bachelor's degree and close to 100% in occupations that require master's degree or higher.

93. A strong correlation between the use of ICT and educational attainment is also found at the individual level, after controlling for country-specific effects, industry effects, and age (Table 7.1, models 1 and 3). Moving two degrees on the scale of ICT use at work, e.g., from not being a user, to being a medium-frequency user, corresponds to a full educational degree, e.g., from lower secondary to upper secondary. This also holds, and is even more pronounced for those that at the time of the survey were not in paid employment. The partial correlation remains strong even if instead of industry, we control for occupational choice (Models 2 and 4). Since education and occupation are typically simultaneously decided by people (i.e., one decides whether to study business, law or arts in college), occupational controls are not very interesting covariates and this latter set of models is only presented to demonstrate the robustness of relationship between ICT and educational achievement even within occupational groups.

Figure 7.1. Share using computer at work by level of education



Note: The sample includes working adults, 25-54 years old from 32 countries, with valid occupational entries. Each observation represents one of the 553 occupational classes in the 4-digit ISCO-08 classification.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Table 7.1. Partial correlations – Education as a function of computer use

	(1)	(2)	(3)	(4)
VARIABLES	In paid work		Not in paid work	
ICT (work)	0.525***	0.360***		
	(0.0102)	(0.0118)		
ICT (home)			0.596***	0.557***
			(0.0186)	(0.0191)
Age	-0.0149	-0.021	0.0115	0.0166
	(0.0137)	(0.0129)	(0.0199)	(0.0194)
Age^2	2.33E-05	8.88E-05	-0.00016	-0.00022
	(0.00017)	(0.00016)	(0.00025)	(0.00024)
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	No	Yes	No
Occupation dummies	No	Yes	No	Yes
Constant	1.933***	2.515***	0.729*	0.722*
	(0.267)	(0.251)	(0.396)	(0.385)
Observations	85,067	85,067	30,754	30,754
R-squared	0.402	0.468	0.386	0.407

Note: Results from OLS. The dependent variable is 6-level educational attainment used in Figure 18. The sample includes adults 25-54 years old from 32 countries, with valid occupation and industry entries. For those currently not working, we use information about their last industry and job. Robust standard errors in parentheses. All observations weighted using survey design weights. ISCO 2-digit has 50 occupational categories; ISIC 2-digit has 92 industry categories. Significance: *** p<0.1
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

7.2. Computers, general skills and specific skills

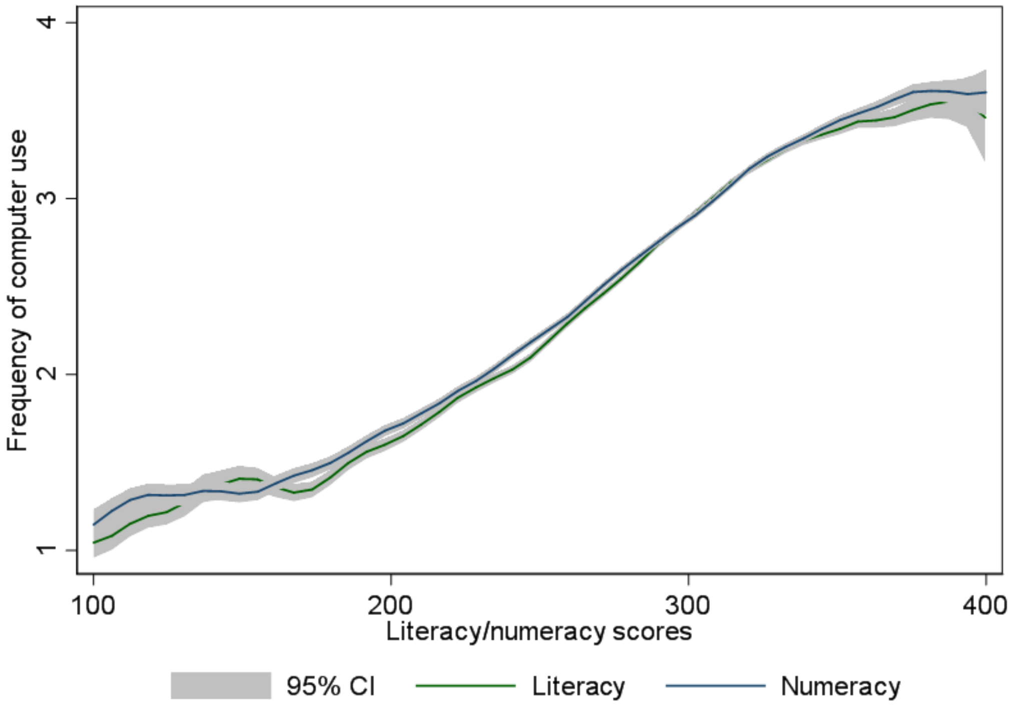
94. Through education one acquires various skills: some foundation ones, such as literacy and numeracy, but also job-specific ones, such as marketing, arts or medical knowledge and some generic skills such as working in teams, being autonomous, managing the work of others. Which of these are actually complemented by the use of ICT? One of the most important contributions of PIAAC is the assessment of foundation skills among adults through an actual test (OECD 2012).

95. Figure 7.2 shows the relationship between literacy, numeracy and the use of computers at work using fitted polynomials and the corresponding 95% confidence intervals. Both literacy and numeracy are strongly, and for the most part monotonically, related to the use of computers. Strong correlations between general skills and the use of ICT at work are found even after controlling for age, educational attainment, country-specific effects, and industry-specific effects (Table 7.2).[30] This is also the case for the use of literacy and numeracy at work (Figure 7.3 and Figure 7.4): a very clear pattern emerges where higher use of numeracy and literacy correspond to more frequent use of ICT. The relations seem particularly strong in the case of numeracy use at work,

[30] The coefficients do not have the most intuitive reading. One standard deviation higher literacy corresponds to a quarter of a quintile higher computer use.

and somewhat weaker when it comes to writing reports and filling out forms (measures of literacy).

Figure 7.2. Assessed literacy and numeracy, and computer use frequency



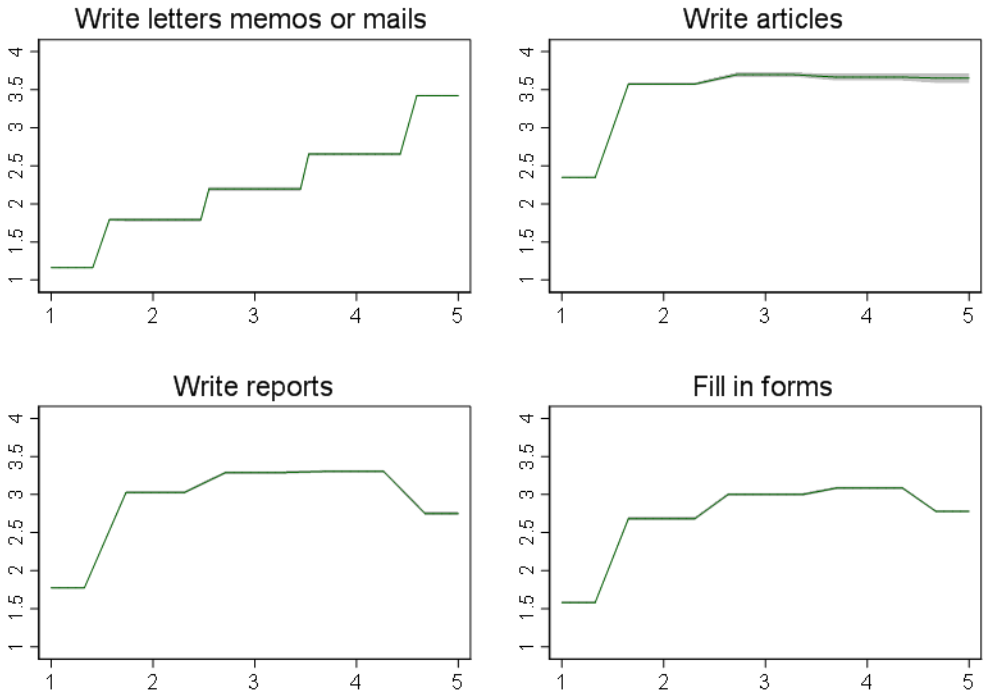
Note: The lines are fitted polynomials with their 95% confidence intervals. The y-axis variable is always the frequency of computer use at work. The x-axis variables are various skills, as noted above each sub-chart in the figure. The scales for all variables are: 1 – never used; 2 – less than once a month; 3 – less than once a week but at least once a month; 4 – at least once a week, but not every day; 5 every day. The sample includes people in paid work who are 25-54 years old from 32 countries.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Table 7.2. Partial correlations – Computer use as a function of literacy and numeracy

VARIABLES	(1)	(2)
LITERACY	0.264***	
	(0.0112)	
NUMERACY		0.294***
		(0.0125)
EDU: UPPER SECONDARY	0.435***	0.435***
	(0.0233)	(0.0233)
EDU: POST-SECONDARY, NON-TERTIARY	0.553***	0.553***
	(0.0465)	(0.0465)
EDU: PROFESSIONAL DEGREE	0.800***	0.800***
	(0.0321)	(0.0321)
EDU: BACHELOR DEGREE	1.149***	1.149***
	(0.0316)	(0.0316)
EDU: MASTER/RESEARCH DEGREE	1.322***	1.322***
	(0.0361)	(0.0361)
EDU: BACHELOR/MASTER/RESEARCH DEGREE	1.051***	1.051***
	(0.0515)	(0.0515)
AGE	0.0323***	0.0323***
	(0.0103)	(0.0103)
AGE^2	-0.000424***	-0.000424***
	(0.000128)	(0.000128)
COUNTRY DUMMIES	Yes	Yes
INDUSTRY DUMMIES	Yes	Yes
CONSTANT	1.352***	1.328***
	(0.201)	(0.201)
OBSERVATIONS	85,443	85,443
R-SQUARED	0.426	0.426

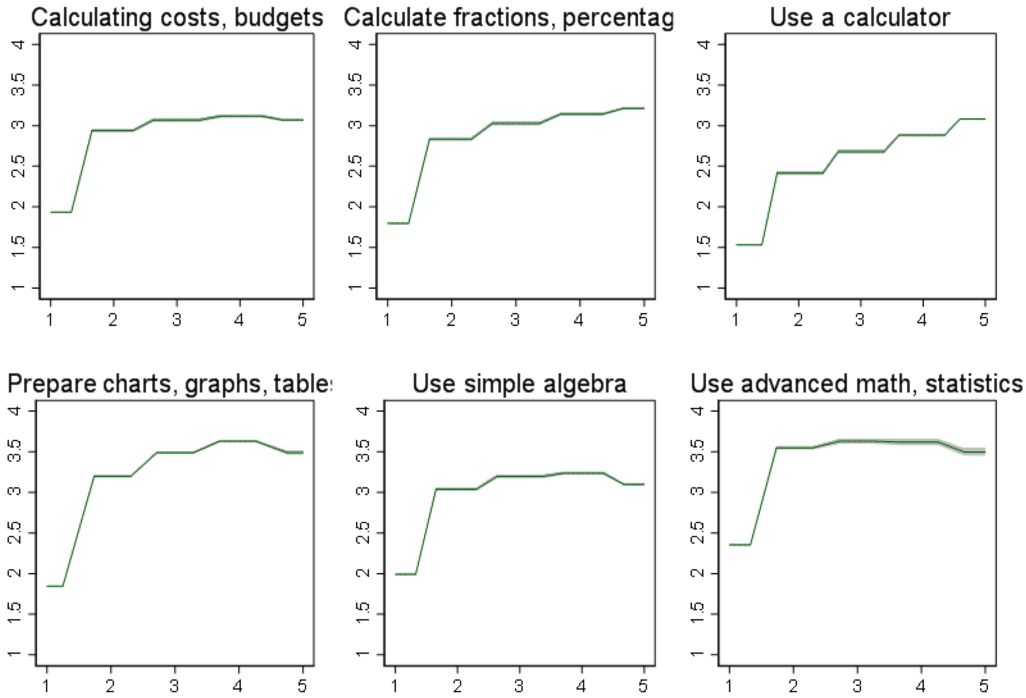
Note: The literacy and numeracy scores were normalized to have mean zero and S.D. of one. Results from OLS. Sample includes working adults 25-54 years old from 32 countries, with valid literacy or numeracy scores. Robust standard errors in parentheses. All observations weighted using survey design weights. ISIC 2-digit has 92 industry categories. Significance: *** p<0.1
Source: PIAAC 2012 and 2014.

Figure 7.3. Use of literacy and computers at work frequency



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

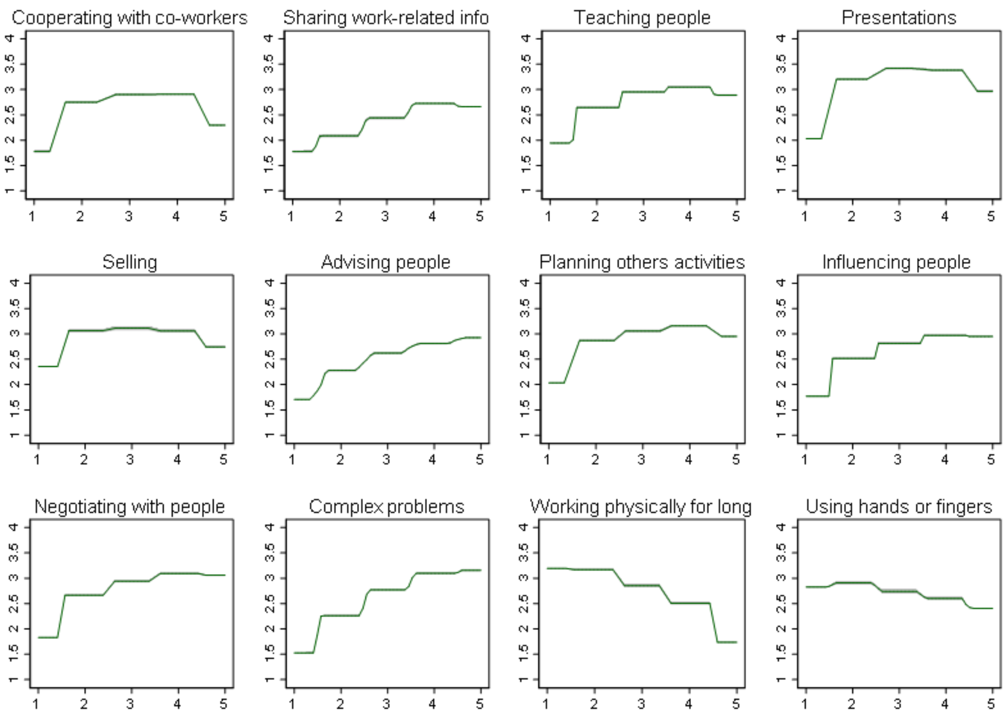
Figure 7.4. Self-reported numeracy and computer use frequency



Note: Skill frequency and computer use frequency
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

96. Turning to other skills, PIAAC asked its participants about the frequency with which they perform various tasks such as cooperating, teaching and selling. The frequency with which workers engage in these tasks at work are plotted against the frequency of ICT use (Figure 7.5). Three general patterns emerge. First, positive relationships between computer use and sharing information, teaching, advising, planning work of others, influencing, negotiating and complex problem-solving. Second, negative relationships between computer use and working physically for a long time and between ICT use and using hands and fingers. Third, inversed U-shape relationship between ICT use and cooperating, presenting and selling. In the last set of cases, the use of ICT is most frequent among those with medium intensity in these skills. One could speculate that people who engage in these job tasks very intensely spend significantly more time in direct communication with partners and customers and less in performing these over the computer. In general, computers act as augmenting to the analytical skills which trends we analysed in Section 5, while the use of ICT becomes irrelevant in jobs requiring frequent use of physical skills. ICT use becomes more frequent among those who employ social skills, but not always. Cooperation, presentation and sales require moderate use of ICT when performed frequently.

Figure 7.5. Skill frequency and computer use frequency

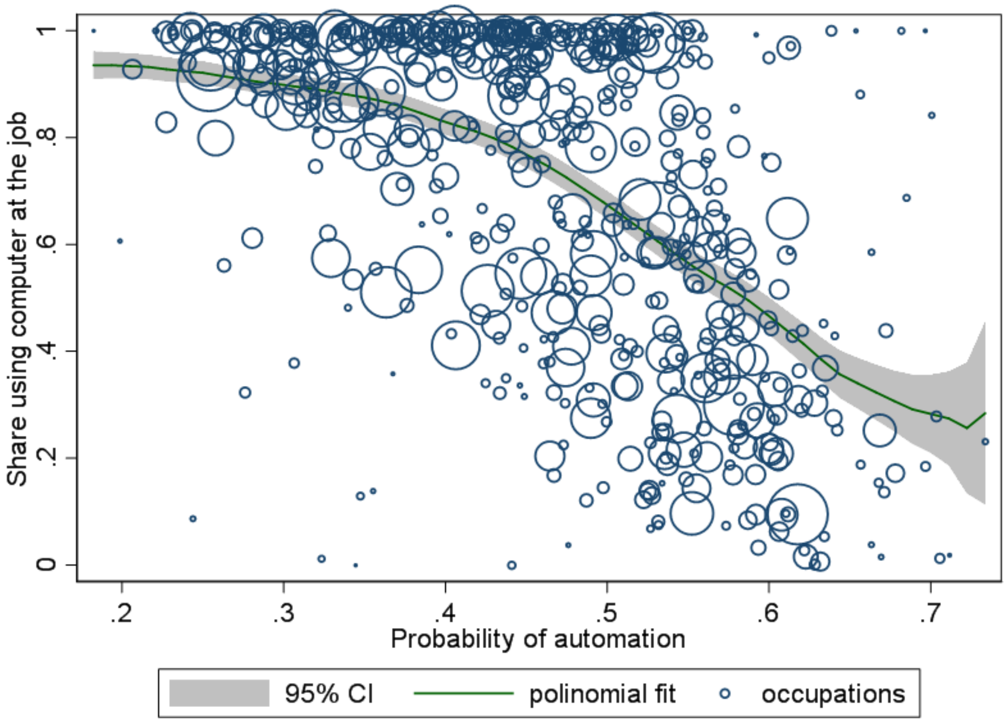


Source: Survey of Adult Skills (PIAAC) 2012, 2015.

7.3. Computers and automatability

97. Finally, in order to understand the argument of computer-skill complementarity, it is instructive to point out the relationship between the occupation-specific use of computers and the occupational risk of automation (Figure 7.6). Two observations stand out. First, the relationship is negative, meaning that occupations that use computers more frequently are at lower risk of automation. This suggests that computers are likely augmenting rather than substituting those who use them. Second, the variance in computer use increases with the risk of automation. Occupations that are at low risk are almost without exception intense computer users. At very high levels of risk, one tends to see mainly low users. However, a wide range of occupations in terms of computer use are bunched up between the 40 and 60% probability of automation. This is an interesting group of occupations and further analysis of the other technologies that they employ, in addition to computers, would better reveal what technologies are likely to be labour-substituting. In other words, there is lots of unexplained variance in the risk of automation if we only focus on the use of computers (or lack of) as potentially labour-substituting technology.

Figure 7.6. Automatability and computer use



Note: Each observation is one occupation. There are 493 occupations in the chart. Only occupations with at least 10 observations are included. The size of the circles is proportional to the size of the occupation. The fitted polynomials are weighted by the final design weights.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

98. If ICT act like skill augmenting technologies, which are the technologies that directly substitute human work? First, robots directly substitutes labour (Acemoglu and Restrepo 2016). But this is also the case for a wide range of moving, driving and construction machinery used in the storage, manufacturing, construction and mining industries. Assembly line machinery, but also monitoring and checking equipment substitute labour. Nowadays, all of these technologies are digitally enabled, but here the principles of digitalisation are used in a different way than in typical IC technologies: computers, internet, smart phones, wireless technologies etc. Typical ICT is general purpose and better skilled people make more creative and more productive use of it, while digital solutions in robotics are currently still employed for specific job tasks that robots can perform semi-independently over extended periods of time.

99. Recent developments in computer vision, natural language and translation could potentially get integrated into labour substituting and even skill substituting technologies, but their commercialisation is still rather limited. Moreover, computers do substitute labour, but not the labour of those who use them directly. Let’s take the tax fraud risk assessment systems as an example. Tax administrations around the world have been recently adopting big data algorithms for tax fraud risk assessment at the taxpayer level. These are computer algorithms that evaluate complex data from tax and bank records. The employees that develop and use these algorithms are highly educated users of ICT. The successful implementation of risk assessment systems does not diminish the need for

these employees (quite on the contrary), but it reduces the need for tax inspectors and customs inspectors who traditionally detected fraud without the assistance of algorithms. The fraud detection is now partially relegated to the algorithm, where previously it was a task fully performed by inspectors.

8. Robustness checks using country-specific occupational surveys

100. Throughout this study, PIAAC is used as the main dataset for the empirical analysis, except for Section 6 where, in the absence of longitudinal data on skills in PIAAC, two country-specific skill surveys, one for the UK and another one for Germany, are exploited. In this Section, parallels are drawn between the main findings on the relationship between skills and automation in PIAAC and other surveys. In particular, the German and the UK surveys are well suited for replicating the estimates of job automatability presented in Section 3.

8.1. Replicating the measurement of the risk of automation for Germany

101. Every six to seven years since 1979, the German Federal Institute for Vocational Education and Training (BIBB) conducts individual-level surveys (BIBB Employment Surveys) among employed Germans, asking, among other things, detailed questions about the job content, the skills, the knowledge and the technologies used at work. The latest survey (BIBB/BAuA Employment Survey) was conducted in 2011 and 2012 and the one before that was conducted in 2005/2006 (Rohrbach-Schmidt 2009; Rohrbach-Schmidt and Hall 2013). We use these two surveys to assess the risk of job automation among workers and to describe the basic characteristics of workers at risk.

102. To do this, the same approach described in Section 3. is applied to country-specific data. The first step consist in finding the best variables to match the engineering bottlenecks identified in FO, and in creating a correspondence between the binary occupation-level variables of automatability put forward by FO and the occupational classification used in the German data (ISCO-88, 4-digit). Table 8.1 shows the variables corresponding to FO engineering bottlenecks.

Table 8.1. BIBB variables corresponding to FO-identified engineering bottlenecks

Engineering Bottlenecks	Variable in BIBB 2006/2012	Variable code	Variable description
Perception and manipulation	Work very fast	F411_13	Working very fast
	Awkward positions	F600_07B, F600_07	Working in a ducked, crouching, kneeling or lying position
Creative intelligence	Improve processes/new ideas	F411_05	Improve existing processes, try out new ideas
	R&D	F311	Research, develop, construct
	Closing knowledge gaps	F327_03, F325_05	Close own knowledge gaps
Social intelligence	Teaching	F312	Educate, teach, train, raise
	Advise, inform others	F314	Advise and inform
	Decision-making	F327_02, F325_04	Make difficult decisions independently
	Responsibility for others	F327_04, F325_09	Take responsibility for other people
	Plan for others	F310	Organise, plan, prepare work processes for others
	Care	F316	Care for, look after, heal
	Persuasion/negotiation	F327_05, F325_03	Persuade others and reach compromises
	Communication	F327_06, F325_07	Communicate with others professionally

Source: BIBB/IAB and BIBB/BAuA Employment Surveys 2006 and 2012. All variables are expressed in terms of frequency, either as 3 or as 4 degrees Likert scales.

103. The results of estimating the probability of automation as a function of engineering bottlenecks are shown in Table 8.2. While most variables behave as expected – they reduce the probability of automation – two do not: communication and working very fast. This is similar to the estimates using PIAAC, where dexterity, communications and sales were positively associated with the risk of automation. We also noted that in FO, finger dexterity, manual dexterity and cramped workspace are all positively correlated with the probability of automation while the opposite is true in the BIBBIn terms of analysis of variance (not shown here), R&D and care contribute most. R&D explains 18% of the partial and 4.4% of the total variance, while care explains 14% of the partial and 3.5% of the total variance. This is different from PIAAC estimates, where planning for others, selling and influencing explained most of the variance while the closest variable to R&D (complex problem solving) had very little explanatory power.

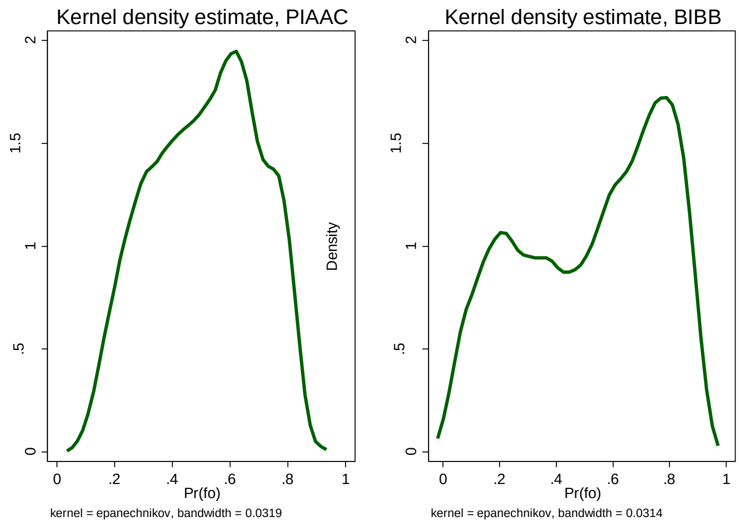
104. Figure 8.1 compares the probability of automation for Germany, as estimated using PIAAC (left) and using the BIBB Employment Survey (right). The distributions differ substantially, with the one estimated using the BIBB showing particularly heavy density in the right tail of the distribution. Since both surveys are representative of the working population and conducted at about the same time, the differences can be mainly attributed to the differences in the variables representing the engineering bottlenecks. Hence, as discuss next, one needs to be cautious when making statements about the estimated risk of automation.

Table 8.2. Automatability as a function of engineering bottlenecks in the BIBB

Variables	Beta	Robust standard errors
Work very fast	0.137***	0.0353
Awkward positions	-0.221***	0.0364
Improve processes/new ideas	-0.0748*	0.0444
Close knowledge gaps	0.150**	0.0627
R&D	-0.875***	0.058
Teaching	-0.0949*	0.0492
Advise, inform others	-0.141**	0.059
Decision-making	-0.284***	0.0556
Responsibility for others	-0.393***	0.0454
Persuasion/negotiation	-0.175***	0.0576
Care	-0.731***	0.0519
Communication	0.254***	0.0537
Constant	1.554***	0.13
Observations	4855	
Pseudo R2	0.1947	
Wald Chi2	931.72	
Area under the curve	0.7821	

Note: Results from a logit regression. All observations weighted using survey weights. Significant at: *** p<0.1
Source: BIBB/IAB and BIBB/BAuA Employment Surveys 2006 and 2012. All variables are expressed in terms of frequency, either as 3 or as 4 degrees Likert scales.

Figure 8.1. Density of the probability of automation for Germany (PIAAC vs. BIBB Employment Survey)



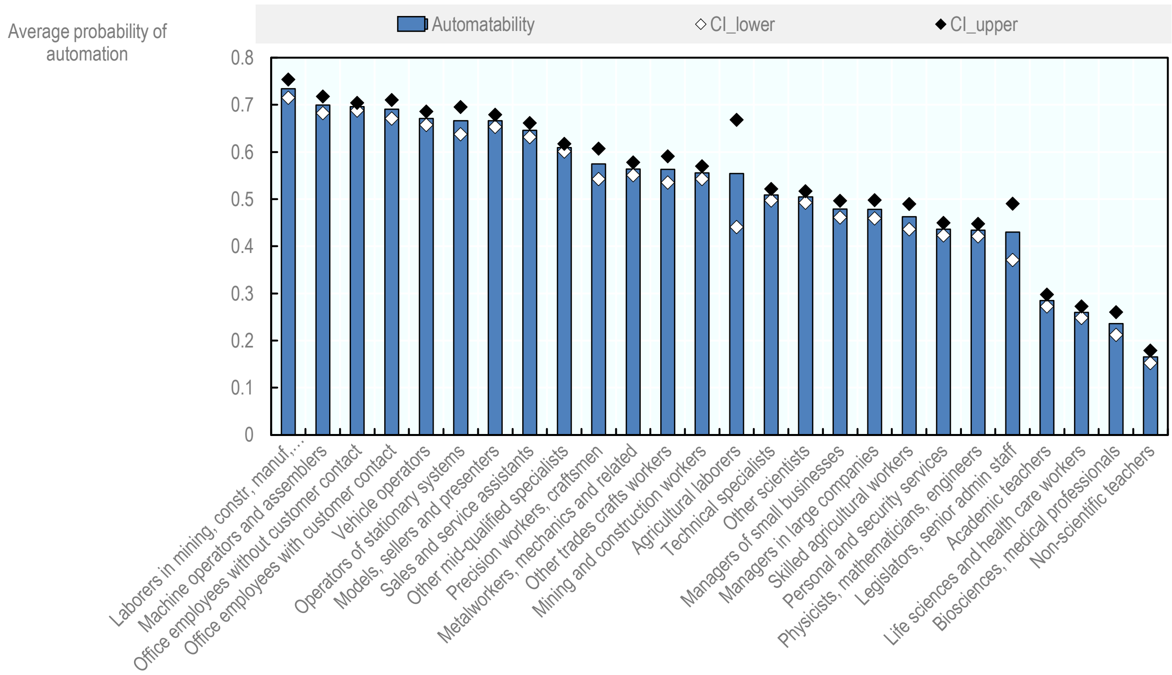
Source: Survey of Adult Skills (PIAAC) 2012 for Germany (2012) and BIBB/BAuA Employment Survey 2012. The samples include employed Germans, age 21-65.

8.2. Characteristics of jobs at risk in the German data

105. Using the same method, but different data and a somewhat different set of variables results in very different estimates of the probability of automation. For Germany, using PIAAC we estimate that about 18% of the current jobs are at high (over 70%) risk of automation. The results using the BIBB/BAuA 2012 job survey suggest that about 33% of the jobs in Germany are at high risk of automation. This suggests that we need to be very cautious when interpreting the findings of this and similar studies. [31] On the other hand, the results from the two datasets are more aligned when it comes to the relative ranking of affected occupations.

106. Similar to the ranking of occupations by risk of automation in PIAAC, the occupational groups that are estimated to have the highest probability of becoming automated in the BIBB do not require specific skills or training – notably, labourers in mining, construction and manufacturing (Figure 8.2). Then come machine operators and assemblers, clerks and sales people. At the other end of the risk spectrum, the probability of automation is significantly lower for professionals specialised in teaching and healthcare activities.

Figure 8.2. Mean probability of automation by occupation in the BIBB



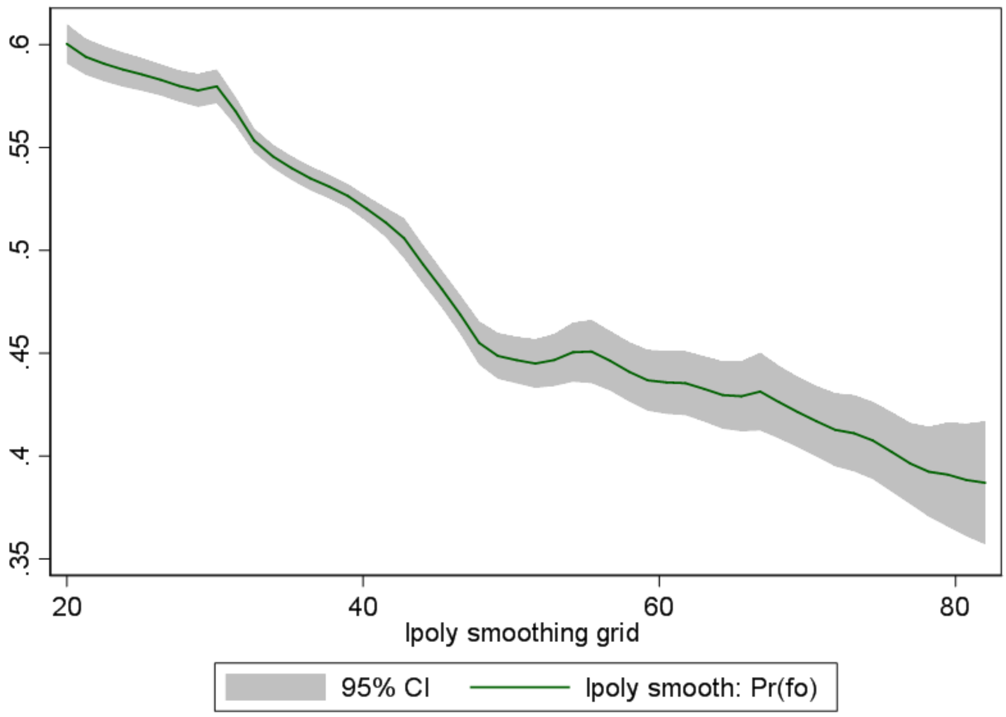
Source: BIBB/BAuA Employment Survey 2012. The sample includes employed Germans, age 21-65.

107. Similar to the findings using PIAAC, the risk of automation is found to decline with the level and the length of education (Figure 8.3 and Table 8.3). Again, no evidence

[31] In addition to differences in the variables, there is also a purely statistical reason for these differences, which has to do with the level of data aggregation, but this discussion is beyond the interest of this study.

of polarisation in terms of skill levels is found. Germany is widely known for its highly developed system of vocational training. Interestingly, while having vocational training is better than not having one, people in jobs requiring vocational training are still at significantly higher automation risk than those in jobs requiring tertiary education. Moreover, consistent with the findings using PIAAC, the risk of automation is lower among computer users than among non-users (Table 8.4). A mixed picture emerges when looking at the complexity and intensity of computer use: non-users or very basic users always have the highest risk of automation but the risk does not fall monotonically with more complex or frequent use. Finally, also consistent with the international findings in PIAAC, the risk of automation first sharply declines and then gradually increases with age (Figure 8.4).[32]

Figure 8.3. Risk of automation by length of education



Source: BIBB/BAuA Employment Survey 2012. The sample includes employed Germans, age 21-65.

[32] The respondents in the BIBB/BAuA survey are 21 years old or older, while the ones in the PIAAC can be as young as 16. This is why we miss seeing the risk of automation among those younger than 21 in the German data.

Table 8.3. Risk of automation by qualification level in the BIBB

Type of training required for the job	Average automatability	Share of jobs at higher than 70% risk
No vocational training	64.30%	53.70%
Vocational training	55.10%	37.80%
Master craftsmen, technical training	44.80%	19.20%
University (applied or theoretical sciences)	41.50%	15.50%

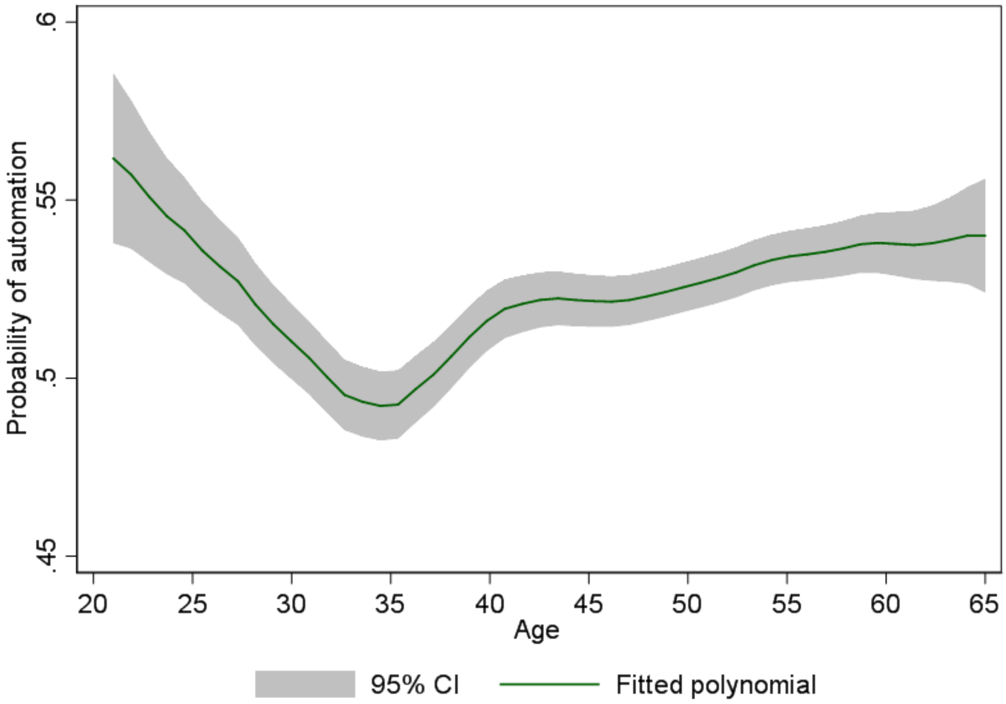
Source: BIBB/BAuA Employment Survey 2012. The sample includes employed Germans, age 21-65.

Table 8.4. Risk of automation by among jobs with different ICT penetration in the BIBB

	Mean automatability	95% CI, lower	95% CI, upper
How often do you use a computer?			
Often	51.90%	51.40%	52.30%
Sometimes	47.00%	46.00%	48.00%
Never	61.10%	60.30%	61.90%
What is your level of computer use?			
Not a user	60.40%	59.60%	61.20%
User	51.90%	51.50%	52.30%
More than a user	44.10%	43.10%	45.10%
Have new computer programs been introduced in the last 2 years?			
Yes	50.80%	50.30%	51.40%
No	53.90%	53.40%	54.40%
For your job, do you need knowledge of computer programs?			
No knowledge	58.00%	56.30%	59.70%
Basic knowledge	49.30%	48.70%	49.80%
Specialised knowledge	52.30%	51.70%	52.90%

Source: BIBB/BAuA Employment Survey 2012. The sample includes employed Germans, age 21-65.

Figure 8.4. Risk of automation by age in the BIBB



Source: BIBB/BAuA Employment Survey 2012. The sample includes employed Germans, age 21.

8.3. Replicating the measurement of automation for the UK

108. The UK introduced its own version of a Skills Survey in 1986. The survey is smaller in terms of sample size than the German skills survey. It is repeated at five to six year intervals. The last two surveys were conducted in 2006 and 2012. In this section, the same approach as for PIAAC (Section 4) and the BIBB is followed to estimate the probability of automation using the UK Skills Survey.

Table 8.5. UK Skills Survey variables corresponding to FO-identified engineering bottlenecks

Engineering Bottlenecks	Variable in UK Skills Surveys	Variable code	Variable description
Perception and manipulation	Dexterity	chands	Importance of: skill or accuracy in using hands/fingers
	Problem/fault spotting	cfaults	Importance of: spotting problems or faults
Creative intelligence	Complex problem solving	canalyse	Importance of: analyzing complex problems in depth
Social intelligence	Teaching	cteach	Importance of: teaching people (individuals or groups)
	Persuasion/influence	cpersuad	Importance of: persuading or influencing others
	Selling	cselling	Importance of: selling a product or service
	Counsel/advice/care	ccaring	Importance of: counseling, advising or caring for customers/clients

Notes: The variable scale is: 1 – not important at all, 2 – not very important, 3 – fairly important, 4 – very important, 5 – essential.
Source: UK Skills Surveys 1997, 2001, 2006, 2012.

109. Figure 8.5 shows the variables that correspond to the three types of engineering bottlenecks[33] identified by FO and Table 8.6 shows the estimates from a logit model linking these variables to the risk of automation. In the case of the UK Skills Survey, allowing for non-linear relationships between the indicator of automatability and the variables corresponding to engineering bottlenecks improves the model fit significantly and hence a specification that allows for non-linearity is chosen to conduct the analysis. As a general pattern, most variables are negatively associated with the indicator of automatability, as they should be. Exceptions are spotting problems/faults and sales of products and services. The latter had a positive sign both in PIAAC and in the BIBB, while spotting problems/faults as a variable is somewhat unique to the UK Skills Survey. This kind of problem/faults spotting is most common in manual jobs. A good example would be spotting irregularities in the functioning of a machine or the quality of a product. Unlike all other studies, finger and hand dexterity is negatively correlated with the indicator of automatability, just as theorized by FO. This is a peculiarity of this survey.

[33] The UK Skills Survey has richer set of variables that seemed appropriate for capturing aspects of the engineering bottlenecks, but these were often only available for specific survey waves and were hence limiting the analysis. Moreover, some variables that were available, were not significant predictors of automatability. In the current analysis, we only used variables that were consistently asked in more than one survey wave, usually in the last three waves and which are significant predictors of automatability.

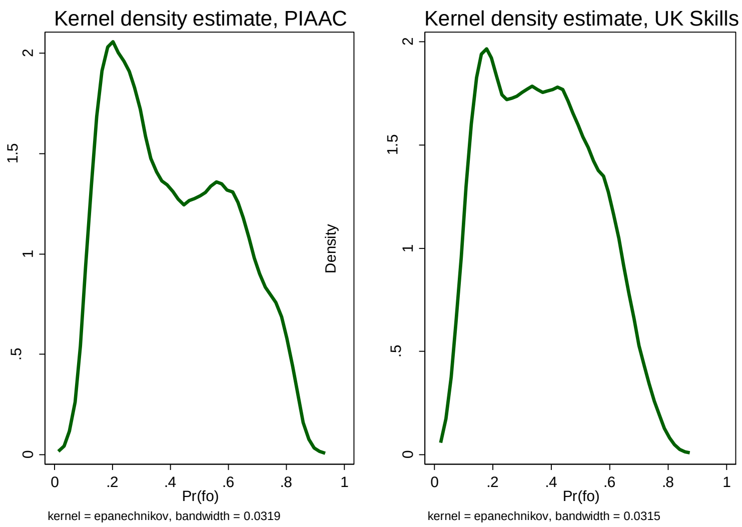
Table 8.6. Automatability as a function of engineering bottlenecks in the UK Skills Survey

Variables	Beta	Robust standard errors
Dexterity		
Not very important	-0.575***	0.137
Fairly important	-0.759***	0.148
Very important	-0.419***	0.142
Essential	-0.583***	0.136
Spot problems/faults		
Not very important	0.189	0.269
Fairly important	0.503**	0.235
Very important	0.639***	0.228
Essential	0.972***	0.23
Analyze complex problems		
Not very important	0.455***	0.155
Fairly important	-0.053	0.163
Very important	-0.168	0.16
Essential	-0.293*	0.173
Teach		
Not very important	0.138	0.173
Fairly important	0.12	0.167
Very important	-0.344**	0.167
Essential	-0.827***	0.172
Persuade/influence		
Not very important	-0.352**	0.173
Fairly important	-0.406**	0.171
Very important	-0.551***	0.186
Essential	-0.522***	0.201
Sell product/service		
Not very important	0.432***	0.141
Fairly important	0.367**	0.153
Very important	0.739***	0.143
Essential	0.579***	0.143
Counsel, advise, care for		
Not very important	0.153	0.189
Fairly important	-0.0841	0.172
Very important	-0.0821	0.155
Essential	-0.927***	0.146
Constant	-0.0595	0.204
Observations	2,567	
Pseudo R^2	0.109	
log likelihood	-1498	
Chi square	321.2	
Area under the curve	0.7203	

Note: Results from a logit regression. Significant at: *** p<0.1
Source: UK Skills Surveys 1997, 2001, 2006, 2012.

110. Figure 8.5 shows the estimated probability density function of the risk of automation. The resulting probability density function for the UK has a number of features in common with the one estimated using PIAAC for England and Northern Ireland.[34] One is that the mode is in the left tail of the distribution, suggesting that the typical job in the UK is at low risk of automation. Moreover, in both estimates the density is shifted away from high risk values, which is the opposite of the estimates for Germany. The mean automatability in the UK survey is similar to the one estimated for the UK in PIAAC (0.39 vs. 0.42). However, the estimated share of jobs at higher than 70% risk of automation is significantly different. Based on the UK Skills Survey estimates, less than 3% of the jobs are at such high risk of automation. PIAAC estimated that about 12% of the jobs in the UK are at high risk. Hence, although this way of reading the estimated distribution is attractive, it is highly sensitive to the choice of data.

Figure 8.5. Density of the probability of automation for Germany (PIAAC vs. UK Skills Survey)



Note: The samples include UK employees, age 21-65.
Source: Survey of Adult Skills (PIAAC) 2012 for England and Northern Ireland (2012) and UK Skills Survey 2012.

8.4. Characteristics of jobs at risk in the UK data

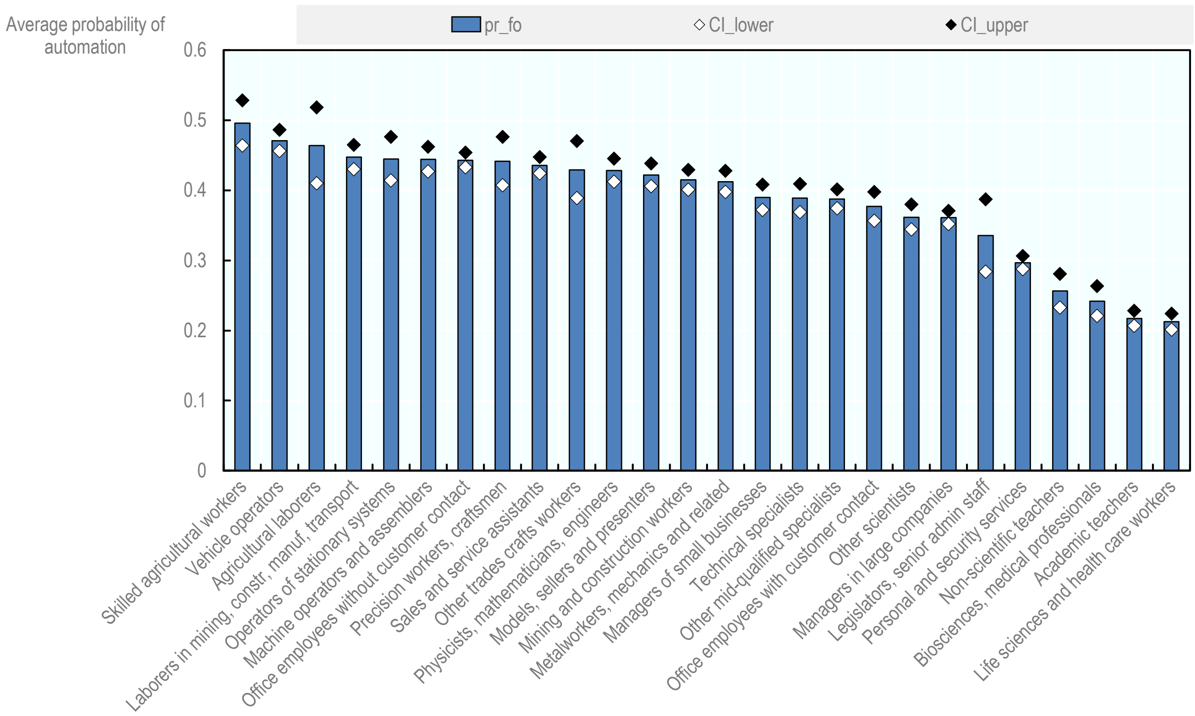
111. For the UK, as we did for the BIBB and PIAAC data, we identify how the risk of automation correlates with key individual and job characteristics. First, we look at the mean probability of automation by occupation (Figure 8.6). What the UK, the German and PIAAC occupational rankings all have in common is that they rank health and teaching professionals among the occupations with the lowest risk of automation. For the UK skills survey, the risk of automation increases as the level of skill declines, just like in PIAAC and the BIBB, and labourers, machine and vehicle operators are found among the occupations at highest risk of automation. They are closely followed by office clerks and

[34] Scotland and Wales were not surveyed in the PIAAC.

sales workers. There are differences as well. Somewhat unexpected judging by the previously described occupational rankings of automatability in PIAAC and BIBB, skilled agricultural workers have on average the highest estimated probability of automation and natural science professionals have a high estimated automatability too.

112. The average risk of automation declines with the level of education, just as we observed in the PIAAC and in the BIBB-based studies (Table 8.7). The share of jobs at high risk of automation seems to first increase and then decline with education, but we need to be cautious with this interpretation as sample size is small. Also in line with previous findings, the risk of automation is higher among those who do not use computers than among those who do[35] (Table 8.8). Those who say that the use of computers is not important for their job have significantly higher probability of automation than those who say that the use of computers is fairly important, very important or essential. When asked about the complexity of computer use, the risk first declines and then increases with the level of complexity, but the differences are statistically insignificant.

Figure 8.6. Mean probability of automation by occupation in the UK Skills Survey



Source: UK Skills Survey 2012. The sample includes employed UK employees, age 21-65.

35 The UK Skills Survey asks about the use of computers or automated equipment. This is unfortunate because while computers seem skill augmenting, automated equipment (e.g., industrial robots) has been shown to directly substitute labour.

Table 8.7. Risk of automation by qualification level in the UK Skills Survey

	Average automatability	Share of jobs at higher than 70% risk
No schooling	43.00%	1.70%
Primary	41.30%	4.50%
Lower secondary	38.80%	3.90%
Upper secondary	37.90%	3.00%
Tertiary	33.80%	1.90%

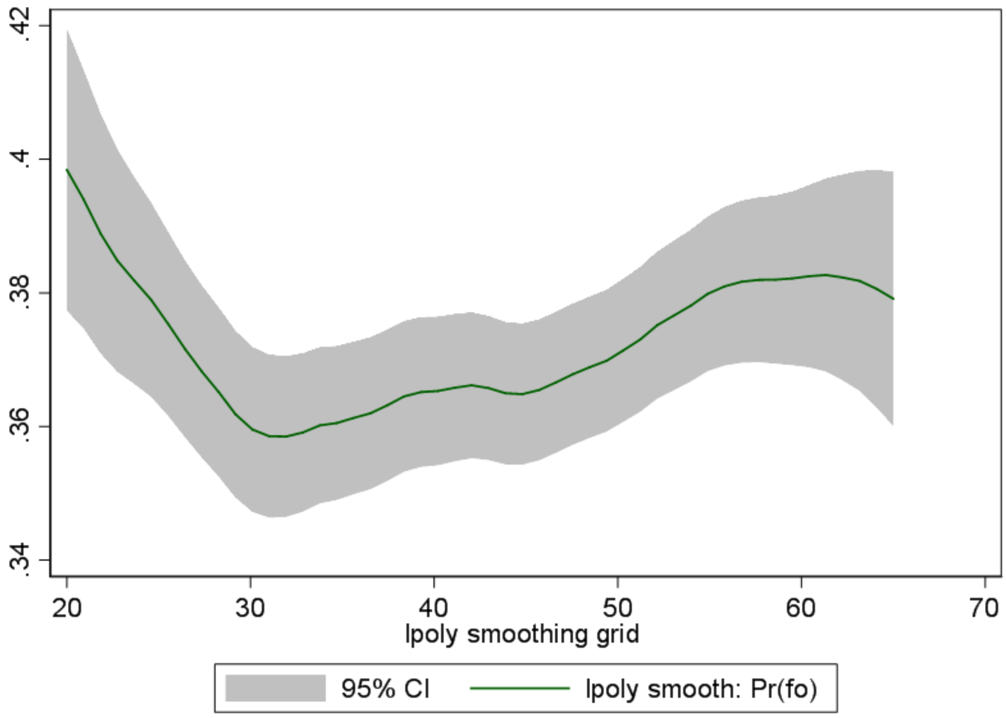
Source: UK Skills Survey 2012. The sample includes employed UK employees, age 21-65.

Table 8.8. Risk of automation by computer use in the UK Skills Survey

	Mean automatability	95% CI, lower	95% CI, upper
Does the job involve use of computerised or automated equipment?			
Yes	36.20%	35.50%	36.90%
No	40.00%	38.80%	41.10%
Importance of using a computer/PC/other computerised equipment			
Essential	36.20%	35.30%	37.00%
Very important	35.10%	33.50%	36.80%
Fairly important	35.70%	33.90%	37.40%
Not very important	39.30%	37.50%	41.20%
Not important at all	42.20%	40.70%	43.70%
Complexity of computer use in job			
Does not use PC at all	38.20%	35.70%	40.80%
Straightforward	37.70%	36.30%	39.10%
Moderate	35.30%	34.30%	36.30%
Complex	36.00%	34.60%	37.50%
Advanced	37.50%	35.30%	39.70%

Source: UK Skills Survey 2012. The sample includes employed UK employees, age 21-65.

Figure 8.7. Risk of automation by age in the UK Skills Survey 2012



Source: UK Skills Survey 2012. The sample includes employed UK employees, age 21-65.

113. Finally, the age pattern of automatability in the UK data has a shape which we have observed before: it declines until the age of 30 and then it gradually increases again (Figure 8.7).

114. To sum up, when the robustness of the PIAAC-based findings is tested agaist the German BIBB Employment Survey and the UK Skills Survey, a surprising level of similarity in the findings if found along with some significant differences. What is common is how the measure of automatability ranks occupations by their risk of automation. Occupations that specialise in teaching and health are among the safest occupations. Low skilled occupations, such as labourers in various sectors are at a very high risk of automation, but so are occupations with moderate training: machine operators, office clerks, and sales personnel. In all three surveys, the risk of automation monotonically declines with the level of education. Computer users are at a significantly lower risk of automation. The age pattern is very interesting and similar across surveys: the risk of automation first sharply declines until the age of 30 to mid-30 and then it gradually increases. What is different across the surveys is the absolute estimate of the risk of automation. The German data, for instance, gives a significantly higher average risk of automation, although the relative ranking of occupational titles along the distribution of automatability is similar to our estimates using the PIAAC. The share of workers at high or low risk of automation is particularly sensitive to the data source and the selected variables. As a result, presenting the risk of automation for these two groups might be particularly misleading. It is preferable to focus on average risk and on

individuals and jobs most affected by automation where results are more robust to the choice of data.

9. The role of initial, employer-sponsored and informal training in helping workers adapt to changing skill needs

115. This Section investigates the role of informal and on-the-job training in helping employees at risk of automation to adjust to new skill demands. Before analysing the relationships between job automatability and training, it is important to identify incentives to provide and participate in training by the different actors involved: the incentives of firms to offer training, the incentives of individuals to seek training and the role of government sponsored programs to fill the training gap that the private sector may fail to fill.

116. *Firms*. Human capital theory (Becker 1964) argues that on-the-job training is an investment in human capital. Firms train because they expect such training to make workers more productive in the future. If firms anticipate that certain tasks are going to be automated, they may provide less training to workers in such jobs. However, more often than not automation affects a subset of workers' tasks, and workers in these jobs may require training to adapt to the task restructuring that is caused by automation, i.e., automation may even increase the need for training. Bessen (2015) showed how the diffusion of ATMs, a typical labour substituting technology, transformed the job content of bank tellers rather than eliminating these jobs. Cash-handling became less important, and marketing and interpersonal skills became more important. The modern tellers are now in charge of customer relationships and not only of cash-handling. Larger shares of new hires now have a bachelor degree instead of only a high school diploma. In the case of ATMs, therefore, employees affected by automation received more and not less training.

117. *Employees* at risk of automation could of course invest in training on their own account. If they anticipate that their current job is being automated, they may spend their free time training in a different profession. In such scenario, one should see higher incidence of outside-the-job training for those at higher risk. Here as well, the patterns may be more complicated. As shown above, the risk of automation declines with educational attainment, suggesting that workers who sort themselves in more automatable jobs tend to invest less in human capital to start with. As a result, they might also be less motivated to learn new things. There might also be financial reasons: lower earnings in such jobs result in lower savings that can be invested in education. As a result, even though workers in automatable jobs are in higher need of retraining, they may be more reluctant to seek retraining. Moreover, the demand for requalification may not be met by adequate supply. Government-sponsored training may be in low supply and private sector training may either be undersupplied or it may offer marketable skills that are very different from those of the affected workers, and hence difficult for them to master. It is beyond this study to disentangle demand and supply factors, but the analysis below could offer novel insights into the general training propensity and training patterns of these employees.

118. Overall, the relationship between the risk of automation and training participation will depend on several factors: the skill level and interest of workers at risk of automation when it comes to obtaining training, the opportunities to reallocate workers within the same organisation following re-training, the level of mismatch between their skills and the job requirements of the available jobs, and the availability of training outside the job through government-sponsored or private sector programmes. The relationship may differ for on-the-job training and training that is undertaken to improve the chances of finding a new job. Workers at high risk of automation may receive less on-the-job training, but may be more likely to invest in training that helps them find a new job.

119. The analysis below takes advantage of the broad cross-country coverage of PIAAC and its training module in order to establish basic empirical facts about the relationship between training and automatability, without attempting to disentangle the multiple complex factors that lead to these observable patterns. The training module distinguishes between on-the-job and off-the-job education and training,[36] and it also asks about the degree to which the training was motivated by job or career perspectives. Only job-related training is used in the analysis below. The module, however, does not contain information about the actual content of training. To gain insights into this, this analysis is complemented with information about occupational qualification and requalification in Germany.

120. The first finding that is consistent among most surveyed countries is that workers at risk of automation receive less and not more job-related training than other workers. This is the case both with training provided by employers (on-the-job training) and training obtained outside the firm (formal education, online courses etc.). Overall, 67% of those in the lowest decile of automatability report having attended at least one type of job-related training in the last 12 months (employer-sponsored or on own account), while this is only the case with 31% of workers in the highest decile of automatability. Moreover, in the lowest decile of automatability, people spent 25 hours in job-related training annually on average, while in the highest decile of automatability, they spent about 59 hours in job-related training. These findings are presented in Figure 9.1. Training incidence by degree of job automatability

121.

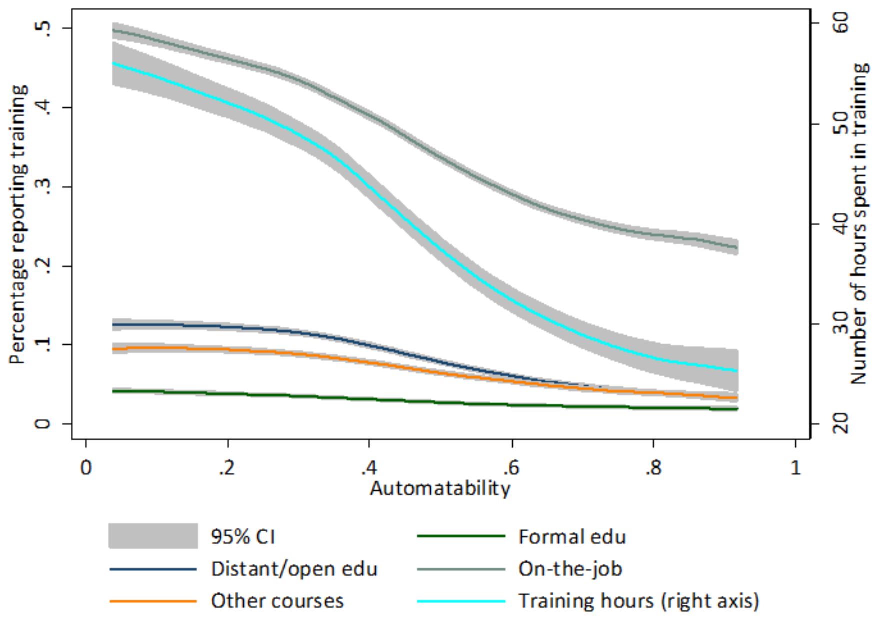
122. In more detail, the Figure 9.1 shows the share of people that have participated in job-related training in the last 12 months as a function of automatability (left axis), distinguishing between different types of learning: formal education, distant or open education, on-the-job training and other courses/training. The figure additionally shows the average number of hours spent in job-related training in the last 12 months (right axis). The prevalence of all types of training, as well as the number of hours spent in training decline with the risk of automation.

123. Participation in on-the-job training is the highest among employees in jobs with low automatability but declines slowly up to a risk of automation of about 30%, after which the decline in the likelihood of on-the-job training accelerates. This suggests that employers invest in the retraining of workers even when their tasks are at low or moderate risk of automation, but they offer significantly less training to those at the highest risk of automation. The observed trend corroborates the argument that re-training

[36] Both related and not to current and prospective job opportunities.

is often provided when occupational tasks are partially automatable, such that workers can transition to new tasks within the same organisation, but less so when jobs are almost fully automatable, in which case employers may not plan to retain such workers.

Figure 9.1. Training incidence by degree of job automatability



Note: Sample includes adults 25-54 years old from 32 countries.
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

124. This bivariate analysis is likely to suffer from omitted variable bias. For instance, the majority of training is typically obtained early in one's career and, at the same time, the estimated risk of automation is the highest among youth. Moreover, it has been shown above that the use of ICT correlates highly with the risk of automation and there are reasons to believe that the use of ICT causally impacts the incidence and level of training. To reduce this bias, logistic regressions[37] are estimated where the type of job-related training is modelled as a function of automatability and a set of control variables: use of ICT, age, educational attainment and country-specific effects.[38] The results are shown in Table 9.1. The odds of obtaining any type of training, on-the-job and outside the job are significantly lower among workers in jobs at higher risk of being automated. Workers in fully automatable jobs (automatability = 1) are 4 times (1/0.253) less likely to have participated in job-related in the last 12 months than workers in non-automatable jobs (automatability = 0). Similarly, they are twice less likely to have obtained formal job-related training, 3.5 times less likely to have take online or distant learning, and 3

[37] OLS in the case of training hours.

[38] In spite of the controls, these estimates need to be read with caution as we cannot rule out the additional bias stemming from unobservable individual and group characteristics which influence individuals' choices to participate in training.

times less likely to have participated in on-the-job training. They have also spent 29 hours less in training annually than those in non-automatable jobs, ceteris paribus.[39]

Table 9.1. Partial correlations between training received in the last 12 months and automatability

	(1)	(2)	(3)	(4)	(5)	(6)
	logit	logit	logit	logit	logit	OLS
VARIABLES	Any job related	Formal education	Distant/open education	On-the-job training	Other courses	Hours in training
Automatability	0.253***	0.504***	0.285***	0.327***	0.444***	-29.43***
	(0.0101)	(0.0573)	(0.0198)	(0.0133)	(0.0341)	(2.609)
ICT at the job (yes/no)	2.239***	1.202***	2.440***	2.136***	1.557***	14.80***
	(0.0422)	(0.0735)	(0.105)	(0.0437)	(0.0675)	(1.166)
Edu: upper secondary	1.353***	1.156*	1.234***	1.288***	1.159***	2.217
	(0.0345)	(0.0942)	(0.0705)	(0.0353)	(0.0659)	(1.381)
Edu: post-secondary, non-tertiary	1.771***	1.612***	1.863***	1.569***	1.299***	8.947***
	(0.0631)	(0.167)	(0.132)	(0.0585)	(0.0998)	(1.964)
Edu: Professional degree	1.978***	1.833***	1.952***	1.648***	1.600***	13.32***
	(0.0594)	(0.162)	(0.119)	(0.0518)	(0.100)	(1.890)
Edu: Bachelor degree	2.472***	2.047***	2.177***	1.826***	1.861***	22.33***
	(0.0762)	(0.183)	(0.131)	(0.0579)	(0.117)	(2.079)
Edu: Master/research degree	2.572***	2.185***	2.478***	1.710***	2.183***	24.97***
	(0.0854)	(0.208)	(0.154)	(0.0574)	(0.138)	(2.140)
Edu: Bachelor/Master/research degree	1.843***	1.213	1.867***	1.430***	2.210***	9.907***
	(0.136)	(0.195)	(0.264)	(0.103)	(0.350)	(3.349)
Age	1.006	0.941**	1.011	0.988	1.029*	-2.257***
	(0.00902)	(0.0229)	(0.0155)	(0.00896)	(0.0174)	(0.593)
Age^2	1.000	1.001*	1.000	1.000	1.000**	0.0215***
	(0.000112)	(0.000307)	(0.000191)	(0.000113)	(0.000211)	(0.00720)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.588***	0.126***	0.0441***	0.363***	0.0932***	123.2***
	(0.107)	(0.0587)	(0.0131)	(0.0668)	(0.0263)	(14.31)
Observations	88,634	88,657	88,657	88,657	88,657	88,657
R-squared						0.025
Pseudo R^2	0.115	0.0666	0.0935	0.0791	0.0681	
log likelihood	-54381	-11206	-23598	-53361	-20911	
Chi square	11633	1503	3997	7677	3053	

Note: Sample includes adults 25-54 years old from 32 countries. Robust standard errors in parentheses. Significance: *** p<0.1
Source: Survey of Adult Skills (PIAAC) 2012, 2015.

[39] Two other observations are worth pointing out. First, the odds of obtaining training increase with the level of education. Skills breed skills, it seems. Second, using ICT at work is associated with 2.2 times higher odds of any training and in particular distant/open education and on-the-job training. It is also associated with 15 hours more training over 12 months. This supports the hypothesis made earlier in this report that ICT are skill complementing technologies.

125. After establishing that workers at high risk of automation receive less job-related training overall, this section looks at whether those who do participate in training, and in particular those who acquire an additional occupational qualification (i.e. those who requalify), choose qualifications for jobs that are less susceptible to automation. In the absence of information on the content of training in PIAAC, the BIBB Employment Surveys for Germany are used instead (see Section 7 for a description). The data can help study whether people use re-qualification to move away from jobs at higher risk of automation.

126. Section 2 showed that over time (1960-2012), in Germany, jobs specialised in interactive and non-routine tasks became more common while those rich in manual (routine and non-routine) and routine cognitive tasks declined. However, that analysis did not explore if this shift in the structure of employment by occupation was driven by younger cohorts opting for jobs at lower risk of automation by requalification by adult workers from more to less automatable jobs. This section provides evidence that this transition was partially enabled by requalification.

127. The BIBB/BAuA Employment Surveys ask respondents to report up to five consecutive trainings that lead to occupational qualification, including information about the 2-digit ISCO code corresponding to each qualification.[40] Such data, in combination with the task characteristics of each ISCO category, allowed us to study whether individuals transited towards "safer" jobs through requalification. A striking 39.5% of all participants in the survey reported having completed at least one re-qualification. A clear pattern occurs when the job tasks of the first qualification are compared to those of the second qualification. The second qualification has significantly lower risk of automation (Table 9.2).

128. Looking in more detail, the second qualification involves significantly more tasks that require creative and social intelligence and fewer tasks that require perception and manipulation of objects. As a robustness check, Table 9.2 shows the risk of automation calculated with ALM instead of FO job tasks, and it also shows the results for each type of ALM task separately. Here as well the same pattern emerges: the second qualification is at significantly lower risk of automation, it requires significantly more non-routine tasks and fewer routine tasks.

129. It is important to note that, if anything, the measured adaptation towards "safer" jobs is understated. In absence of historical job task data, it is assumed that the job task contents within occupations did not change over time (they are kept at constant 2006 levels). Adaptations which happened within occupational qualifications, like in the case of the bank tellers described above, are not captured in this exercise. The analysis basically assumes that at any point of time, the job task structure of any occupation is just like the one observed in 2006 in Germany.

130. Also noteworthy is that, although the direction of the requalification is clear and significant, the movements away from automatable jobs are very gradual. On average, the difference in automatability between the first and second occupational qualification is only about 1/7 standard deviation (1/9 S.D. in the case of ALM automatability). People do adjust, but radical requalification seems rare. This means that, if the growing jobs are

[40] Prior to 2012, information is even available at the 3-digit ISCO level.

very different from the declining jobs, requalification may be a less effective mechanism of adaptation.

Table 9.2. Differences in the risk of automation between the first occupational qualification and the second occupational qualification

Job task features	Mean (1st occ. qualification)	Mean (2nd occ. qualification)	Difference	t-value	p-value	Obs.
Automatability (FO)	0.54	0.51	(0.03)	19.19	0.00	6,968
Automatablity (ALM)	0.53	0.50	(0.03)	17.73	0.00	6,968
Engineering bottlenecks (FO)						
Creative intelligence	0.76	0.82	0.05	(30.94)	0.00	6,968
Social intelligence	0.94	0.96	0.02	(37.04)	0.00	6,968
Perception and manipulation	0.50	0.46	(0.04)	23.31	0.00	6,968
ALM routine and non-routine tasks						
Non-routine interactive	0.76	0.83	0.07	(35.76)	0.00	6,968
Non-routine cognitive	0.52	0.64	0.12	(43.51)	0.00	6,968
Routine cognitive	0.51	0.45	(0.06)	22.28	0.00	6,968
Non-routine manual	0.47	0.39	(0.08)	19.39	0.00	6,968
Routine manual	0.50	0.41	(0.09)	34.00	0.00	6,968

Source: BIBB/BAuA Employment Survey 2012.

10. Conclusions

131. This study assesses the current and potential disruption brought about by automation in the labour markets of OECD countries. It identifies workers who are most likely to be affected and looks at the extent to which training is helping them adjust to the resulting changes in their job tasks. It builds on expert views collected by Frey and Osborne (2013) but applies Frey and Osborne's approach to individual jobs, instead of occupations, using PIAAC data for 32 OECD countries. The estimates suggest that 14% of jobs in OECD countries participating in PIAAC are at high risk (probability of over 70%) of being automated based on current technological possibilities. An additional 32% of jobs have a probability of being automated between 50% and 70% and could face significant changes in their job content. There is large variation in the risk of automation across countries. In general, jobs in Anglo-Saxon, Nordic countries and the Netherlands are less automatable than jobs in Eastern European countries, South European countries, Germany, Chile and Japan. More than two thirds of the variation across countries is explained by differences in the way economies organise work within the same economic sectors (i.e., their occupational mix within industries and the job task mix within occupations), and only 30% is explained by differences in the economic structure of economies (i.e., the mix of industries).

132. The risk of automation declines with the level of education, with the level of measured skills (PIAAC's numeracy and literacy) and with the wage level across almost all countries, suggesting that this wave of automation is skill biased. The study, however, does not find support for the hypothesis that AI already has a measurable impact on the job security of occupations characterised by high levels of education and skills and high degrees of non-routine cognitive job tasks. On the other hand, AI appears to affect low-skilled jobs more significantly than previous waves of automation.

133. Another notable finding is that the risk of automation peaks among teen jobs. More precisely, the relationship between the risk of automation and age is U-shaped. The highest automatability is found among jobs held by youth. The risk then declines to reach its lowest value at age 30-35 and then gradually increases again. Although this pattern is largely driven by the sorting of youth into automatable occupations (youth are over-represented in sales, personal care and many elementary occupations), the pattern persists even after occupational sorting effects are accounted for. In other words, youth and adults do different things at work, even when they hold jobs with the same occupational title. These results suggest that automation may have more implications for youth unemployment policies than for early retirement policies. The warnings in some developed countries that teen jobs have been harder to come by in recent years should be taken seriously and studied in the context of job automation.

134. The study presents evidence that re-qualification is an important mechanism to aid the transition from more to less automatable jobs. For Germany more specifically, where close to 40% of all employees have undergone at least one occupational re-qualification in their career, the second qualification is towards occupations with systematically lower risk of automation than the first one. These transitions are however

gradual in the sense that workers choose to requalify to occupations that are skill-related to their previous qualification. This means that re-qualification might be more effective in situations where differences in the skills content of declining and growing jobs in the economy is not too large. In this context, it is encouraging (or at least less discouraging) to find that the risk of automation is highly concentrated among youth jobs. Education and re-qualification are easier early in one's career. If teen and student jobs are about to decline, education and training will have to find different – possibly, class-based – ways of helping youth prepare for the labour market. Separate policies will have to address the elevated risk of automation among "older" jobs. Future research should focus on the effectiveness of life-long learning, and in particular adult education in helping older workers transition to safer jobs.

135. Overall, it is important to stress that, while job destruction figures estimated in this paper are smaller than those obtained based on occupational titles, it is important not to dismiss the importance of providing retraining and social protection for the 14% of workers whose jobs are at high risk, as well as to those 32% who are likely to face significant changes in the way they carry out their work tasks. In addition, the unequal distribution of the risk of automation raises the stakes involved in policies to prepare workers for the new job requirements even further.

136. Finally, this study highlights, but does not deal with, some important issues that will be the focus of further work. First, as mentioned throughout the report, the focus is placed on technological possibilities, abstracting from technology penetration and adoption. Ongoing work is expected to shed light on the timing of the risk of automation in different industries and countries. Secondly, this study only touches on how technological progress may affect wages by highlighting the negative association between the estimated risk of automation and hourly wages. This relationship is being looked at more in-depth in the context of work on wage polarisation and inequality, leading to a broader discussion on the potential need for income redistribution. Thirdly, the regional concentration of the risk of automation could amplify its social and economic impact, particularly in countries where geographical mobility is low. The OECD is currently working on deriving regional estimates of the risk of automation and highlighting the policy implications of risk concentration.

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Annex A.

Table A A.1. Correspondence between Frey and Osborne (2013) occupations and ISCO-08

Training data set codification	Frey and Osborne (2003)	ISCO-08 equivalent occupation	Training data set codification	Frey and Osborne (2003)	ISCO-08 equivalent occupation
0	Physicians and Surgeons	Generalist medical practitioners; Specialist medical practitioners	1	Bus Drivers, Transit and Intercity	Bus and tram drivers
0	Dentists, General	Dentists	1	Light Truck or Delivery Services Drivers	Heavy-truck and lorry drivers
0	Social and Community Service Managers	Social welfare managers	0	Maids and Housekeeping Cleaners	Domestic housekeepers; Domestic helpers and clearners
0	Preschool Teachers, Except Special Education	Early childhood educators	1	Civil Engineering Technicians	Civil engineering technicians
0	Clergy	Religious professionals; Religious associate professionals	1	Dishwashers	
0	Registered Nurses	Nursing and midwifery professionals; Nursing associate professionals	0	Hunters and Trappers	Hunters and trappers
0	Marriage and Family Therapists	Psychologists	1	Cooks, Fast Food	Cooks
0	Chief Executives	Directors and chief executives	1	Electrical and Electronics Drafters	Electrical engineering technicians; Electronics and telecommunications engineering technicians
0	Education Administrators, Preschool and Childcare Centre/Program	Education managers	1	Sheet Metal Workers	Sheet metal workers
0	Civil Engineers	Civil engineers	1	Meter Readers, Utilities	Meter readers
0	Fashion Designers	Product and garment designers	1	Computer-Controlled Machine Tool Operators, Metal and Plastic	Stationary plant and machine operators, other
0	Substance Abuse and Behavioral Disorder Counselors	Social work and counselling professionals	1	Parking Lot Attendants	
0	Lawyers	Lawyers	1	Medical Transcriptionists	Medical assistants; Medical secretaries
0	Meeting, Convention, and Event Planners	Conference and event planners	1	Technical Writers	
0	Landscape Architects	Landscape architects	1	Sewing Machine Operators	Sewing-machine operators
0	Healthcare Practicioners and Technical Workers, All	Health professionals, other; Health associate professionals, other	1	Taxi Drivers and Chauffeurs	Car, taxi and van drivers

	other				
0	Compliance Officers	Process control technicians, other	1	Human Resources Assistants, Except Payroll and Timekeeping	Personnel clerks
0	Childcare Workers	Child-care workers	1	Tax Examiners and Collectors, and Revenue Agents	Government tax and excise officials
0	Chefs and Head Cooks	Chefs	1	Industrial Truck and Tractor Operators	Mobile farm and forestry plant operators
0	Electrical Engineers	Electrical engineers	1	Accountants and Auditors	Accountants
0	Physicists	Physicists and astronomers	0	Waiters and Waitresses	Waiters
0	Hairdressers, Hairstylists, and Cosmetologists	Hairdressers; Beauticians and related workers	1	Couriers and Messengers	Messengers, Package Deliverers and Luggage Porters
0	Concierges	Hotel receptionists	1	Paralegals and Legal Assistants	
0	Athletes and Sports Competitors	Athletes, sportspersons and related associate professionals	1	Electrical and Electronic Equipment Assemblers	Electrical and electronic equipment assemblers
0	Zoologists and Wildlife Biologists	Biologists	1	Switchboard Operators, Including Answering Service	Telephone switchboard operators
0	Plimbers, Pipefitters, and Steamfitters	Plumbers and pipe fitters	1	Gaming Dealers	
0	Flight Attendants	Travel attendants and travel stewards	1	Farm Labour Contractors	
1	Surveyors	Cartographers and surveyors	1	Cashiers	Cashiers and ticket clerks
0	Judges, Magistrate Judges, and Magistrates	Judges	1	File Clerks	Filing and copying clerks
1	Judicial Law Clerks	Legal secretaries; Legal and related associate professionals	1	Credit Authorizers, Checkers, and Clerks	Credit and loans officers
0	Economists	Economists	1	Claims Adjusters, Examiners, and Investigators	
1	Cost Estimators	Valuers and loss assessors	1	Credit Analysts	Financial analyst
0	Transportation, Storage, and Distribution Managers	Supply, distribution and related managers	1	Loan Officers	Credit and loan officers
1	Market research Analysts and Marketing Specialists	Advertising and marketing professionals	1	Data Entry Keyers	Data entry clerks
1	Motorboat Operators	Ships' deck officers and pilots	1	Insurance Underwriters	Insurance representatives

Note: Seven occupations could not be identified in ISCO-08: dishwashers; parking lot attendants; technical writers; paralegals and legal assistants; gaming dealers; farm labour contractors; claim adjusters, examiners and investigators. Additionally, the same ISCO-08 code – credit and loan officers – is used for two of the 70 FO occupations: credit authorisers, checkers and clerks; and loan officers.
Source: Correspondence derived by the authors based on the list provided in Frey and Osborne (2013) and the ISCO-08 official occupational codes.

Annex B.

137. This appendix explains how we estimate the probability of automation as a function of ALM tasks: routine, non-routine and interactive. We follow Antonczyk et al. (2008) in classifying tasks into the ALM groups (Table A B.1).

Table A B.1. ALM tasks in the German Skills Data

	Table Column Heading (Alt+O)
Non-routine analytic	Developing, researching, designing
	Gathering information, investigating, documenting
Non-routine interactive	Informing, advising
	Training, teaching, tutoring, educating
	Organizing, planning, preparing work processes
	Promoting, marketing, public relations
	Buying, providing, selling
	Be a supervisor
Routine cognitive	Measuring, controlling, quality checks
Routine manual	Fabricating, producing goods
	Supervising, controlling machines
	Transporting, stocking, posting
Non-routine manual	Repairing, patching
	Nursing, healing
	Serving

Source: BIBB/BAuA BIBB/IAB Employment Surveys 1998/99, 2005/06, 2011/12.

Using a logistic regression we then model the FO 0/1 variable as a function of these job tasks. Table A B.2 shows the results of this estimation.

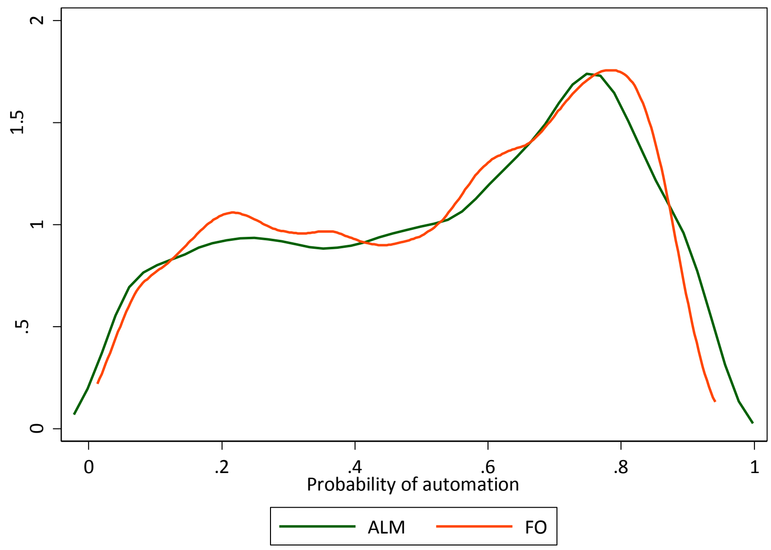
138. Figure A B.1shows how the distribution of the estimated ALM probability of automation compares with the distribution of the estimated FO probability of automation. The distributional forms are quite similar, with the ALM probability having somewhat higher average (0.53 vs. 0.523, t value = 9.95) and median (0.575 vs. 0.568) values.

Table A B.2. Automatability as a function of routine, non-routine tasks

	Logit coefficients	Robust standard errors
Developing, researching, designing	-0.757***	0.0672
Informing, advising	-0.133*	0.0681
Training, teaching, tutoring, educating	-0.0950	0.0587
Gathering information, investigating, documenting	-0.0471	0.0567
Organizing, planning, preparing work processes	-0.110**	0.0528
Promoting, marketing, public relations	-0.0650	0.0604
Be a supervisor	-0.188**	0.0907
Measuring, controlling, quality checks	-0.320***	0.0512
Fabricating, producing goods	0.0867	0.0710
Supervising, controlling machines	0.213***	0.0578
Transporting, stocking, posting	0.630***	0.0527
Repairing, patching	-0.400***	0.0680
Nursing, healing	-0.900***	0.0586
Serving	-0.422***	0.0686
Buying, providing, selling	0.0685	0.0523
Constant	1.477***	0.142
Wald chi2	726.82	
Pseudo R-squared	0.2087	
Log pseudolikelihood	-2561.73	
Observations	4760	

Note: Results from logistic regression. Significant at: *** p<0.01, ** p<0.05, * p<0.1.
Source: BIBB/BAuA BIBB/IAB Employment Surveys 1998/99, 2005/06, 2011/12.

Figure A B.1. Probability distribution of the ALM automatability and the FO automatability



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Source: BIBB/BAuA BIBB/IAB Employment Surveys 1998/99, 2005/06, 2011/12.