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The Risk of Automation for Jobs in OECD Countries

A COMPARATIVE ANALYSIS

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Ulrich Zierahn

JEL Classification: J20, J23, J24

**DIRECTORATE FOR EMPLOYMENT, LABOUR AND SOCIAL AFFAIRS
EMPLOYMENT, LABOUR AND SOCIAL AFFAIRS COMMITTEE**

**THE RISK OF AUTOMATION FOR JOBS IN OECD COUNTRIES:A COMPARATIVE ANALYSIS.
OECD SOCIAL, EMPLOYMENT AND MIGRATION WORKING PAPERS No. 189**

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JEL Classification: J20, J23, J24

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SUMMARY

In recent years, there has been a revival of concerns that automation and digitalisation might after all result in a jobless future. The debate has been fuelled by studies for the US and Europe arguing that a substantial share of jobs is at “risk of computerisation”. These studies follow an occupation-based approach proposed by Frey and Osborne (2013), i.e. they assume that whole occupations rather than single job-tasks are automated by technology. As we argue, this might lead to an overestimation of job automatibility, as occupations labelled as high-risk occupations often still contain a substantial share of tasks that are hard to automate.

Our paper serves two purposes. Firstly, we estimate the job automatibility of jobs for 21 OECD countries based on a task-based approach. In contrast to other studies, we take into account the heterogeneity of workers’ tasks within occupations. Overall, we find that, on average across the 21 OECD countries, 9 % of jobs are automatable. The threat from technological advances thus seems much less pronounced compared to the occupation-based approach. We further find heterogeneities across OECD countries. For instance, while the share of automatable jobs is 6 % in Korea, the corresponding share is 12 % in Austria. Differences between countries may reflect general differences in workplace organisation, differences in previous investments into automation technologies as well as differences in the education of workers across countries.

The second purpose of this paper is to critically reflect on the recent line of studies that generate figures on the “risk of computerisation” and to provide a comprehensive discussion on possible adjustment processes of firms and workers to automation and digitalisation. In particular, we argue that the estimated share of “jobs at risk” must not be equated with actual or expected employment losses from technological advances for three reasons. First, the utilisation of new technologies is a slow process, due to economic, legal and societal hurdles, so that technological substitution often does not take place as expected. Second, even if new technologies are introduced, workers can adjust to changing technological endowments by switching tasks, thus preventing technological unemployment. Third, technological change also generates additional jobs through demand for new technologies and through higher competitiveness.

The main conclusion from our paper is that automation and digitalisation are unlikely to destroy large numbers of jobs. However, low qualified workers are likely to bear the brunt of the adjustment costs as the automatibility of their jobs is higher compared to highly qualified workers. Therefore, the likely challenge for the future lies in coping with rising inequality and ensuring sufficient (re-)training especially for low qualified workers.

RÉSUMÉ

Ces dernières années, les craintes que l'automatisation et la numérisation aboutissent finalement à un futur sans emploi se sont réveillées. Le débat a été alimenté par des études sur les États-Unis et l'Europe arguant qu'une grande partie des emplois étaient en « risque d'informatisation ». Ces études utilisent une méthode basée sur les professions proposée par Frey et Osborne (2013), c'est-à-dire qu'elles supposent que les professions dans leur ensemble et non les tâches isolées sont automatisées. Comme nous l'avancions, cette hypothèse peut mener à la surestimation de l'automatisation des emplois, puisque les professions dites à haut risque comprennent souvent une part substantielle de tâches difficiles à automatiser.

Notre article a un double objectif. D'une part, nous estimons par une approche basée sur les tâches la possibilité d'automatiser les emplois pour 21 pays de l'OCDE. A la différence d'autres études, nous prenons en compte l'hétérogénéité des tâches au sein des professions. Globalement, nous estimons que 9 % des emplois sont automatisables en moyenne dans les 21 pays de l'OCDE. La menace générée par les avancées technologiques semble donc bien moindre que celle donnée par la méthode basée sur les professions. Nous trouvons également que les pays de l'OCDE sont hétérogènes en la matière. Par exemple, alors que la part des emplois automatisables représente 6 % en Corée, elle s'élève à 12 % en Autriche. Les différences entre pays peuvent être le reflet des diversités concernant l'organisation du lieu de travail en général, des différences dans les investissements faits auparavant dans les technologies d'automatisation ou encore des variations dans les niveaux d'éducation des travailleurs.

Le second objectif de cet article est de procéder à une réflexion critique sur un groupe d'études récentes qui produisent des chiffres sur le « risque d'informatisation » et de fournir une discussion approfondie sur les processus possibles d'adaptation à l'automatisation et à la numérisation pour les entreprises comme pour les travailleurs. En particulier, nous avançons que l'estimation de la part des « emplois à risque » ne doit pas être assimilée aux pertes d'emplois effectives ou prévues liées aux avancées technologiques. D'une part, l'utilisation de nouvelles technologies est un processus long, ralenti par les obstacles économiques, légaux et sociaux, de telle sorte que souvent la substitution technologique ne s'effectue pas comme prévu. D'autre part, même si des changements technologiques sont introduits, les travailleurs peuvent s'y adapter en changeant leurs tâches, de manière à prévenir le chômage technologique. Enfin, le changement technologique génère aussi des emplois supplémentaires liés à la demande pour les nouvelles technologies et à l'accroissement de la compétitivité.

La conclusion principale de notre article est qu'il est peu probable que l'automatisation et la numérisation détruisent un grand nombre d'emplois. Cependant, les travailleurs peu qualifiés souffriront plus des coûts d'ajustement car leur emploi est davantage susceptible d'être automatisé que pour les travailleurs qualifiés. Ainsi, le défi futur consiste probablement à faire face à la croissance des inégalités et à veiller à former (ou former à nouveau) les travailleurs peu qualifiés.

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INTRODUCTION

1. In the past, technological change often stoked fears that new technological means displace workers, hence giving rise to what has been called technological unemployment (see Mokyr et al., 2015 for a comprehensive review of the literature). While such fears have not proven true for past technological advances in the 19th and 20th century as the creation of new jobs usually outran the labour-saving impact of the adoption of new technologies, fears have recently been growing again that technological advances in the field of automation and digitalisation may after all herald the “End of Work”, as has already been proposed by Rifkin (1995). The underlying notion is that automation and digitalisation are increasingly penetrating the domain of tasks that until recently used to be genuinely human such as reasoning, sensing and deciding. In a widely discussed book, Brynjolfsson and McAfee (2014) present numerous examples of what they call “The Second Machine Age” such as the driverless car, the largely autonomous smart factory, service robots or 3D printing. These technologies are driven by advances in computing power, robotics and artificial intelligence and ultimately redefine what type of human capabilities machines are able to do.

2. Hence, at least in the public debate, the prevalent perception seems to be that the substitutability of humans by machines reaches a new and unprecedented quality. Such fears have also been fuelled by a study conducted by Frey and Osborne (2013) that tries to estimate the susceptibility of employment to computerisation. In this widely cited paper, they classify occupations in the US with respect to the risk of being susceptible to automation by asking experts about the technological potential for automation in the near future. As a result, the study suggests that 47% of all persons employed in the US are working in jobs that could be performed by computers and algorithms within the next 10 to 20 years. Several follow-up studies applied the risk of automation at the level of occupations to other countries, thereby assuming that the risk of automation for a particular occupation is comparable across countries. Hence, cross-country differences in the estimated share of workers that are prone to automation are driven by differences in the occupational structure only. With this approach, Pajarinen and Rouvinen (2014) estimate the share of jobs that are susceptible to automation to be around 35% in Finland while Brzeski and Burk (2015) estimate the share of jobs at risk of automation to be as high as 59% in Germany. Bowles (2014) finds the share of jobs that are susceptible to automation in Europe to range between 45 to more than 60%, with southern European workforces facing the highest exposure to a potential automation.

3. Given these numbers, the potential for automation is perceived as a threat that will ultimately foster technological unemployment. However, the study by Frey and Osborne (2013) has also spurred a discussion about the interpretation of these results. In particular, one critique targets the fact that automation usually aims at automating certain tasks rather than whole occupations. Since occupations usually consist of performing a bundle of tasks not all of which may be easily automatable (Autor 2014, 2015), the potential for automating entire occupations and workplaces may be much lower than suggested by the approach followed by Frey and Osborne. Moreover, even within occupations, the heterogeneity of tasks performed at different workplaces appears to be huge as recently shown by Autor and Handel (2013). In fact, most of the adjustment to the past computerisation occurred through changing task structures within occupations, rather than changing employment shares between occupations (Spitz-Oener 2006).

4. A second critique aims at confounding the potential for automation with actual employment losses. In particular, the technical possibility to use machines rather than humans for the provision of certain tasks need not mean that the substitution of humans by machines actually takes place. In many cases, there are legal as well as ethical obstacles that may prevent such a substitution or at least substantially slow down its pace. Moreover, the substitution may not be reasonable from an economic

point of view. However, even in the absence of such obstacles, workers may adjust to a new division of labour between machines and humans by switching tasks.

5. The aim of this study is to estimate the risk of automation for jobs in 21 OECD countries¹ based on the approach by Frey and Osborne (2013), while relaxing one of their major assumptions as in our earlier study for Germany (Bonin et al. 2015). Rather than assuming that it is occupations that are displaced by machines, we argue that it is certain tasks that can be displaced. To the extent that bundles of tasks differ across countries and also within occupations, occupations at risk of being automated according to Frey and Osborne may well be less prone to automation when considering the fact that most occupations contain tasks that are difficult to substitute at least in the foreseeable future.

6. In this paper, we re-estimate the share of jobs at risk of automation for 21 OECD countries including the US using a task-based approach. For this purpose, we use the recently released PIACC database (Programme for the International Assessment of Adult Competencies) that surveys task structures across OECD countries. Overall, we find the share of jobs at risk of automation to be, on average across OECD countries, 9 %. However, these numbers may be limited in informing us about the potential impact of technological advances. In particular, the paper discusses several reasons why these numbers may still not be equated with actual expected employment losses from technological advances.

7. We find that applying a task-based approach results in a much lower risk of automation compared to the occupation-based approach. For instance, while Frey and Osborne find that 47 % of US jobs are automatable, our corresponding figure is only 9 %. The threat from technological advances is thus much less pronounced compared to the occupation-based approach by Frey and Osborne. This substantial difference is driven by the fact that even in occupations that Frey and Osborne considered to be in the high risk category, workers at least to some extent also perform tasks that are difficult to automate such as tasks involving face-to-face interaction.

8. As a final result, we find heterogeneities across OECD countries. For instance, while the share of automatable jobs is 6 % in Korea, the corresponding rate is 12 % in Austria. As we show, parts of the differences across countries may reflect general differences in workplace organisation, differences in previous investments into automation technologies as well as differences in the education of workers across countries.

1. We estimate the automatibility for all countries which are included in the currently available PIAAC data, excluding Russia.

THE THREAT OF AUTOMATION ACCORDING TO FREY AND OSBORNE

9. With their analysis of the susceptibility of jobs to computerisation, FO (from now on referring to Frey and Osborne 2013) started a controversial discussion about the potential threats from current and future technological advances. In the public debate, their result that 47% of all US jobs might be at risk of being automated in the near future clearly stoked fears that technological unemployment is likely to affect a large and increasing share of the population. Yet, in order to actually interpret these results correctly, it is important to better understand their empirical approach in the first place.

10. FO focus on the technological advances in what they call Machine Learning (ML) and Mobile Robotics (MR). Their starting point is the assumption that these advances differ from previous technological advances in that the technological capabilities to perform tasks that have until recently been considered genuinely human are increasing rapidly. In particular, these tasks are no longer confined to routine tasks as has been the assumption of most studies in labour economics in the past decade (see Acemoglu and Autor, 2011, and Autor, 2013, for reviews of the literature). Instead, machines are increasingly capable of performing non-routine cognitive tasks such as driving or legal writing. In particular, advances in the field of Machine Learning (ML, e.g. computational statistics and vision, data mining, artificial intelligence) allow for automating cognitive tasks, while the use of ML in Mobile Robotics (MR) also allows for automating certain manual tasks.

11. FO argue that due to these advances, creative destruction, i.e. technological unemployment as a result of workers seeking new jobs after being laid off, is likely to exceed what has been called the capitalization effect (Aghion and Howitt 1994). The latter effect refers to the growth-enhancing and ultimately job-creating effect of technological advances that in the past apparently outweighed the initial, labour-saving effect of technology. Since the current speed with which human labour becomes potentially obsolete is high and even increasing, attempts to upgrade skills and education may no longer suffice to win the “Race Against the Machines” as titled by Brynjolfsson and McAfee (2011). Hence, unprecedented levels of technological unemployment may arise. The only domain of tasks that according to FO appears to be exempt from this threat, is related to what they call Engineering Bottlenecks. Such bottlenecks refer to tasks that cannot be substituted by machines in the near future as these tasks cannot be defined in terms of codifiable rules and thus algorithms.

12. One of these bottlenecks refers to tasks that are related to perception and manipulation, especially when such tasks are performed in unstructured situations. The capability of workers in handling objects in such contexts is still a huge challenge for engineers. In particular, humans are likely to have long-lasting comparative advantages when it comes to orienting oneself in complex situations and to react to potential failures and unstructured challenges.

13. Other tasks that are likely to remain the domain of humans are related to creativity and social intelligence. According to FO, creativity is the ability to develop new and meaningful ideas or artefacts such as new concepts, theories, literature, or musical compositions. Although certain parts of these tasks might be automatable to some extent, FO consider true creativity that relates these new ideas to the cultural and contemporary context of changing societal perceptions as a domain that is likely to be dominated by humans in the foreseeable future. Similarly, tasks that necessitate social intelligence, i.e. the ability to intelligently and empathically respond to a human counterpart, remain a highly challenging domain from an engineering point of view. Tasks such as persuading, negotiating or caring for others are thus likely to remain genuinely human even in the long run.

14. Against this background, FO discuss the task model of Autor et al. (2003) that considers a constant return to scale aggregate production function with two types of labour inputs: Routine tasks that are technically substitutable by capital and non-routine tasks that are not substitutable. FO adapt this model by redefining the domain of tasks that are susceptible to automation and those that, due to the engineering bottlenecks, are not. Hence, tasks that could potentially be automated go beyond the routine tasks as defined in Autor et al. (2003), reflecting new advances in ML and MR.

15. An important difference between the task model as used by Autor et al. (2003) and FO is that the former discuss the substitution of routine tasks by machines as a result of profit maximising firms. Hence, whether substitution takes place hinges not only on technological capabilities, but on the relative price of performing tasks by either humans or machines. In contrast, FO only assess the technical capability of substituting a certain tasks by machines and not its economic feasibility.

16. In order to identify the capability of substituting occupations with machines, their empirical analysis is based on the 2010 version of the O*NET data. This database contains information about the task content of 903 occupations in the US and is based on the assessment of labour market analysts as well as experts and workers in a particular occupation. In order to merge wage and employment data to these occupations, FO aggregate the 903 O*NET occupations to 702 occupations of the Labour Department's Standard Occupational Classification (SOC) by taking the mean of the tasks as reported in the O*NET data whenever occupations had to be aggregated.

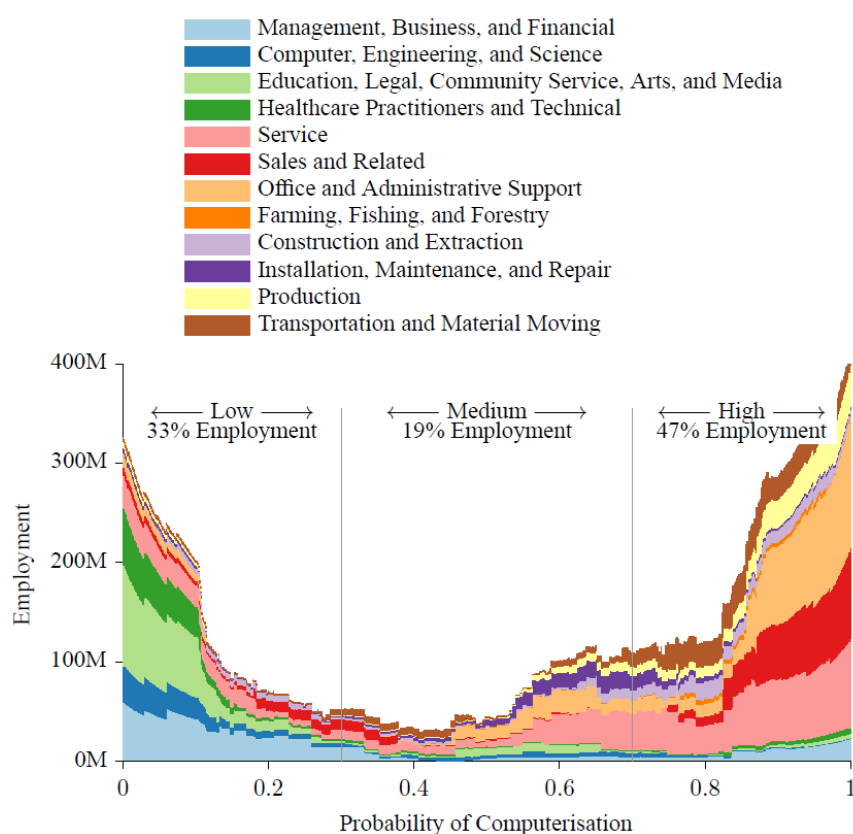
17. Afterwards, they ask ML researchers in the context of a workshop at Oxford University Engineering Sciences Department to classify occupations into being either automatable or not based on the reported task structures.² From this classification purpose, they select only 70 occupations whose labelling the experts were highly confident about. FO then impute the automatibility to the remaining 632 occupations by proceeding as follows. First, they examine whether this subjective classification is systematically related to nine objective attributes of the occupations that are related to the identified engineering bottlenecks (e.g. manual dexterity, originality, social perceptiveness). These bottleneck-tasks were defined only after the workshop and had not been part of the occupational task structures that formed the basis for the experts' assessment. FO then estimate various variants of a probabilistic model to examine the power of these bottleneck-related attributes in predicting an occupation's automatibility. They repeat this exercise with 100 randomly selected subsamples of the 70 classified occupations and find a high predictive power of these attributes for the subjective assessment of each occupation's automatibility.

18. The model estimates are used to predict the probability with which each of the 632 occupations that had not been assessed by the experts could potentially be automated. FO then distinguish between low risk (less than 30%), medium risk (30-70%) and high-risk (>70%) occupations. Combining this information with the number of employees in each occupation in the US, as reported for 2010 by the Bureau of Labor Statistics, FO infer that 47% of all jobs in the US are in the high risk category, "*meaning that associated occupations are potentially automatable over some unspecified number of years, maybe a decade or two*" (FO 2013, p. 38). According to this, it is especially service, sales and office jobs that fall in the high-risk category, see Figure 1. Beyond high-risk occupations, FO assume that automation will take place at a much lower pace as the engineering bottlenecks have to be resolved first. Moreover, they find that the risk of automation is higher for low-skilled workers and for low-wage occupations, suggesting that automation could disproportionately affect these groups of workers.

2. Experts were 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“ (Frey and Osborne, 2013: 30)

19. Although FO repeatedly stress that they focus on technological capabilities only, their results of jobs being “at risk” of automation and the follow-up studies by other scholars (see next section) set off a heated debate about the potential threats from technological advances. Yet, there are many reasons why the automatibility of jobs might not resolve in actual job losses. Besides several other reasons (see Section “Interpretation and Critique”), one main factor that FO leave aside is that it is usually not an occupation, but rather a certain task that can be automated or not, i.e. it is tasks rather than occupations that are at risk. In the next section, we therefore provide an alternative approach to estimate the risk of automation for 21 OECD countries based on the actual task content of jobs.

Figure 1. **US Employment by Risk Category (Frey/Osborne 2013, p.37)**



Source: Frey and Osborne (2013), *The Future of Employment: How Susceptible are Jobs to Computerization?* University of Oxford.

AUTOMATIBILITY OF JOBS IN OECD COUNTRIES – A TASK-BASED APPROACH

20. Below, we transfer the automatibility as provided by FO to other OECD countries. Some authors have done this by assuming that occupations in the studied countries are comparable to US occupations. In order to derive similar automation scenarios as in FO, they directly transferred the automatibility as reported by FO at the occupational level to occupation-specific employment data in Germany (Brzeski and Burk 2015), Finland (Pajarinen and Rouvinen 2014) or European Countries (Bowles 2014). We refer to this method as the occupation-based approach. A main drawback of the occupation-based approach is that it assumes occupations to be similar across countries. Moreover, direct correspondences between the occupational classifications of these countries and the Standard Occupational Classification (SOC) of the US typically do not exist. Finally, FO assume that occupations can be automated, assuming that workers within the same occupation have identical task structures. However, workers' task structures differ remarkably within occupations (Autor and Handel 2013). Hence, even within occupations, workers likely are very differently exposed to automation depending on the tasks they perform. Therefore, we follow an alternative task-based approach that copes with these issues. In short, we estimate the relevance of tasks for the automatibility of jobs in the US and use this empirical relationship to transfer the automatibility to other OECD countries. In the remainder of the chapter, we first present the data and methodology. Then, we present the results of the task-based approach for the US, before transferring the automatibility to other OECD countries.

A. Data and Methodology

21. In this paper, we follow a task-based approach to transfer the results by FO to other OECD countries. The approach is based on the idea that the automatibility of jobs ultimately depends on the tasks which workers perform for these jobs, and how easily these tasks can be automated. We therefore estimate the relationship between workplace tasks in the US and the automatibility by FO. We then use this statistical relationship to transfer the automatibility to jobs in other OECD countries. At first sight, this procedure has some similarities with the analysis of FO, who estimate how the experts' assessment of the automatibility at the occupational level is related to some bottleneck-tasks, to transfer these results to other occupations. However, while they use only a limited set of bottleneck-tasks that reflect average task structures at the occupational level, we rely on individual survey data regarding a comprehensive list of tasks that people actually perform at their workplace. Using individual-level data, we thus take into account that individuals within the same occupation often perform quite different tasks. Moreover, the task structures are self-reported by the individuals and thus likely a better indicator of workers' actual tasks.

22. The analysis is based on data from the Programme for the International Assessment of Adult Competencies (PIAAC). The PIAAC data is a unique data source which contains micro-level indicators on socio-economic characteristics, skills, job-related information, job-tasks and competencies. Most importantly, the data is comparable across the countries in the program. Hence, the data also allows for relaxing the assumption that task structures are the same across countries.

23. To implement our task-based approach, we estimate the relationship between workers' tasks and the automatibility of jobs in the US. For this we match the automatibility indicator by FO to the US observations in the PIAAC data based on the occupational codes. As only 2-digit ISCO codes are available in the PIAAC, an assignment problem arises. We therefore assign multiple values of the automatibility to each individual in the PIAAC data and follow a multiple imputation approach. For each individual in the PIAAC data, we identify the automatibility with the highest probability based on this method. In particular, we follow Ibrahim (1990) and implement the following Expectation-Maximization (EM) algorithm:

(1) In a first step, we regress the automatibility y on the N characteristics x of the jobs:

$$y_{ij} = \sum_{n=1}^N \beta_n x_{in} + \epsilon_{ij}$$

where i are the individuals in the PIAAC-data and j are the duplicates of these individuals, since multiple automatibilities y_{ij} are assigned to each individual i . β_n are the parameters to be estimated, which represent the influence of the job-related characteristics on the automatibility of each job. The automatibility is restricted to the interval 0% to 100%. We use the Generalized Linear Model (GLM) by Papke and Wooldridge (1996) where the dependent variable of the model is transferred to a non-restricted interval. In addition, we take into account two weights which we connect multiplicatively. The first weight is necessary, because we have duplicated the individuals in the dataset. This weight is therefore constructed such that it sums to unity for each individual. For the initial step of the algorithm, we set this weight to the inverse number of duplicates of each individual. The second weight is the replication weight of the PIAAC data.

(2) In a second step, we predict the automatibility \hat{y}_i . Note that these values do not vary within individuals, as the job-related characteristics x_{in} are constant within individuals. By comparing the automatibilities y_{ij} and the predicted automatibility \hat{y}_i we can determine the likelihood that y_{ij} , given the job-related characteristics x_{in} and the estimated model, is the true automatibility. Based on this likelihood, we recalculate the first weight and continue with step 1 (see Ibrahim 1990).³ We run this algorithm until the weights converge.

24. We implement this model for employed individuals based on US observations in the PIAAC data, excluding armed forces and individuals with missing occupational information or individuals whose occupation is available only at the 1-digit ISCO level. Our explanatory variables mostly cover indicators of workplace tasks, but we further consider gender, education, competences, income, sector, firm-size and further auxiliary variables. The explanatory variables and their descriptive statistics are outlined in Table 2 in Annex A. Variable definitions can also be found in Annex A. The model and estimated parameters then show the influence of the explanatory variables on the automatibility in the US. We then apply this model and the estimated parameters to the PIAAC data in other OECD countries to predict the automatibility for these countries.

25. Through this procedure, we take into account that not whole occupations, but specific jobs are exposed to automatibility, depending on the tasks performed at these particular jobs. The procedure is based on the idea that jobs with larger shares of automatable tasks are more exposed to automatibility than jobs with larger shares of non-automatable tasks (bottlenecks, using the wording of FO). The procedure allows for differences in task-structures within occupations and specifically focuses on the individual job. This approach is less restrictive than the occupation-based approach, which relies on the assumption that occupational task structures are identical in the US and other countries. However, with this procedure we assume that workers with the same task structure face the same automatibility in all OECD countries. Any differences of automatibilities between the countries then originate from differences in task structures or other explanatory variables between the countries.

3. More precisely, the first weights w_{ij} are calculated as $w_{ij} = \frac{f(\hat{y}_i - y_{ij} | x_{in}, \beta_n)}{\sum_{j=1}^J f(\hat{y}_i - y_{ij} | x_{in}, \beta_n)}$ where $f(\cdot)$ is the standard normal density. This is based on equation 3.4 in Ibrahim (1990) and follows from Bayes theorem. Note that Ibrahim (1990) presents the EM algorithm for the case of missing explanatory variables, but the procedure can also be applied to missing dependent variables, as in our case.

B. Results for the US

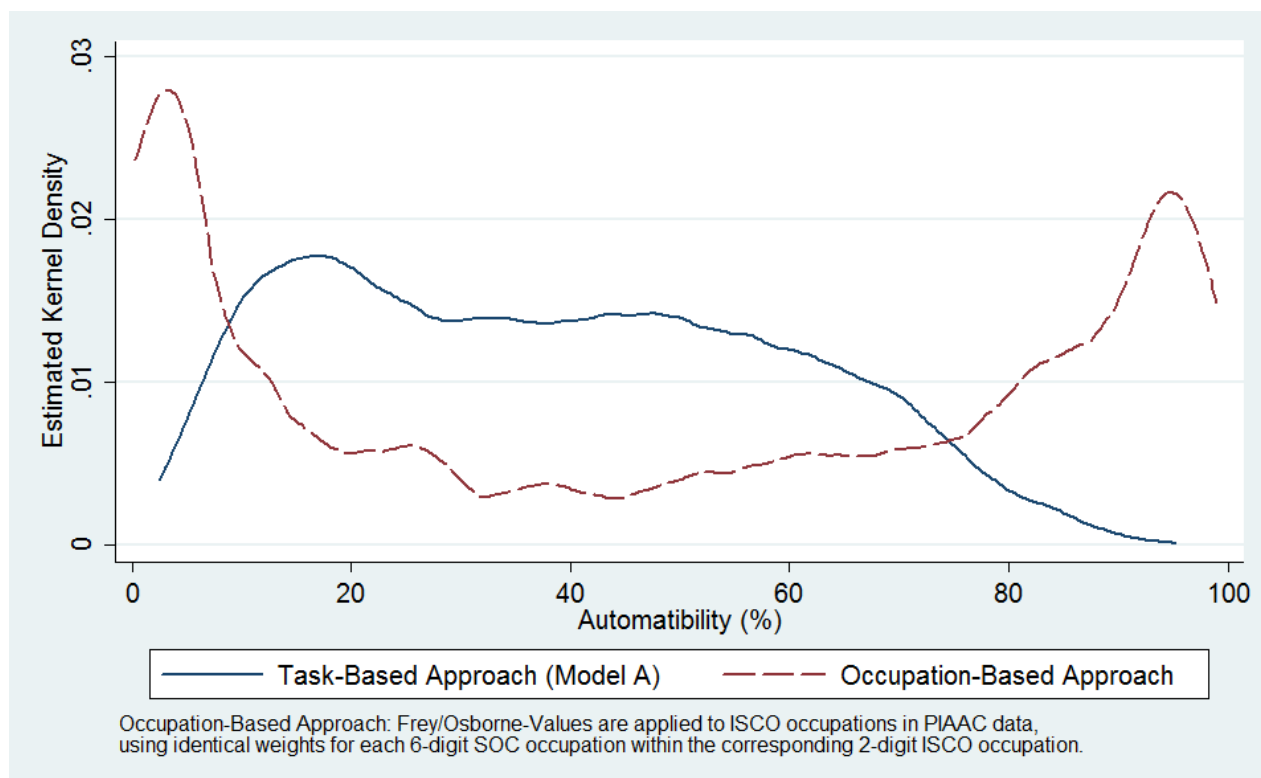
26. We present the main results for the US below, the detailed results of our model can be found in Annex B. Overall, we find that the automatibility of jobs is lower in jobs with high educational job requirements or jobs which require cooperation with other employees or where people spend more time on influencing others. Hence, the low-risk tasks partially reflect what FO called engineering bottlenecks. The automatibility is higher in jobs with a high share of tasks that are related to exchanging information, selling or using fingers and hands. This resembles the evidence from the task-based literature which argues that so-called routine tasks are subject to automation, whereas interactive or cognitive tasks are less likely to be substituted by machines and computers (see Acemoglu and Autor (2011) or Autor (2013) for an overview of the literature).

27. Figure 2 compares the predicted automatibility of jobs in the US using the PIAAC data when applying the task- and the occupation-based approach. For the occupation-based approach, we matched all potential FO-values to each individual in the US-PIAAC-data based on the 2-digit ISCO occupation.⁴ The result strongly resembles the bi-polar structure which is known from FO and shown in Figure 1 – the majority of jobs is assigned either a very high or a very low automatibility, only few jobs have a medium automatibility. In contrast, the result from the task-based approach show a very different pattern – the two poles of the distribution move to less extreme values of the automatibility. Hence, fewer jobs have either very high or very low values of automatibility when taking into account the variation of task-structures within occupations. As a result, only 9% of all individuals in the US face a high automatibility, i.e. an automatibility of at least 70%. This figure stands in contrast to FO, who argue that 47% of US jobs are at high risk of being automated. Apparently, not taking account of the variation of tasks within occupations exerts a huge impact on the estimated automatibility of jobs. This is because even in occupations that FO expect to be at a high risk of automation, people often perform tasks which are hard to automate, such as for example interactive tasks (e.g. group work or face-to-face interactions with customers, clients, etc.). This can be illustrated by two examples:

- According to FO, people working in the occupation “Bookkeeping, Accounting, and Auditing Clerks” (SOC code: 43-3031) face an automation potential of 98%. However, only 24% of all employees in this occupation can perform their job with neither group work nor face-to-face interactions.
- According to FO, people working in the occupation “Retail Salesperson” (SOC code 41-2031) face an automation potential of 92%. Despite this, only 4% of retail salespersons perform their jobs with neither both group work nor face-to-face interactions.⁵

4. For the occupation-based approach, we matched all potential FO-values to each individual in the US-PIAAC-data based on the 2-digit ISCO occupation. Each individual is assigned multiple FO-values due to the assignment problem. We equally weight each observation within each individual.

5. These results are based on the Princeton Data Improvement Initiative (PDII). We rely on this data rather than the PIAAC, because in the PDII 6-digit SOC codes are available, which allows us to circumvent the assignment problem.

Figure 2. **Distribution of Automatability in the US (Task-Based vs. Occupation-Based Approach)**

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

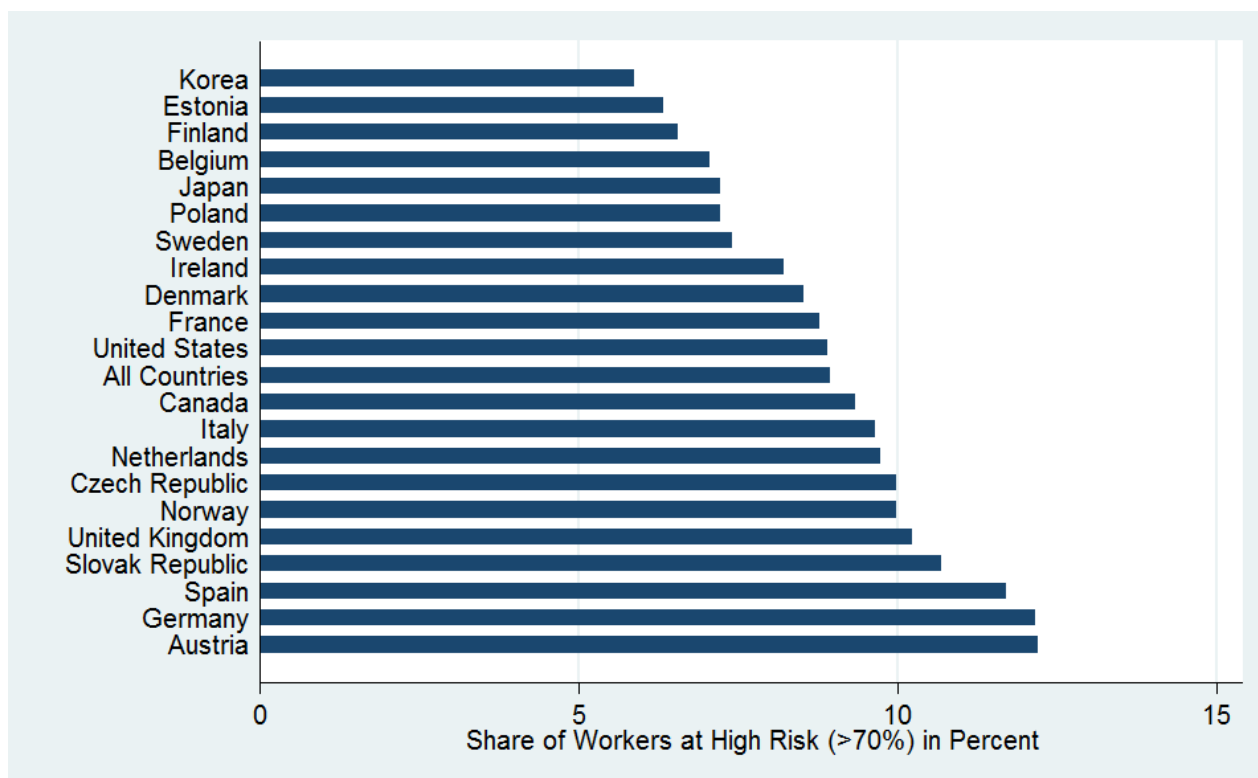
28. In conclusion, using information on task-usage at the individual level leads to significantly lower estimates of jobs “at risk”, since workers in occupations with – according to FO – high automatabilities nevertheless often perform tasks which are hard to automate.

C. Results for other OECD countries

29. Figure 3 3 shows the share of workers at high risk by OECD countries, i.e. the share of workers whose automatability is at least 70%. This share is highest in Germany and Austria (12%), while it is lowest in Korea and Estonia (6%).⁶ The results for Germany are very similar to the results of a recent representative survey among German employees, where 13 % of employees consider it likely or highly likely that their job will be replaced by machines (BMAS 2016). Furthermore, our results for Germany are comparable to a recent study by Dengler and Matthes (2015), who use a different methodological approach but also find that 15% of all jobs in Germany are at risk of automation. Moreover, they also find a bi-polar distribution of automatability with moderate polarisation.

6. We exclude the Russian Federation from our sample. This is because when we restrict the Russian PIAAC sample to those observations where all relevant variables are non-missing, then the distribution of these variables is not representative. The results for Canada should be treated with some caution, as relevant explanatory variables for extrapolating the automatability are missing, see Annex B.

Figure 3. Share of Workers with High Automatability by OECD Countries



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

30. An interesting result from Figure 3 is that the distribution of automatibility across countries does not lend itself to an immediate interpretation of potential underlying factors. To gain deeper insights into the underlying reasons for these country differences, we decompose the difference of the share of workers at high risk between each country and the US into a within- and between-industry component regarding three dimensions: industry, occupation, and education.⁷ In each case, the between-component reflects the difference in automatibility that is due to the cross-country difference in industry, occupation or educational structure, while the within-component reflects the difference in automatibility that is due to the fact that workers in the same industries, occupations, or education group perform more (or fewer) automatable tasks.

31. The results in Table 1 show that differences in industry and occupational structures explain only little of the differences in the share of workers at high risk between each country and the US, as the between-industry and -occupation components matter only little for most countries. Instead, workers in the same industries and occupations perform differently automatable tasks in these countries than workers in the US. However, education plays a large role for many countries. In most countries, the within-education component is negative, which implies that people with the same education typically perform less

7. To compute the between-industry component, we first assign weights to each individual. These weights are the same for all individuals of the same industry. We choose the weights such that the share of workers by industry of each country resembles the US industry structure. We then recalculate the share of workers at high risk and calculate the difference of this figure to the original share of workers at high risk in each country. This difference resembles the between-component. The remaining difference of the country to the US-figures then resembles the within-component.

automatable tasks compared to the US. However, in many countries the between-education component is positive, which implies that in those countries a larger share of workers has educational levels which are associated with more automatable tasks (i.e. low or medium qualified workers). This is because the US has a larger share of highly educated workers, who typically perform fewer automatable tasks. These results also hold when focusing on educational requirements of the jobs rather than actual education.⁸

Table 1. **Decomposition of Country Differences in the Share of Workers at High Risk**

Country	Difference to the US	Industries		Occupations		Education	
		within	between	within	between	within	between
Austria	3.2%	2.7%	0.6%	3.3%	-0.1%	-2.2%	5.5%
Belgium	-1.9%	-1.6%	-0.3%	-1.1%	-0.7%	-3.1%	1.2%
Canada	0.4%	0.3%	0.0%	1.3%	-0.9%	-0.8%	1.2%
Czech Republic	1.0%	-0.2%	1.3%	-0.8%	1.8%	-2.0%	3.0%
Denmark	-0.4%	0.1%	-0.5%	-0.2%	-0.2%	-3.3%	2.9%
Estonia	-2.6%	-3.0%	0.4%	-1.4%	-1.2%	-2.9%	0.3%
Finland	-2.4%	-2.9%	0.6%	-3.3%	0.9%	-2.8%	0.4%
France	-0.2%	-0.3%	0.1%	-0.3%	0.1%	-1.5%	1.4%
Germany	3.2%	3.6%	-0.4%	2.0%	1.2%	0.1%	3.1%
Ireland	-0.7%	-0.6%	-0.1%	-0.5%	-0.2%	0.0%	-0.7%
Italy	0.7%	0.2%	0.5%	0.7%	0.0%	-3.7%	4.4%
Japan	-1.7%	-1.7%	-0.1%	-2.5%	0.8%	-0.8%	-0.9%
Korea	-3.1%	-2.8%	-0.3%	-3.6%	0.6%	-1.7%	-1.4%
Netherlands	0.8%	0.9%	-0.1%	1.2%	-0.4%	-4.9%	5.7%
Norway	1.0%	1.6%	-0.6%	1.4%	-0.4%	-3.4%	4.4%
Poland	-1.7%	-3.3%	1.6%	-2.7%	1.0%	-1.8%	0.1%
Slovak Republic	1.7%	1.2%	0.6%	2.0%	-0.2%	-0.2%	2.0%
Spain	2.8%	2.5%	0.3%	2.3%	0.5%	-1.4%	4.1%
Sweden	-1.5%	-1.0%	-0.5%	-1.5%	0.0%	-4.1%	2.6%
United Kingdom	1.3%	2.1%	-0.8%	0.1%	1.2%	-1.3%	2.6%

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

32. As an example, in Austria, workers perform typically fewer automatable tasks compared to US-workers with the same educational level, but Austria has a higher share of low- and medium-skilled workers which perform more automatable tasks. Since the latter effect dominates, Austria has on aggregate a larger share of workers at high risk. In Korea, in contrast, both effects are negative, which implies that Koreans both perform fewer automatable tasks at each educational level compared to the US, and a larger share of Korean workers achieved educational levels which are associated with fewer automatable tasks compared to the US.

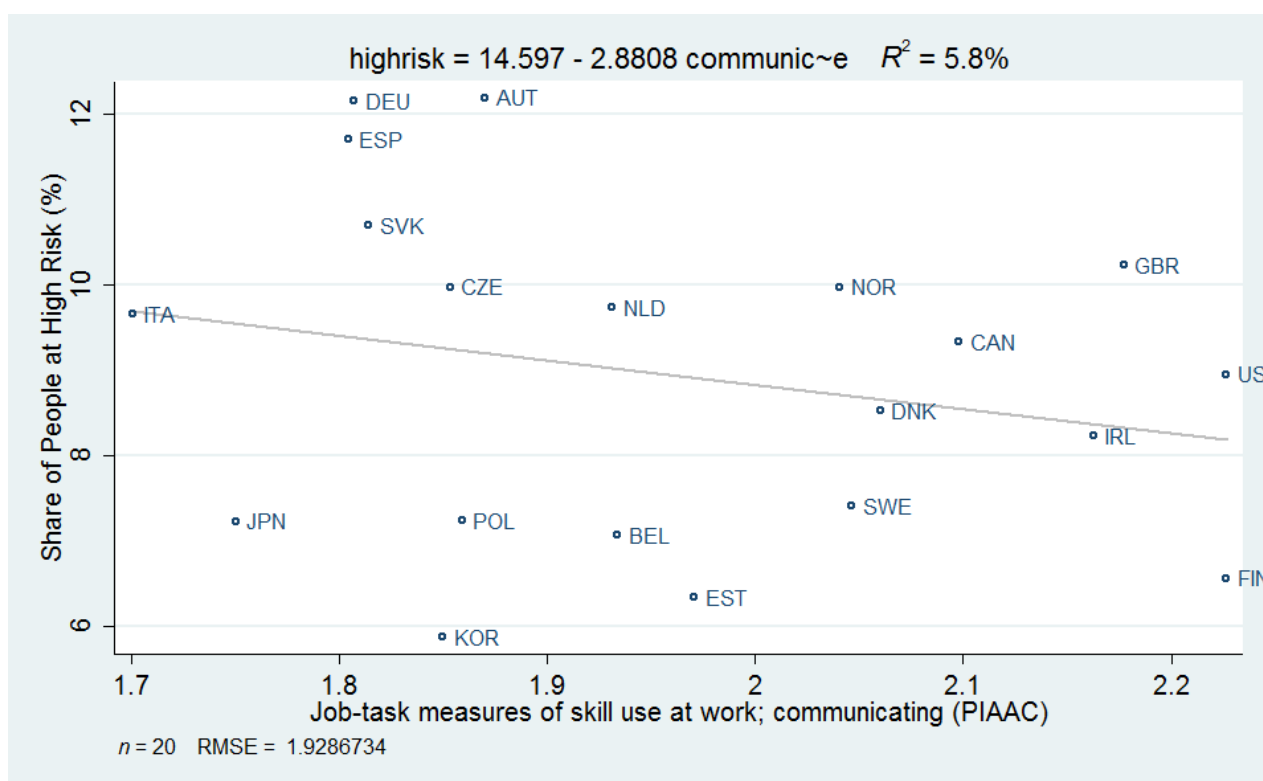
33. Hence, we can conclude that cross-country differences often reflect that individuals in the same industry, occupation or even education group perform different tasks. But what might be the reason behind such differences? In the following, we aim to briefly discuss two potential explanations: (1) general differences in the workplace organisation, and (2) differences in the adoption of new technologies.

34. In order to illustrate the first reason, consider, for example, two countries A and B which have adopted comparable technologies. The automatibility might nevertheless be higher in country A than in country B, because workplace organisation in country A generally relies less on group work or face-to-face interactions than country B. This is illustrated in Figure 4, which shows the relationship between the share

8. Results are available upon request.

of people at high risk and the incidence of communication tasks at the country level. On average, countries which have a stronger focus on communicative tasks in their workplace organisation also have a lower share of jobs at high risk. For instance, jobs in Italy and Germany show low degrees of communication, whereas jobs in the US and UK are more communicative. Overall, the analysis shows that genuine differences in workplace organisation are relevant for differences in automatibilities between countries.

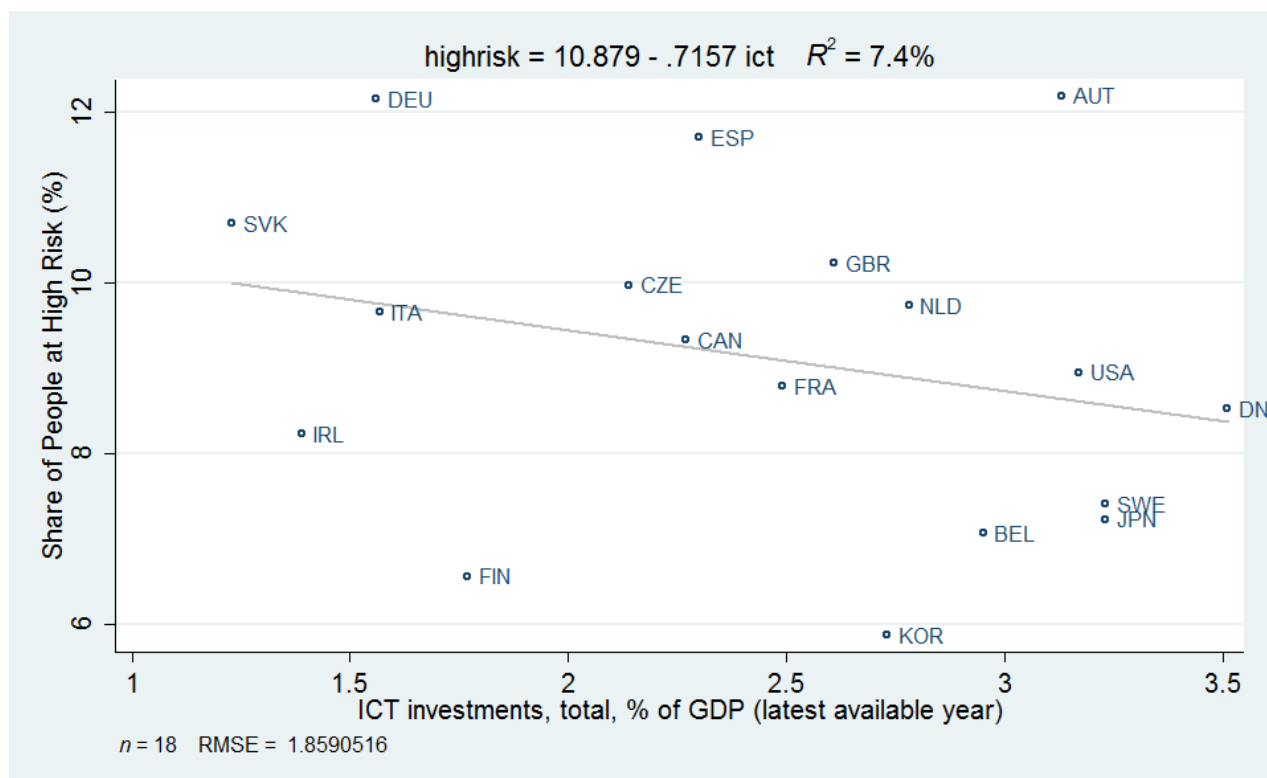
Figure 4. **Automatibility and Communicating**



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

35. To illustrate the second reason, assume that there are no genuine differences in the workplace organisation of countries A and B. The automatibility of country A might still be higher than in country B, because country B invests stronger in new automation technologies and has hence already replaced labour by capital for performing the automatable tasks. Indeed, the automatibility is lower in countries which already invest a lot in ICT (see Figure 5). Hence, a high automatibility may reflect an unused potential for automation. Whether an extended use of automation technologies comes with beneficial or adverse effects on workers is unclear ex ante.

Figure 5. ICT Investments and Automatability



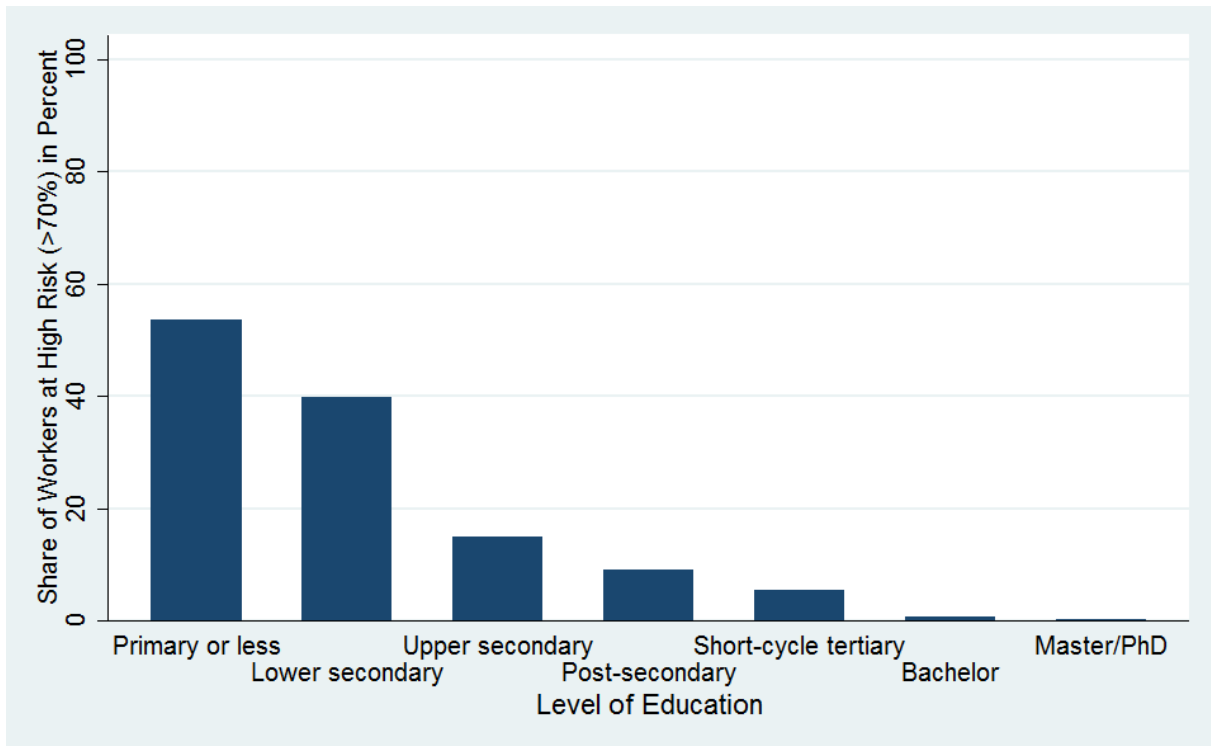
Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

36. Overall, we can conclude that comparing the automatibilities between countries is not straightforward and necessitates further insights into a country's adoption of new technologies, its economic and educational structure, its workplace organisation and the resulting task structures. Education and in particular the educational structure of the workers seem to play a large role. Countries with a strong focus on high qualified workers typically have lower shares of workers at high risk, since these workers typically perform fewer automatable tasks than low qualified workers. We therefore focus on the relationship between education and automatability, below.

37. Despite the cross-country differences, a main feature of all countries is that the automatability strongly decreases in the level of education and in the income of the workers: It is mostly low skilled and low-income individuals who face a high risk of being automatable. This is shown in Figure 6 and Figure 7 for a weighted average⁹ of all OECD countries. Results for the individual countries can be found in Annex C.

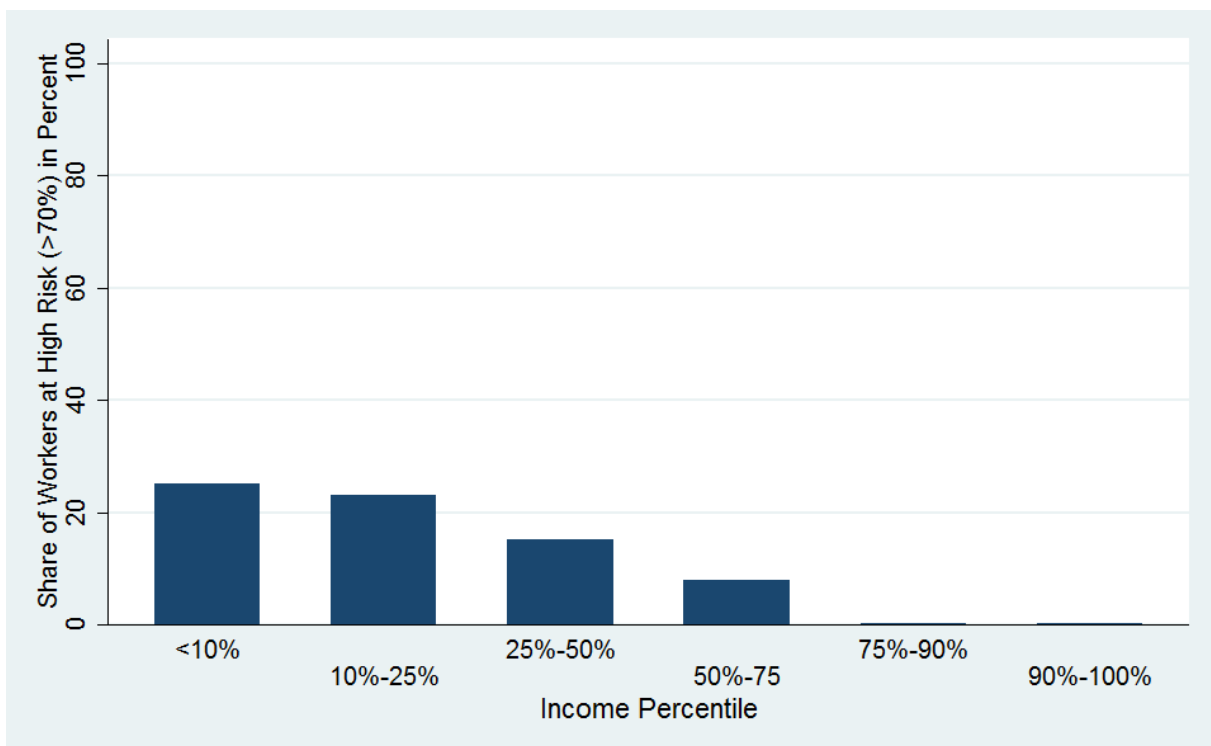
9. The figures are based on weighted data, so that large countries have a larger influence on the results. Nevertheless, the results are very similar when using unweighted data.

Figure 6. **Share of Workers with High Automatability by Education**



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

Figure 7. **Share of Workers with High Automatability by Income**



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

INTERPRETATION AND CRITIQUE

38. As discussed, FO predict that technologies allow for automating a substantial share of jobs within the next two decades. In addition, they assume that this process continues beyond the most-prone jobs in the medium run and ultimately affects even those that today appear to be relatively safe from automation. As discussed in the last chapter, applying a task-based approach that takes account of the heterogeneity of workplace tasks within occupations already strongly reduces the predicted share of jobs that are at a high risk of automation. This deviating result clearly sounds a note of caution regarding the interpretation of such predictions. Apparently, the mere fact that FO chose an occupation-based approach that abstracts from within-occupation variation in the tasks performed and that transfers the expert assessments for 70 occupations to the remaining occupations based on only three engineering bottlenecks and nine related tasks, has a strong effect on the outcome.

39. However, even for the less restrictive task-based approach, there are good reasons to be cautious when interpreting the results. Firstly, the approach still reflects technological capabilities based on experts' assessments rather than the actual utilisation of such technologies, which might lead an overestimation of job automatibility. Secondly, even when new technologies are increasingly used, the effect this has on employment prospects depends on whether workplaces adjust to a new division of labour or not. Workers might adjust by increasingly performing tasks that are complemented by the new technologies. Thirdly, the approach considers only existing jobs. Yet, the use of these technologies is likely to create new jobs. Moreover, new technologies may also exert positive effects on labour demand if they raise product demand due to an improved competitiveness and a positive effect on worker's incomes. Hence, workplaces are likely to be less "at risk" than suspected at first sight. In the following, we discuss these three aspects in more detail.

A. Overestimation of technological capabilities and its lagging utilisation

40. The experts assessing the automatibility of the 70 occupations in the FO study were asked whether "[...] *the tasks of this job [can] be sufficiently specified conditional on the availability of big data, to be performed by state of the art computer-controlled equipment*" (Frey and Osborne, 2013: 30). It is very likely that the resulting assessment overstates technological possibilities. First of all, experts tend to overestimate the potential of new technologies (Autor 2014, 2015, Pfeiffer and Suphan 2015). In particular, the comparative advantage of machines as compared to workers is typically overstated for tasks involving flexibility, power of judgement and common sense. More generally, the classification of occupations or tasks into the distinct domains automatable and not-automatable is problematic (Green 2012, Rohrbach-Schmidt and Tiemann 2013, Pfeiffer and Suphan 2015).¹⁰ In addition, most jobs are probably not sufficiently well defined to be actually substituted by machines. As Pratt (2015) states for the advances in robotics "*specialized robots will improve at performing well-defined tasks, but in the real world, there are far more problems yet to be solved than ways presently known to solve them*" (Pratt 2015:52).

10. Green (2012, p. 41) finds that the classification of tasks into the distinct domains "routine" (i.e. automatable) and "non-routine" (i.e. non-automatable) using UK data. Also Rohrbach-Schmidt and Tiemann (2013) find that the results on the effects of technological change in Germany are sensitive to the subjective classification of tasks into either routine or non-routine. Pfeiffer and Suphan (2015, p. 11) criticises that "*the reasons why specific tasks are characterized as routine or non-routine [...] are not clear. The decision process introduces a potential for circular reasoning because assignment follows an assumption already made about the likelihood of automation.*"

41. Moreover, the necessary condition for the utilisation of these technologies in terms of data and computer availability may not be met, at least not immediately. In fact, a monitoring report on the digitalisation of the German economy for the Federal Ministry of Economic Affairs recently revealed that the digitalisation of the manufacturing sector is still rather low and will advance only slowly until 2020 (Graumann et al. 2015). For example, a recent survey among German firms by the ZEW (2015) shows that only 18% of all firms are familiar with the concept “Industrie 4.0”, which is a project put forward by the German government to foster the digitalisation and interconnectedness of the German industry. Up to now, only 4% of firms have started or are about to start such projects. Hence, the utilisation of technologies clearly lags behind the technological possibilities. This may also be related to a shortage of qualified personnel that is able to handle these new technologies, as the introduction of new technologies may require the supply of complementary skills on the labour market (Acemoglu 1998). For example, Janssen and Mohrenweiser (2014) investigate the introduction of the new computer-based control system (Computerized Numerical Control, CNC) in the field of cutting machine operation into the German apprenticeship regulation. They find that this regulatory change in the apprenticeship regulation negatively affected workers who graduated before this regulatory change, and hence did not learn the use of the technology in their formal training. However, only workers who switched their occupation after the change were negatively affected, suggesting that the remaining workers learned the technology on the job. This indicates that the technology was only implemented by firms on a large scale after the application of the CNC technology had been introduced to the curricular of the apprenticeship training program.

42. Furthermore, even if sufficiently qualified personnel were available, firms decide on investing in new technologies depending on the relative factor prices of capital and labour in performing a certain task in the production process. Although the literature on routine-biased technological change showed that the reduction in prices for computer capital reduced the demand for routine-intensive jobs, it is not clear when the break-even point for machines to perform more complex tasks will actually be reached. This will, of course, also depend on the wage level which itself is endogenous and would thus react to an excess labour supply by lowering wages, hence improving worker’s employment prospects again. For this reason, technological capabilities need not translate into technological obsolescence of human labour (cf. Acemoglu and Restrepo 2015). The empirical approach of FO clearly leaves aside many factors that ultimately determine the decision to automate tasks and substitute human labour and that would prevent all technological capabilities from being exhausted. Hence, FO explicitly state that their empirical approach focusses on technological capabilities. The susceptibility of jobs to automation that they aim at identifying hence refers to such capabilities only.

43. Apart from company-related reasons for a rather low speed of technological adoption, there may also be ethical or legal obstacles to the utilisation of new technologies. As a prominent example that has recently been discussed by Thierer and Hagemann (2015) and Bonnefon et al. (2015), the autonomous car bears new legal challenges regarding e.g. liabilities in case of an accident. Moreover, there are unresolved ethical questions concerning how an algorithm should decide between crashing into a car or a truck. While some of these obstacles may be resolved at some point, they clearly slow down the pace with which technologies are spread. This can be illustrated using the example of driverless cars, which are often said to have a high disruptive potential. According to the Boston Consulting Group (2015), the share of driverless vehicles will reach 10% by the year 2035 which suggests a rather slow speed of change.

44. Finally, another aspect that should be considered is a strong societal preference for the provision of certain tasks and services by humans as opposed to machines. As an example, nursing or caring for the elderly may remain labour-intensive sectors, even if service robots increasingly complement these professions in the future. Hence, “*some human services will probably continue to command a premium compared to robotically produced one*” (Pratt 2015, p. 58), meaning that there is a societal value attached to humans performing certain tasks that tends to preserve their comparative advantage.

45. For all these reasons, the technological capabilities as assessed by FO are likely overestimated and should not be equated with the actual utilisation of technological advances.

B. Adjustment of workplace tasks

46. Even if a technology actually enters the production process, the impact on employment depends on whether workplaces are able to adjust to new demands. In particular, the new technologies may substitute for certain tasks and complement others. Hence, whether a workplace will be automated or not clearly depends on whether the tasks performed at a certain workplace shift from the first to the latter set of tasks. In fact, several studies suggest that although there has been a decline in jobs with predominantly routine and automatable tasks, the adjustment mainly takes place by changing the set of tasks within occupations (e.g. Autor et al. 2003, Spitz-Oener 2006). Workers seem to shift worktime from routine and automatable tasks to tasks that are complementary to machines.

47. The adoption of new technologies seems to come along with a new division of labour where workers increasingly perform tasks that complement machines (Autor 2013) of new and more complex tasks (Acemoglu and Restrepo 2015). As an example, tasks involving the monitoring of machines are likely to gain in importance. Hence, new technologies are unlikely to fully automate workplaces or occupations on a large scale, but rather change workplaces and the tasks involved in certain occupations. As long as workers are able to adjust to these new task demands, machines need not crowd out workers. However, as the findings from FO as well as the predictions in chapter 3 suggest, low-qualified workers perform a much higher share of potentially automatable tasks than high-qualified workers. If the tasks that complement machines become increasingly complex and demanding, the employment prospects for workers lacking certain skills may deteriorate.

C. Macroeconomic adjustment and indirect effects

48. The risk of automation as predicted by FO refers to the (likely overestimated) threat regarding the labour-saving impact of new technologies. This “risk of automation”, however, must not be equated with employment losses since there are macroeconomic feedback mechanisms that may also result in an increase in labour demand. Arntz et al. (2014) review the literature regarding these macroeconomic adjustment mechanisms. In particular, there are three mechanisms that counteract the labour-saving impact of technological advances.

49. First of all, labour-saving technologies need to be produced in the first place, thereby creating a demand for labour in new sectors and occupations. According to the OECD Digital Economy Outlook (OECD 2015) the ICT sector is a key driver of economic growth in OECD countries. Between 15 and 52% of all investments in OECD countries were related to the ICT sector between 2008 and 2013. Moreover, after a slack in the sector’s contribution to employment growth during the economic crises, the share of jobs created by the ICT sector in OECD countries amounts to 22% in 2013. FO do not take into account such positive demand effects. Moreover, due to focusing on the perceived risk for currently existing jobs only, FO neglect the fact that jobs of the future are likely to be complementary to the new technologies.

50. Secondly, new technologies may boost a firm’s competitiveness since new technologies typically increase a firm’s productivity. With lower costs and prices, firms face a higher product demand and hence demand more labour, which can (partially) compensate for the labour-saving effect of technologies. Graetz and Michaels (2015), for example, examine the effect of the utilisation of industrial robots in 17 countries and find no negative impact on the total working hours at the sector level. Hence, the use of new labour-saving technologies did not reduce the demand for labour. Similarly, Goos et al. (2014) develop a model of labour demand at the industry level for 16 European countries and find that routine-intensive industries that are at a higher risk of introducing labour-saving technologies gain in competitiveness and face an

increasing product demand. Similarly, Gregory et al. (2015) estimate a labour demand model at the level of European NUTS2 regions and show that regions with an initially high share of routine and highly automatable tasks actually gained in competitiveness, with the indirect positive effect on the regional product demand more than compensating the labour-saving substitution effect. In total, they find that the computerisation in fact generated 11.6 Million jobs on net across 27 European countries between 1999 and 2010.

51. Thirdly, to the extent that the new technologies complement workers, labour productivity increases. This may lead to either higher wages, or higher employment, or both, which in turn raises labour income. As a consequence, these workers may demand more products and services, thereby again increasing the demand for labour in the economy. In their labour demand model, Gregory et al. (2015) take these adjustment processes into account and find that they played a strong role for the positive net effect of technological change on employment in Europe. For past waves of technological innovations, several studies suggest that workers at least in the long run benefited from technological advances in terms of higher wages and income, although there is also evidence that there was at least a temporary increase in income inequality related to some technological innovations (see Mokyr et al 2015 for a review). For the recent past, Graetz and Michaels (2015) also find that the use of industrial robots at the sector level increased both labour productivity and wages for workers. Hence, to the extent that workers benefit from technological change in terms of higher wage income, technological progress can additionally boost labour demand via an increase in product demand.

52. Altogether, these macroeconomic mechanisms may compensate for the negative labour-saving effects of new technologies, so that large job-losses remain unlikely. On the contrary, total employment might even increase as argued above. Moreover, a recent study by Wolter et al. (2015) simulates the potential effects of the future digitalisation on the German economy (labelled as “Industry 4.0”). Even though they find only small negative effects on overall employment, their results suggests large shifts in employment between industries and occupations. In another paper, Nordhaus (2015) develops a theory of how new technologies can fully substitute for labour and analyses the conditions that need to be fulfilled for labour to become obsolete. He compares these to recent indicators for the US economy and this test suggests that the obsolescence of labour is unlikely to become relevant during this century. Hence, while the overall employment effects of future automation are presumably small, the development of digitised economies is likely associated with large shifts between occupations and industries, forcing workers to adjust to the changing economic environment.

CONCLUSIONS

53. In recent years, a series of studies have revived concerns that technological change might cause widespread technological unemployment. Especially Frey and Osborne triggered a public debate by claiming that 47% of US jobs are at risk of being automated. The present paper contributes to this debate by reflecting on some of the methodological problems of these studies. In particular, we argue that one of their major limitations is that they view occupations rather than tasks as being threatened by automation. We therefore focus on the task-content of jobs, as workers within the same occupation often perform different tasks. As we argue throughout this article, many workers in occupations that have been classified as vulnerable to automation in these studies may in fact be less exposed to automation than previously thought. The reason is that workers often perform a substantial share of non-routine interactive tasks, which are known to be less automatable.

54. In this paper, we therefore estimate the automatibility for 21 OECD countries following a task-based rather than an occupation-based approach. For this, we use data on actual workplace tasks as recently surveyed in the PIACC database for OECD countries. Overall, our figures suggest that 9 % of OECD jobs are potentially automatable. Moreover, we find that in the US only 9% of jobs rather than 47%, as proposed by Frey and Osborne face a high automatibility. The threat from technological advances thus seems much less pronounced compared to studies following an occupation-based approach. We further find heterogeneities across OECD countries: while the share of automatable jobs is 6 % in Korea, the corresponding share is 12 % in Austria. The differences across countries may reflect general differences in workplace organisation, differences in previous investments into automation technologies as well as differences in the education of workers across countries.

55. The study demonstrates the necessity to view technological change as substituting or complementing certain tasks rather than occupations. Neglecting the differences in tasks of comparable jobs may lead to an overestimation of job automatibility. Moreover, difference in the task structure are to a large extent able to explain differences in the employment projections.

56. Nevertheless, our figures should be interpreted with caution. Firstly, the approach still reflects technological capabilities rather than the actual utilisation of such technologies, which might lead to a further overestimation of job automatibility. Secondly, even if new technologies are increasingly adopted in the economy, the effect on employment prospects depends on whether workplaces adjust to a new division of labour, as workers may increasingly perform tasks that are complementary to new technologies. Thirdly, the approach considers only existing jobs, although new technologies are likely to create also new jobs. Moreover, new technologies may also exert positive effects on labour demand if they raise product demand due to an improved competitiveness and a positive effect on workers' incomes. Even though this suggests that fewer workplaces are likely to be "at risk" than suspected, differences in automatibility between educational levels are large. This suggests that low educated workers likely will bear the brunt of adjustment costs to technological change in terms of requirements for further training and occupational re-training. Moreover, for this group of workers, regaining the competitive advantage over machines by means of upskilling and training may be difficult to achieve, especially since the speed of the current technological revolution appears to exceed the pace of its predecessors. Hence, this study clearly points towards the need to focus more on the potential inequalities and requirements for (re-)training arising from technological change rather than the general threat of unemployment that technological progress might or might not cause.

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ANNEX

ANNEX A. Descriptive Statistics and Variable Definitions

Table 2. Descriptive Statistics (unweighted)

code	Variable content	mean	sd	min	max
gender	Gender	0.472	0.499	0.000	1.000
AGEG5LFS	Agegroup	5.823	2.604	1.000	10.000
education	Education	2.264	0.595	1.000	3.000
pvlit	Literacy	277.447	44.096	119.735	406.088
pvnum	Numeracy	263.608	50.170	74.333	415.966
pvpsl	Problem Solving	279.890	39.473	124.798	411.289
D_Q03R	Sector	0.255	0.436	0.000	1.000
D_Q06aR	Firm Size	1.910	0.558	1.000	3.000
D_Q08a	Responsibility for Staff	0.670	0.470	0.000	1.000
D_Q12aR	Educational Job Requirements	0.377	0.485	0.000	1.000
D_Q12cR	Required Job Experience	0.513	0.500	0.000	1.000
D_Q16aR	Payment Scheme	0.414	0.492	0.000	1.000
G_Q04R	Computer Use at Work	0.224	0.417	0.000	1.000
G_Q06R	Level of Computer Use	0.629	0.483	0.000	1.000
F_Q01b	Cooperating with Others	3.713	1.355	1.000	5.000
F_Q02a	Exchanging Information	0.054	0.047	0.000	0.784
F_Q02b	Training Others	0.024	0.028	0.000	0.269
F_Q02c	Presenting	0.008	0.017	0.000	0.198
F_Q02d	Selling	0.018	0.032	0.000	0.476
F_Q02e	Consulting	0.038	0.031	0.000	0.342
F_Q03a	Planning Own Activities	0.039	0.036	0.000	0.500
F_Q03b	Planning Activities of Others	0.020	0.027	0.000	0.333
F_Q03c	Organizing Own Schedule	0.051	0.041	0.000	0.500
F_Q04a	Influencing	0.030	0.031	0.000	0.267
F_Q04b	Negotiating	0.024	0.028	0.000	0.226
F_Q05a	Solving Simple Problems	0.050	0.038	0.000	0.597
F_Q05b	Solving Complex Problems	0.023	0.024	0.000	0.280
F_Q06b	Working Physically for Long	0.048	0.064	0.000	1.000
F_Q06c	Using Fingers or Hands	0.068	0.063	0.000	1.000
F_Q07a	Not Challenged Enough	0.073	0.260	0.000	1.000
F_Q07b	More Training Necessary	0.788	0.409	0.000	1.000
G_Q01a	Reading Instructions	0.043	0.040	0.000	0.476
G_Q01d	Reading Professional Publications	0.013	0.018	0.000	0.172
G_Q01e	Reading Books	0.008	0.019	0.000	0.323
G_Q01f	Reading Manuals	0.022	0.024	0.000	0.240
G_Q02b	Writing Articles	0.001	0.006	0.000	0.072
G_Q02d	Filling Forms	0.033	0.034	0.000	0.330
G_Q03c	Calculating Shares or Percentages	0.029	0.031	0.000	0.329
G_Q03h	Complex Math or Statistics	0.003	0.011	0.000	0.163
G_Q05c	Internet Use for Work-Related Info	0.035	0.025	0.000	0.269
G_Q05g	Using Programming Language	0.003	0.011	0.000	0.103
G_Q05h	Using Communication Software	0.005	0.013	0.000	0.089
YEARLYINCPRR	Yearly Income (Percentile)	0.330	0.470	0.000	1.000

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

57. The variables are defined as follows:

- Gender dummy: Male (0), Female (1)
- Education: ISCED 0, 1, 2, 3C (short) (1), ISCED 3A-B, 3C (long), 4A-B-C, 5B (2), ISCED 5A 6 (3).
- Sector-dummy: private sector (0), public sector or non-profit organisations (1)
- Firm size / number of employees: 1-10 (1), 11-1000 (2), >1000 (3)
- Responsibility for staff: yes (0), no (1)
- Educational job requirements: ISCED 0-4 (0), ISCED 5-6 (1)
- Required work experience: less than 1 year (0), at least one year (1)
- Payment scheme: piece or hourly wage or no wage (0), monthly/yearly wage (1)
- Computer use at work: yes (0), no (1)
- Level of computer use: simple (0), moderate or complex (1)
- Not challenged enough at work: yes (0), no (1)
- More training required at work: yes (0), no (1)
- Yearly income (percentile rank): 0 %-10 % (1), 10 %-25 % (2), 25 %-50 % (3), 50 %-75 % (4), 75 %-90 % (5), 90 %-100 % (6).
- Cooperating with others: up to a quarter of the time (0), more than a quarter of the time (1)

58. The task-measures in the PIAAC-data are recorded by the frequency of use. We re-define these data to calculate work-time shares. For this, we first re-define the answers into a work-time scale (e.g. we redefine “less than once a month” as 1/30, “less than once a week” as 1/7, and so on). We then calculate the sum of this across all tasks (for each worker) and divide each task-item by this sum. This way, we receive the share of work time spent on each individual task (assuming that the tasks are not performed simultaneously).

ANNEX B. Estimation results

59. Results for the main model (Model A) are presented in **Error! Reference source not found.** The table shows the US estimates of job automatibility as a function of job tasks and other covariates. Note that the coefficients in the table are parameter estimates of a non-linear model, so that they cannot be interpreted as marginal effects. Results for alternative models can be found below.

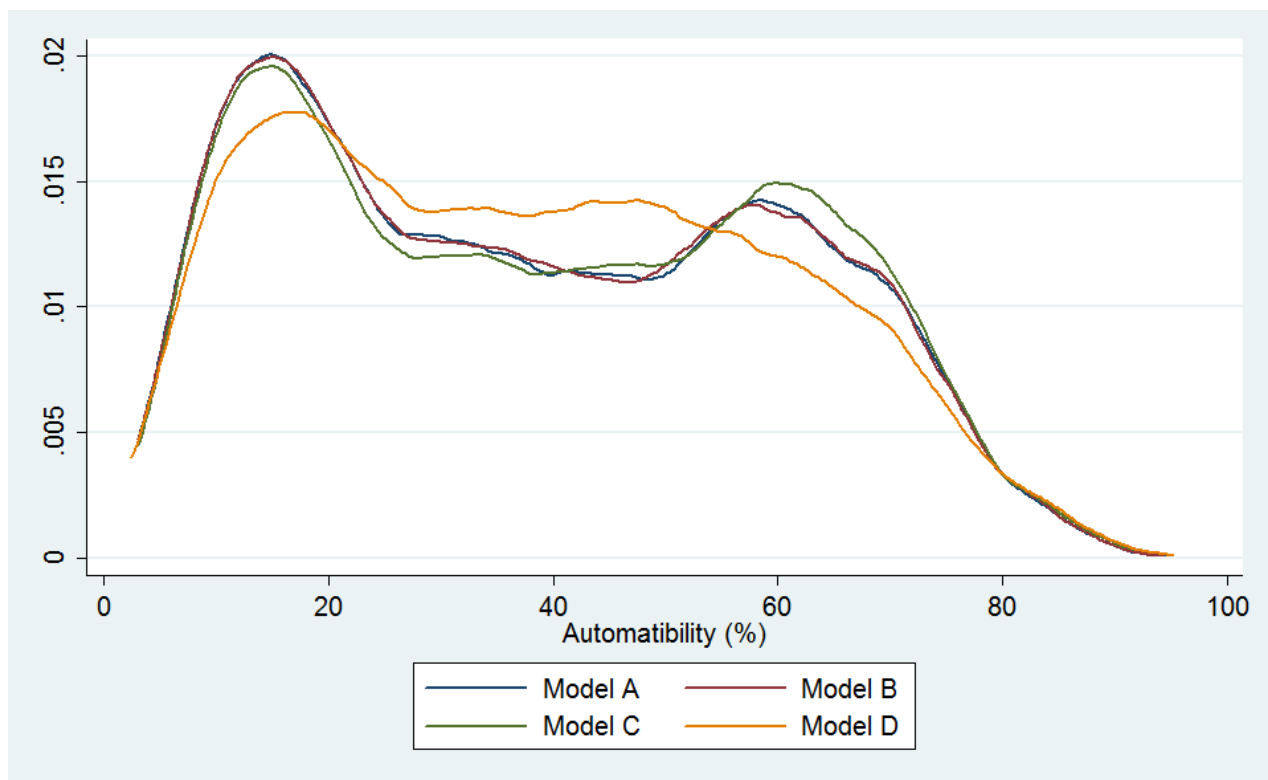
Table 3. **Determinants of job automatibility (Model A)**

	Variable	Coef.	Std. Err.	p
worker characteristics	gender	-0.034	0.012	0.006
	age group			
	20-24	0.020	0.039	0.614
	25-29	0.161	0.038	0.000
	30-34	0.027	0.038	0.477
	35-39	0.053	0.039	0.168
	40-44	0.100	0.038	0.009
	45-49	0.093	0.039	0.018
	50-54	0.067	0.039	0.083
	55-59	0.077	0.041	0.061
60-65	0.190	0.041	0.000	
	education			
	medium	-0.255	0.035	0.000
	high	-0.497	0.039	0.000
skills	literacy	-0.002	0.000	0.000
	numeracy	0.001	0.000	0.030
	problem solving	-0.001	0.000	0.003
job characteristics	sector	-0.168	0.013	0.000
	firm size			
	11-1000	0.103	0.016	0.000
	>1000	-0.006	0.022	0.794
	responsibility for staff	0.135	0.013	0.000
	educational job requirement:	-0.479	0.017	0.000
	required job experience	-0.044	0.013	0.001
	payment scheme	-0.075	0.014	0.000
	yearly income (percentiles)	-0.270	0.014	0.000
	not challenged enough	-0.154	0.020	0.000
	more training necessary	0.061	0.014	0.000
	level of computer use	0.010	0.013	0.475
cooperating with others	-0.008	0.005	0.094	
tasks	exchanging information	0.806	0.220	0.000
	training others	-2.886	0.265	0.000
	presenting	-4.884	0.386	0.000
	selling	2.782	0.235	0.000
	consulting	0.482	0.255	0.059
	planning own activities	-1.785	0.264	0.000
	panning activities of others	-2.052	0.278	0.000
	organizing own schedule	-0.965	0.245	0.000
	influencing	-4.522	0.258	0.000
	negotiating	0.237	0.266	0.373
	solving simple problems	-0.889	0.233	0.000
	solving complex problems	-1.395	0.285	0.000
	working physically for long	-0.709	0.186	0.000
	using fingers or hands	1.085	0.182	0.000
	reading instructions	-1.492	0.192	0.000
	reading professional publica	-4.069	0.369	0.000
	reading books	-4.670	0.340	0.000
	reading manuals	0.261	0.267	0.330
	writing articles	-3.772	1.082	0.000
	filling forms	-0.808	0.203	0.000
	calculating shares or percent	-0.752	0.235	0.001
	complex math or statistics	-1.365	0.495	0.006
	internet use for work-related	-1.036	0.265	0.000
	using programming language	-4.515	0.568	0.000
	using communication softwa	-1.637	0.454	0.000
constant	1.332	0.084	0.000	

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

60. In the main text, the reference model, Model A, is discussed. This model is applied to other OECD countries to extrapolate the automatibility for these countries. As in some of these countries not all variables are included in the PIAAC data, we had to re-estimate the automatibility of tasks for the US with restricted sets of explanatory variables. In total, we estimate 4 models including our reference model (Model A). In Model B we exclude the *Payment Scheme*, in Model C we exclude *Problem Solving Skills* and in Model D we exclude the *Payment Scheme* and the *Educational Job Requirements*. Results for Models A, B, and C are very similar. This is illustrated in Figure 8, which shows kernel density estimates of the predicted automation potential. Only for Model D, results differ noticeable. Model D is based on the selection of variables which are available in the Canadian PIAAC.

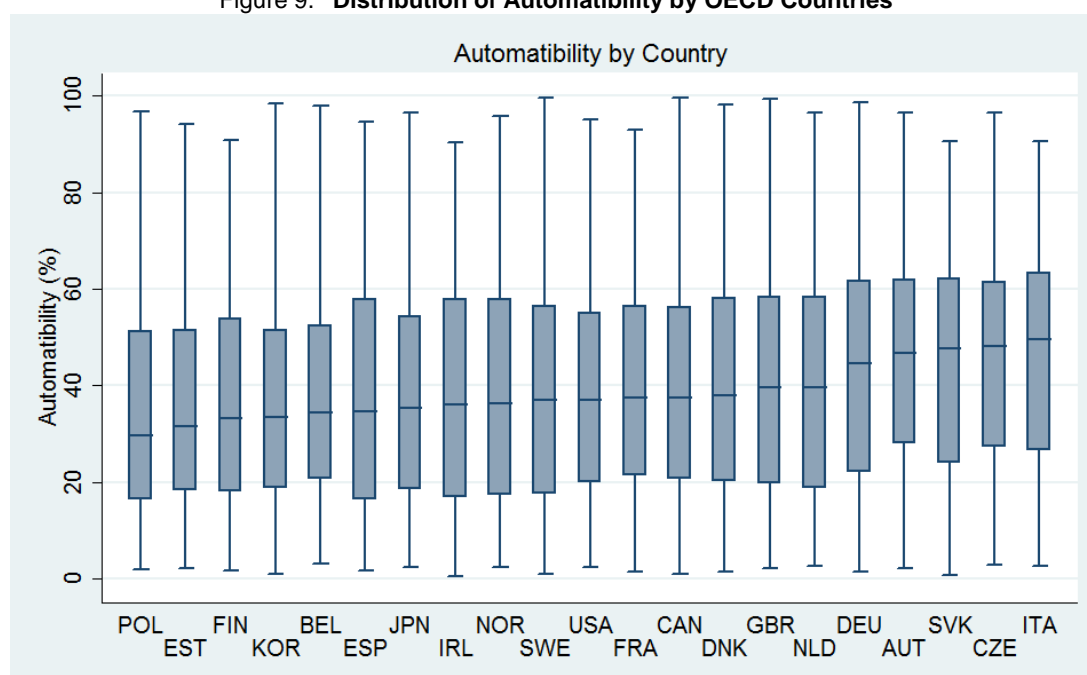
Figure 8. Distribution of the Estimated Automatibility (USA)



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

ANNEX C. Detailed Results by OECD Countries

Figure 9. Distribution of Automatability by OECD Countries



Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

Table 4. Automatability by OECD Countries

Country	Share of People at High Risk	Mean Automatability	Median Automatability
Austria	12%	43%	44%
Belgium	7%	38%	35%
Canada	9%	39%	37%
Czech Republic	10%	44%	48%
Denmark	9%	38%	34%
Estonia	6%	36%	32%
Finland	7%	35%	31%
France	9%	38%	36%
Germany	12%	43%	44%
Ireland	8%	36%	32%
Italy	10%	43%	44%
Japan	7%	37%	35%
Korea	6%	35%	32%
Netherlands	10%	40%	39%
Norway	10%	37%	34%
Poland	7%	40%	40%
Russian Federation	2%	29%	26%
Slovak Republic	11%	44%	48%
Spain	12%	38%	35%
Sweden	7%	36%	33%
United Kingdom	10%	39%	37%
United States	9%	38%	35%

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

Table 5. Share of People with High Automatability by Education and OECD Countries

Country	Share of People at High Risk by Level of Education						
	ISCED 1	ISCED 2, 3Q(short)	ISCED 3A-B, Q(long)	ISCED 4A-B-C	ISCED 5B	ISCED 5A	ISCED 5A, 6
Austria	100%	54%	14%	8%	2%	0%	0%
Belgium	59%	43%	11%	13%	1%	0%	0%
Canada	68%	55%	16%	10%	6%	0%	0%
Czech Republic		55%	12%	9%	8%	2%	0%
Denmark	33%	41%	10%	0%	2%	1%	0%
Estonia		41%	11%	10%	3%	1%	0%
Finland	52%	40%	12%	7%	2%	0%	0%
France	41%	29%	13%		5%	1%	0%
Germany	82%	50%	17%	12%	4%	3%	0%
Ireland	0%	42%	19%	13%	5%	0%	0%
Italy	40%	32%	11%	0%		0%	0%
Japan		28%	15%	3%	7%	1%	0%
Korea	67%	33%	12%		6%	0%	0%
Netherlands	51%	37%	7%		0%	1%	0%
Norway		44%	11%	8%	1%	1%	0%
Poland	25%	48%	13%	9%		3%	1%
Russian Federation		33%	4%	10%	4%	0%	0%
Slovak Republic		56%	17%			2%	0%
Spain	56%	43%	15%	7%	5%	0%	0%
Sweden	30%	38%	9%	7%	2%	1%	0%
United Kingdom	49%	40%	14%		4%		1%
United States	100%	44%	19%	8%	6%	1%	0%

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)

Table 6. Share of People with High Automatability by Income and OECD Countries

Country	Share of People at High Risk by Income Percentile					
	<10%	10%-25%	25%-50%	50%-75%	75%-90%	90%-100%
Austria	38%	30%	21%	13%	1%	0%
Belgium	17%	11%	10%	2%	1%	1%
Canada	21%	40%	26%	11%	1%	0%
Czech Republic	22%	18%	15%	6%	1%	0%
Denmark	35%	16%	10%	4%	0%	0%
Estonia	14%	19%	11%	6%	0%	0%
Finland	16%	8%	8%	4%	1%	0%
France	0%	21%	15%	7%	0%	0%
Germany	33%	24%	17%	9%	0%	0%
Ireland	27%	26%	23%	10%	0%	0%
Italy	9%	19%	18%	11%	0%	0%
Japan	26%	12%	5%	2%	1%	0%
Korea	21%	13%	6%	2%	0%	0%
Netherlands	33%	26%	14%	8%	1%	0%
Norway	33%	16%	11%	4%	0%	0%
Poland	10%	14%	7%	1%	0%	1%
Russian Federation	0%	4%	3%	1%	0%	0%
Slovak Republic	20%	15%	7%	4%		0%
Spain	25%	29%	21%	8%	2%	0%
Sweden	25%	15%	10%	8%	1%	0%
United Kingdom	32%	23%	16%	5%	0%	0%
United States	19%	31%	17%	8%	0%	0%

Source: Authors' calculation based on the Survey of Adult Skills (PIAAC) (2012)