NERI Working Paper Series

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February 2019

NERI WP 2019/No 59

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THE FUTURE OF WORK:
THE IMPACT OF AUTOMATION TECHNOLOGIES FOR EMPLOYMENT IN NORTHERN IRELAND

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Keywords: Automation, Robotics, Employment, Technological Change, Technological unemployment; Future of work.
JEL Codes: D0; J0; J2; O33.

ABSTRACT

The rapid advances in artificial intelligence (AI) robotics and other forms of smart technologies has led to widespread concern about the potential impact of such advances for employment. A lively debate has opened up about the implications of robotics and other technological innovations for the future of work. This paper assesses the potential impact of automation technologies for workers in Northern Ireland based on technological capabilities. The evidence presented suggests that some jobs may indeed be at risk of loss due to automation in the medium term. However, the extent of the job loss is likely to be much lower than that reported in media headlines. We estimate that around 7 per cent of jobs are at high risk from automation. A further 58 per cent are estimated as being at risk of substantial change in the tasks involved in their job over the medium term. This is due to the fact that some of the tasks involved in different occupations can be more readily automated. Other tasks may present 'engineering bottlenecks' to automation - as in some tasks are not substitutable by machines. We find that job automation risk is related to occupation and industry, as well as the characteristics of workers.

That said, we note that factors other than technological capability will ultimately determine the impact of automation technologies for jobs and employment. The point made is that ultimately, the impact automation technologies depends on many factors, including (a) the relative costs of workers and machines, (b) the absorptive capacity of industry to integrate new technologies into production processes, (c) the social and regulatory environment, (d) the policy responsiveness of governments. We conclude by pointing to the need for policy to give attention to not just the risk of automation technologies for workers in terms of the risk of technological unemployment, but also to the various ways in which automation technologies may displace workers.

This version: 13.2.19

* This NERI Working Paper forms part of an NERI project on the related areas of growth, enterprise, industrial, and innovation policy in Northern Ireland and in the Republic of Ireland. ** The authors gratefully acknowledge helpful feedback from a number of reviewers. The usual disclaimer applies. All correspondence to lisa.wilson@nerinstitute.net. *** Sórcha Foster carried out work for this publication during an internship at the NERI, whilst she was studying at Oxford University.

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1. INTRODUCTION AND OVERVIEW OF THE STUDY

Automation technologies refer to technologies that are used to substitute labour in the performance of specific tasks in the production process. As well as replacing the need for human labour, automation technologies can augment the capabilities of, and demand for human labour. From the Industrial Revolution onwards, the utilisation of automation technologies in the production process has transformed how we work, produce, consume and live (Lawrence *et al,* 2017).

The recent rapid advances in artificial intelligence (AI), robotics and other forms of smart technologies have led to widespread concern about the potential impact of such automation technologies for the future of work and sparked a lively debate about the ways in which technology is going to transform the world of work (Brynjolfsson and McAfee, 2014). Although there is no widely shared agreement on the expected impacts, broadly speaking, there are two camps with starkly different views. On the one hand there are those who are pessimistic about the extensity and invasiveness of technological change and fear that automation, AI and new robotic technologies are going to wipe out large numbers of our jobs, and in the end lead to an economic and social dystopia (Brynjolfsson and McAfee, 2014).

Others criticise this view and argue that whilst there will be some disruption and change to the nature of work, the net effect of technological advancements will be positive (Autor, 2014). To support this position, they point to historical periods of rapid technological change when the same fears about technological unemployment existed, but which never materialised - a phenomena that Autor (2015a) describes as 'automation anxiety'. Most famously the Luddite movement in the early 19th century provides an example of automation anxiety, during a period of rapid technological advancement. The Luddite movement refers to a group of English textile artisans who staged a machine-trashing rebellion in protest of the rapid mechanisation of the British textile industry that emerged as part of the first industrial revolution. In the long run however, not only were there still many jobs in the new textile factories but, importantly, huge new wealth was created from the productivity gains of mechanisation. This in turn, in the long run, generated many more jobs across the UK economy than were initially lost in the traditional handloom industry. Importantly, the longer-term gain does not remove the huge human cost that one or two generations had to endure when their jobs and skills were swallowed up by technological progress (Rosen, 1998).

Another example of 'automation anxiety' was seen in the 1960s when electronic data processing rose to prominence in business as a means to automate a large proportion of simple and regular tasks. This, again, prompted fears about technological unemployment, with one Times (1961) journalist commenting that 'the number of jobs lost to more efficient machines is only part of the problem. What worries many job experts more is that automation may prevent the economy from creating enough new jobs.'. Similarly, Hoos (2000: 178) in describing the stance of many at the time explained that 'the machine is seen as the master of men unless government control or workers' revolt intervenes'. The pressure to take seriously the threat posed by technology at the time is clear from the 'blue ribbon' National Commission on Technology, Automation, and Economic Progress commissioned by US President Johnson in 1964. The aim of this Commission was to

> *'identify and assess the past effects of current and prospective role and pace of technological change; to identify and describe the impact of technological and economic change on production and employment, including new job requirements and the major types of worker displacement, both technologically and economic, which are likely to occur during the next 10 years'* (Autor, 2015: 132).

Interestingly, while the Commission concluded that technological developments did not pose a threat to employment at that time, the concerns of those who feared the worst were not allayed and many, including several well-known contemporary social critics, continued to argue to this effect (Autor, 2015).

In contrast, in analysing the response of the UK Government throughout history to technological advancements, Mokyr (1990; 1992; 1998) points to the tendency for a stern view to be taken on any attempts to hinder technological developments. Specifically, Mokyr (1990; 1992) explains that the UK Government has long prioritised the long-term benefits of creative destruction with the reasoning being to ensure the long-term competitive position of the UK economy. Little attention, however, if any, historically, has been given by the UK Government to the short-term impacts of creative destruction and advancements in automation technologies for workers and their living standards, or to the distribution of the benefits of technological advancements.

Recent years have seen a re-emergence of this 'automation anxiety'. Reports and media headlines warning that automation technologies are going to wipe out large proportions of our jobs have become increasingly frequent. Those most cautious about the potential negative impact of automation technologies for employment make the point that the emergence of increasingly advancing computing power, AI and robotic technologies mean that the possibility of technology being used to replace labour is much more likely now than it has ever been. Thus, the attitude is one that maintains that using past interactions between automation and employment provides no guide to future impacts. In particular, the emergence of greatly improved automation technologies in terms of computing power, artificial intelligence and robotics raises the possibility of labour replacement on a scale not previously observed and so does little to allay fears about the possibility of technological unemployment going forward (Akst, 2013).

These fears have, to a large extent, been heightened by a report published in 2013 by researchers Michael Frey and Carl Osborne. They predict that a substantial share of jobs is at new and unprecedented risk of automation over the next couple of decades as technological capabilities continue to advance, and machines are increasingly able to undertake tasks which have historically been the reserve of workers. Frey and Osborne's (2013) paper has led to an inundation of bleak headlines, such as 'Death of the Accountant and Auditor; Advances in artificial intelligence could lead to mass unemployment, warn experts' (The Independent, 2014), 'Robots are leaving the factory floor and heading for your desk – and your job, say experts (The Guardian, 2015) and 'Will robots take your job? Humans ignore the coming AI revolution at their peril' (The Economist, 2018).

However, Frey and Osborne's (2013) study has been the subject of much criticism. One of the most prominent criticisms has been made by Arntz *et al* (2016) who expressed concern at the methodological approach taken by Frey and Osborne (2013) and other researchers who have mirrored their approach. In particular, their criticism targets the fact that Frey and Osborne (2013) follow an occupation-based approach. A key underlying assumption in their study is the assumption that occupations are homogenous regardless of whether tasks within occupations differ by place of work or location. Arntz *et al* (2016) argue that since occupations usually consist of a multifaceted set of tasks, not all of which may be easily automatable, the potential for automating entire occupations is likely to be much lower than that suggested by Frey and Osborne (2013).

In seeking to address these shortcomings, Arntz *et al* (2016) apply what is termed a task-based approach in order to estimate the risk of jobs to automation. Specifically, this approach takes account of the heterogeneity of workplace tasks within occupations, allowing for the idea that the extent to which jobs can be automated depends on the tasks which workers perform within occupations on a day-to-day basis, and how easily these tasks can be automated. In doing so, Arntz *et al* (2016) estimate a much lower share of jobs to be at high risk of automation.

Beyond this, some have argued that the recent focus on 'job loss' or replacement of jobs by machines has served as a distraction to addressing more seriously the future of work and the way technology will alter or change the jobs that people do (Autor, 2013; Autor, 2015; Arntz *et al*, 2016). The point made is not that there will be no substitution of work by automation technologies, but that the impact on employment will be dependent upon whether and how workplaces, jobs and the economy overall is able to adjust to technological advances by switching tasks, thus preventing technological unemployment. Critics, thus, caution that in assessments of the impact of automation on employment, and the future of work more generally, there is a need to consider the various ways which technology can impact on employment by taking into consideration not only the risk of job loss, but also the potential for technology to complement human labour and also to create demand for human labour.

Others critique the narrative surrounding recent public discussions about the future of work. In particular, there has been a questioning of the inference which tends to surround discussions about the future of work, that the only factor which is going to determine the extent of the impact, is the potential of automation technologies to undertake tasks traditionally carried out by humans. Thus, while the authors of studies estimating the potential risk to jobs from automation technologies acknowledge that their estimates are based on the possibility of automation technologies to undertake a set of tasks (Frey and Osborne, 2013; Arntz *et al,* 2016), these estimates tend to be used as evidence of the impact which automation technologies are going to have. However, in order, to have a more nuanced understanding and sensible discussion about the future of work there is a need to take into account and give due consideration to other factors, such as the particular economic, social, ethical, political and institutional environment.

In taking all of the above into consideration, the rest of the paper aims to assess how automation, AI and robotic technologies are likely to affect the future of employment in Northern Ireland. It will begin by considering the potential for automation of employment in Northern Ireland based on technological possibility. The paper supplements this analysis by also examining the potential for automation across occupational skill levels, industrial sectors, levels of educational attainment, as well as across age groups and gender.

Specifically, in recognising the shortcomings of the occupation-based approach developed by Frey and Osborne (2013) to automation, this paper will utilise the task-based approach as developed by Arntz *et al* (2016). While it is recognised that no approach is perfect this paper argues that when compared to the occupation-based approach, the task-based approach provides a much more credible way to assess the potential impact of automation, AI and robotic technologies for employment based on technological capabilities.

Following this, we argue that to sensibly think about the future of work there is a need to move beyond the recent sole focus on job loss and technological unemployment. In particular, we argue for the need to consider how automation technologies might substitute for or complement workers in carrying out specific tasks and how this might vary for different groups of workers. In addition, we draw attention to the particular economic, legal, regulatory and social constraints that might restrict or encourage the utilisation of automation technologies in practice in Northern Ireland.

2. DEBATES ON THE POTENTIAL IMPACT OF AUTOMATION FOR JOBS

2.1 The occupation-based approach

Much of the discussion in recent years around the automation of jobs stems from a study titled *'The Future of Employment: How susceptible are jobs to computerisation?*' published in 2013 by Carl Frey and Michael Osborne. In their work, Frey and Osborne (2013) focus on the risk of job losses from automation technologies in the United States of America. They argue the risk is increasing due to technological advances which mean that machines are increasingly capable of performing a wide range of tasks that historically have been the preserve of human labour, including non-routine manual tasks. They argue, recent technological advances differ from previous technological advances, and that technological unemployment is more likely to arise. In this sense, they argue that the current speed at which human labour is becoming automatable and the range of tasks which machines are capable of will 'put a substantial share of employment, across a wide range of occupations, at risk in the near future' (Frey and Osborne, 2013: 39).

The only domain of tasks that Frey and Osborne (2013) argue are exempt from the risk of automation are what they call Engineering Bottlenecks. These engineering bottlenecks refer to tasks which a group of University of Oxford engineers argue cannot be substituted for by machines, in the near future, because these tasks cannot be defined in terms of codifiable rules and procedures. Computers follow procedures laid out by programmers and so for a computer to accomplish a task, a programmer must first fully understand the sequence of steps involved in performing the task, and then, must write a programme that, in effect, causes the machine to simulate these same steps precisely (Autor, 2015: 10). Thus, the potential risk to jobs from automation is determined by the ability of engineering problems to be sufficiently specified, which in essence sets the boundaries for the scope of tasks to be automated. The engineering bottlenecks identified by the group of engineers relate to three areas of task categories including: perception and manipulation tasks; creative intelligence tasks; and social intelligence tasks.

More specifically, in estimating the risk of automation of jobs in the USA Frey and Osborne (2013) begin from the premise that the probability of an occupation being automated is a function of its task characteristics, and so automation of a job is possible so long as the tasks are not subject to any engineering bottlenecks. They rely on O*NET information which provides information on skills, abilities, knowledge, work activities, and interests associated with occupations (See www.onetonline.org for further details on this). O*NET data defines the key features of an occupation as a standardised and measurable set of variables, and also open-ended descriptions of specific tasks of occupations. This allowed Frey and Osborne (2013) to: (a) objectively rank occupations according to the mix of knowledge, skills, and abilities they require; and (b) subjectively hand-label occupations as automatable based on the variety of tasks they involve according to the identified engineering bottlenecks. Using this information, they begin by having a group of researchers subjectively hand-label 70 occupations by eye-balling the O*NET job description and tasks of each occupation and assigning 1 if automatable and 0 if not on the basis that the tasks involved did or did not present engineering bottlenecks (See Table 1). Following this, they utilised nine objective O*NET variables describing the capabilities and level of perception and manipulation, creativity, and social intelligence required - corresponding to the defined bottlenecks – and developed an algorithm to provide a probability of automation, using a Gaussian process classifier. In doing so, they estimated the probability of automation for 703 detailed occupations, where the higher the value, the higher the likelihood of automation. They identify those with a probability of between 0 and 0.3 as having a low risk of automation, with a probability of between 0.3 and 0.7 classed as medium risk, and 0.7 and 1 classed as high risk. Furthermore, Frey and Osborne (2013) posit that the probabilities can also be interpreted as providing a possible timeline to automation, with higher numbers indicating occupations that are likely to be substituted by investments in computer capital relatively soon.

Table 1: Engineering Bottlenecks and O*NET variables

Engineering Bottleneck	O*NET Variable	O*Net Description
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 move your hand, your hand together with your arm, or your two hands to grasp, manipulate or assemble objects.
	Cramped Work Space	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 situations, 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 & Caring for others	Persuading others to change their minds or behaviour

Source: Frey, C. and Osborne, M. (2013).

Based on this methodology Frey and Osborne (2013) estimate that about 47 per cent of total employment in the USA is at high-risk of automation, 19 per cent is at medium-risk, and 33 per cent is at low-risk - over some unspecified number of years - a decade or two, they suggest. They go on to make the point that the probability figures can also be seen to provide a rough timeline to risk from automation. Thus, high probability occupations are those that are likely to be automated relatively soon, with the extent of automation for the medium and low probability occupations likely to be determined by the pace at which the engineering bottlenecks to automation can be overcome.

In a follow-up study, Frey and Osborne applied the same methodology described above and applied it to the UK labour market. To apply the same methodology, they assumed that occupations in the UK demand the same set of tasks and skills as corresponding to those in the USA O*NET classification of occupations. To translate the 702 O*NET occupations into corresponding occupations in the UK, they used the International Standard Classification of Occupations (ISCO)[1] and then 'cross-walked' these to the corresponding Standard Occupational Classification 2010 (SOC 2010) codes.[2] However, as there are fewer ISCO codes than O*NET codes some occupations were merged for the UK study. For each merged occupational group, the probabilities of automation were calculated as weighted averages of the probabilities of automation for each O*NET occupation within the group. In doing this they estimate that, looking across the UK, 35 per cent of jobs are at high risk, 22 per cent are at medium risk, and 43 per cent are at low risk of automation over the next ten to twenty years. According to this approach, it is especially service, sale and office jobs that fall in the high-risk category. Moreover, others who have mirrored this methodological approach have found, not surprisingly, substantial shares of jobs to be at risk of automation (Bowles, 2014; Brzeski and Burk 2015; Pajarinen and Rouvinen (2014).

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[1] The International Standard Classification of Occupations (ISCO) is an International Labour Organization (ILO) classification structure for organizing information on labour and jobs according to the tasks and duties undertaken in the job.

[2] The Standard Occupational Classification (SOC) is a multi-purpose common classification of occupations. Occupations are classified in terms of their skill level and skill content. Within the context of the classification, 'skill' is defined in terms of the nature and duration of the qualifications, training and work experience required to become competent to perform the associated tasks in a particular job. Technological and organisational changes have significant impact on the occupational structure, not just in terms of the numbers of job holders in particular occupations, but also via the introduction of new jobs not previously embodied within the classification. Thus, the classification is regularly updated to account for such changes. However, because analysts need some stability through time in classification structures for the analysis of occupational trends the classification of occupations is revised on a ten-year cycle by the Office for National Statistics. In 2000 SOC90 was revised to create SOC2000. The most recent revision creates SOC2010.

2.2 The task-based approach

In critiquing the approach taken by Frey and Osborne (2013) and those who follow an occupation-based methodological approach, Arntz *et al* (2016) point to the fact that since automation usually aims at automating certain *tasks*, rather than whole occupations, the potential for automating entire occupations is likely to be much lower than has been suggested. Arntz *et al* (2016) argue that the approach taken by Frey and Osborne (2013) was too restricted given that occupations usually consist of a range of different tasks, not all of which may be easily automatable. Moreover, *within* occupations there is likely to be considerable heterogeneity in the tasks performed across different workplaces and localities. As such, the assignment of whole occupations as high, medium, or low risk from automation is problematic because it fails to capture the actual tasks involved in an individual's job.

Furthermore, Arntz *et al* (2016) critique the research findings of those who apply this same methodological approach in follow-up studies across other countries as they start from the basic assumption that the risk of automation for a particular occupation is the same across countries. As a consequence of this assumption, differences in the estimated share of workers whose jobs are at risk of automation are driven *only* by differences in the occupational structure.

Individual workers within the same occupational group often perform quite different tasks. This needs to be taken into account in the estimation of job risk arising from automation. This methodological approach to assessing automation risk has been termed the 'task-based approach'. Arntz *et al* (2016) estimate the risk of automation for jobs in 21 OECD countries, by following the same approach as Frey and Osborne (2013) but relax one of their major assumptions. Specifically, rather than assuming that occupations are displaced by machines Arntz *et al* (2013) contend that it is particular tasks that may be displaced. Hence, they recourse to individual-level survey data which captures a comprehensive list of the tasks that workers actually perform at their workplace.

To implement the task-based approach Arntz *et al* (2016) estimate, for the USA, the relationship between workers' tasks and the automatability of jobs indicator defined by Frey and Osborne (2013). They match Frey and Osborne's (2013) automatability index to USA observations based on occupational codes using *Programme for the International Assessment of Adult Competencies* (PIACC) survey data. PIAAC is an international survey conducted across OECD countries measures adults' proficiency in key information-processing skills - including literacy, numeracy and problem-solving in technology-rich environments - and also how adults use their skills at work (See:

www.oecd/skills/piacc). The model and the estimated parameters then show the influence of the explanatory variables on the automatability index in the USA. This model and the estimated parameters are then applied to the PIACC data in other OECD countries in order to predict the automatability in these countries.

In utilising this task-based approach Arntz *et al* (2016) find a much lower risk of jobs to automation, with only 9 per cent of workers in the USA assigned as facing a high risk from automation i.e. an automatability of at least 70 per cent. This means that a large proportion of the tasks involved in these jobs are at high risk from automation. This figure is obviously a stark contrast to the 47 per cent figure estimated by Frey and Osborne (2013) in utilising the occupation-based approach. Across OECD countries the share of workers whose jobs are at high risk of automation is 7 per cent, although this estimate varies across countries. The estimated share of workers is highest in Germany and Austria at 12 per cent, and lowest in Korea and Estonia at 6 per cent. In the UK just over 10 per cent of jobs are estimated to be at high risk of automation. The estimate for the Republic of Ireland is 7 per cent.

2.3 The occupation-based approach versus the task-based approach

Aside from anything else, the disparity in estimates between the occupation-based approach and the task-based approach demonstrates, if nothing else, the fundamental importance of the methodological approach for contextualising the arguments around the extent to which jobs are at risk from automation technologies. In comparing the estimates from the different approaches, it is clear that taking account of the variation of tasks within occupations exerts a huge impact on the estimated automatability of jobs, as it allows for the fact that even in occupations that Frey and Osborne (2013) predict to be at high risk of automation, people often perform tasks which are hard to automate. In this sense, by not considering differences in tasks within occupations our conclusions in terms of the estimated risk of jobs to automation are likely to be too crude, and so in turn any discussions which follow may start from a false premise. Henceforth, this paper argues that the task-based approach provides a much more accurate way to assess the potential impact of automation technologies for employment.

Nonetheless, the task-based approach provides an imperfect method. Even Arntz *et al* (2016) acknowledge the reason for caution when interpreting estimates of the risk of jobs to automation using the task-based approach. Prior to applying the task-based approach to Northern Ireland it is worthwhile to bring these to attention.

The estimation of the risk to jobs from automation reflects engineers' assessments of the capability of technology to undertake a range of tasks (Arntz *et al*, 2016). The authors argue this is problematic because other factors, such as the availability of skilled staff capable of working alongside and implementing such technologies has been found to be of significance (Janssen and Mohrenweiser, 2014). Furthermore, the evidence indicates that firms tend to only implement technology on a large-scale after the skills required for their use are already available (Acemoglu, 1998; Janssen and Mohrenweiser, 2014). In addition to this, even if sufficiently skilled staff are available, a firm's decision to invest in new technologies depends on the relative factor prices of capital and labour to perform a certain task in the production process.

In addition, in the methodological approach taken by Arntz *et al* (2016) estimates using the task-based approach is still based on the assumption that the risk to jobs from automation is dependent only upon differences in task structures. This means that there is an assumption that workers with the same task structure face the same automatability risk in all OECD countries. Thus, the paper by Arntz *et al* (2016) presents the risk to jobs from automation as an outcome of occupational structural differences in the labour market.

Specifically, in seeking to further interpret the differences in risk to automation as a result of differences in task structures across countries, Arntz *et al* (2016) decompose the difference of the share of workers at high risk between each OECD country and the USA into within- and between-components regarding three dimensions including industry, occupation, and educational structure. Doing this allows for differences in automatability between countries that are due to (a) cross-country differences in industry, occupation or educational structures; and (b) the fact that workers within the same industries, occupation or educational group perform more (or fewer) automatable tasks to be distinguished. In doing so they found that differences between countries in industry and occupational structures explain little of the differences in the share of workers at high risk. Rather, they find that the majority of difference in estimated risk of job automation is due to differences *within* occupations, industries or educational structures. That is, the largest differences in estimated risks to jobs from automation arise from the fact that workers in the same industry, occupation or with the same educational attainment perform different tasks.

However, in giving priority to differences in task structure the significant impact which other economic, social, political and moral/ethical factors will have in determining the likelihood that jobs will or will not be automated neglected. In doing so the impact of other factors are downplayed, such as legal, ethical, political and social factors which may slow down the utilisation of technology. These other factors are discussed in more detail in Section 4.

3. THE POTENTIAL RISK TO JOBS FROM AUTOMATION IN NORTHERN IRELAND

3.1 Data and methodology

The assessment of task-based automation in this paper uses a similar methodology to Arntz *et al* (2016). Specifically, in replicating their methodology, the analysis begins by applying the so-called automatability of jobs indicator as applied by Frey and Osborne (2013) to Northern Ireland. In this respect, the automatability index was created using the American O*NET database which provides a description of the tasks involved in a vast array of occupations and is based on Standard Occupational Classification (SOC 2010) codes. However, for the Automatability Index to be applicable to Northern Ireland it is necessary to match the Automatability Index based on US SOC codes to UK occupations. To do this we utilise the Standard Occupational Classification – International Classification of Occupations (SOC-ISCO) crosswalk developed by the Bureau of Labor Statistics (2012). In some cases, however, the crosswalk is imprecise with less ISCO codes applying to a single SOC code and vice-versa. In order however to avoid losing as much data granularity as is possible duplicate ISCO codes were created. This created a dataset of 902 automation SOC-ISCO pairs.

In order to apply the task-based approach, and to take into account of the fact that individuals within the same occupation often perform quite different tasks, we merge the cross-walked automatability index with data from the latest Programme for the International Assessment of Adult Competencies survey which was carried out in 2011-2012.

The PIACC survey provides individual survey data regarding a comprehensive list of tasks that individuals actually perform at their workplace. Furthermore, participants are required to complete a variety of tests to assess these skills, as well as to complete a detailed background questionnaire regarding an individual's sociodemographic and socioeconomic characteristics. Importantly, there are no questions in PIAAC about job aspects which have to do with caring for and assisting others. This obviously affects a large part of the workforce in healthcare and services. A potential consequence of this is that automatability of jobs that involve care and assisting others will be overstated. The survey was carried out in 24 countries with Northern Ireland a subset of the UK dataset. The number of unique observations for Northern Ireland is 3,761. However, only those individuals who are currently employed are of relevance in this paper thus generating a subset of 2,453 unique observations. Unfortunately, some of these individuals did not complete large parts of the survey (50% +) and so these respondents were excluded from the analysis. This led to a further reduction in the sample size to 1,873 observations.

The automatability index and the PIACC data are merged based on ISCO codes. Although the majority of the Northern Irish PIAAC data includes four-digit ISCO codes, for a number of observations, only 3-digits are available. These 3-digit codes provide less granular descriptions of occupations, for example, code 511 refers to a travel attendants, conductors and guides whilst code 5113 refers only to travel guides. This poses a problem for the merging process which relies on the presence of identical codes in the automation pairs and PIAAC datasets. To address this, we assign the automatability scores associated with multiple 4-digit ISCO codes to each 3-digit ISCO code. This generates duplicate survey respondents differing only in their automatability score, creating a new data set of 4,447 observations. We assign a weight to each case or data observation equal to the inverse of the number of duplicates plus the original observation. Concretely, an individual for which there are no duplicates receives a weight of 1 whilst an individual for which there are 3 duplicates receives a weight of 0.25 for each observation.

We regress the automatability score of Frey and Osborne (2013) on a variety of explanatory variables (See Appendix 1 for a list of explanatory variables) using a quasi-binomial distribution since the dependent variable is on a continuous 0-1 closed interval (The full results of this regression are reported in Appendix 2). Step-wise iteration is implemented to find the model which is most predictive of the automatability scores. This model is used to predict new values of automatability and weights are recalculated based on the following formula were j are duplicate individuals:

$$w_{i,j} = \frac{\left(\widehat{y_{i,j}} - y_{i,j}\right) \middle| x_{i,n}, \beta_{i,n}\right)}{\sum_{j \in J}\left(\widehat{y_{i,j}} - y_{i,j}\right) \middle| x_{i,n}, \beta_{i,n}\right)} \qquad (Arntz\ et\ al.\ 2016)$$

We iterate this process until the weights converge. This generates a maximum likelihood value of automatability for an observation conditional on the characteristics of their job. Where our approach differs from Arntz *et al* (2016) is in our use of the most predictive model specifically for Northern

Ireland rather than using all variables potentially correlated with automation. This should achieve more accurate probability values for Northern Ireland.

Following this, and in order to provide an up-to-date estimate of the risk to jobs from automation in the Northern Irish labour force we apply the estimated automatability probability values to the estimated total workforce based on the Annual Population Survey relating to January to December 2017. This data allows us to have an up-to-date, full year picture of employment in Northern Ireland and so provides an up-to-date task-based assessment of the percentage of jobs at risk to automation. However, to apply the automatability probability values obtained from the PIACC data to the Annual Population survey, it is necessary to match the probabilities of automation to Northern Ireland occupations. To do this, it is necessary to match four-digit ISCO codes from the PIACC data to occupations in the Annual Population Survey data. However, the Northern Ireland Annual Population Survey uses UK SOC codes to classify occupations, rather than ISCO codes. Thus, it is necessary to cross-walk probability estimates using an ISCO-UK SOC mapping chart as provided by the ONS (available on request). However, in some cases there is no direct match from ISCO to UK SOC and so leading to non-classification of some occupations.

The Annual Population Survey is a continuous household survey, which covers all regions of the UK. It is not a stand-alone survey; it uses data combined from 2 successive waves of the main Labour Force Survey (LFS) over four quarters. Each quarter's LFS sample of private households is made up of 5 waves. Each cohort is interviewed in 5 successive quarters, so that in any one quarter, one cohort receive their first interview (this is wave 1), another cohort their second (this is wave 2), and so on. The APS data set is created by taking waves 1 and 5 from four successive quarters. Over the period of the four quarters, waves 1 and 5 will never contain the same households, so as to avoid the inclusion of responses from any household more than once in the dataset. The APS datasets are reweighted back for 2-years, using the mid-year population estimates and are reweighted back for 10-years using the latest census population estimates. The APS data are disseminated quarterly, with each dataset covering 12 months' data (See Office for National Statistics, 2016). The overall sample for Northern Ireland consists of 6,504 individuals, although the sample used in this paper was 2,712. This latter figure corresponds to those in employment and aged between 16 and 64.[3]

[3] Weighted estimate of workers in employment = 801,856.

For presentation purposes, the results are classified in the following categories by probability of automation:

- High Risk: a probability score of 71per cent or over;
- Mid to High Risk: a probability score of 51per cent or over, but less than 70 per cent;
- Mid to Low Risk: a probability score of 31 per cent or over, but less than 50 per cent;
- Low Risk: probability scores of less than 30 per cent.

The associated probabilities obtained using this task-based approach are also shown, below, by occupation skill level, industrial sector, level of educational attainment, gender and age.

3.2 The potential risk to jobs from automation using the task-based approached as applied by Arntz *et al* (2016)

Table 2, below, details the estimates of automation risk for jobs in Northern Ireland. Specifically, the estimates show that 7 percent had a probability of automation of 70 per cent or higher, and thus were classified as being at high-risk of automation. A further 58 percent were classified as being at high to mid risk of automation.

Table 2: The potential risk to jobs from automation using the task-based approached as applied by Arntz *et al* (2016)

Risk Level	Percentage NI workforce	Number of workers
High	7.1	56,900
High - Mid	31.6	253,224
Mid - Low	26.7	213,845
Low	12.8	102,952
Not classified	21.8	174,935

Estimates of high job risk from automation are much lower using a task-based approach compared to an occupation-based approach. However, at least 7 per cent or almost 60,000 jobs over the year 2016-2017 were estimated to be at high risk from automation.

A large proportion of workers jobs in Northern Ireland are classified as being at medium risk. This is the case partly because many seemingly un-automatable occupations include components which are automatable, while other occupations include tasks which are much less amenable to automation such as those requiring the use of negotiating skills or social or creative intelligence. This group is at risk of significant change because they include several automatable tasks and several non-automatable tasks. The automatable tasks are likely to be automated in time. However, this also means that the tasks which are not likely to be automated will presumably become more prominent tasks in the occupation or will be complemented by similarly non-automatable tasks. Either way, in the medium term at least this would suggest significant change in the task structure of these jobs.

A sizeable share of workers is employed in jobs classified as being at low risk of automation (12.8 per cent). Occupations that are at low risk are those whose principal job tasks involve aspects which have been described as 'engineering bottlenecks' in that they are non-automatable, or as of yet are not possible to be automated.

The estimates suggest that 1 out of every 2 jobs is likely to be substantially impacted by automation (either high or medium risk). Thus, irrespective of whether the impact manifests as the total substitution of jobs or the reconfiguring of the type of tasks associated with other occupations, the risk to jobs from automation presents considerable challenges. Further analysis is needed of the particular barriers which different low-risk occupations present to automation, and of the particular automatable/non-automatable tasks involved in different occupations classified at high or medium risk is needed. Doing so would put us in a better position to understand what tasks are likely to be substituted across different occupations and enable a more accurate policy response to the risks.

Of course, the challenges presented by automation however are not evenly spread across the workforce. In the next section we examine the profile the risk which different groups of workers face by occupations and industry, as well as by sociodemographic and socioeconomic characteristics.

3.3 How does the potential rate of automation vary by type of worker?

The results shown in Table 3, below, indicate that industrial sector of employment is an important factor in determining likelihood of automation. Specifically, over 1 in 4 of those in the *distribution, hotels and restaurant* sector are at high risk of automation (26.8 per cent). A further 46 per cent of workers in this sector are at mid-to-high risk of automation.

A low percentage of workers in the *transport and storage* (4 per cent), *manufacturing* (2.9 per cent) and *construction* sectors (1.8 per cent) are classified as at high risk from automation. However, over two-thirds of those in the *transport and storage* sector (68 per cent), and 51.1 per cent of those employment in the *manufacturing* sector and 63 per cent of those in the *construction* sector are at mid-to-high risk of automation. Consequently, we can deduct from this that such workers are at risk of significant change in that these are jobs that presumably include several automatable tasks that are likely to disappear from job descriptions in the future. To balance this, it may be inferred that some of the bottleneck tasks associated with these jobs will come to the fore and may be complemented by other non-automatable tasks.

The sectors with the lowest automation risk are those employed in public administration, education and health. These are relatively shielded from the risks of automation. An estimated 28.1 per cent of workers in these sectors are classified as being at low risk, with a further 38.5 per cent classified at low-to-mid risk. Only 0.4 per cent are classified at high risk of automation, although a further 12 per cent are at high to mid risk.

Next, we turn to assess the risk of automation based on occupational skill level, where it is clear that the risk of automation declines as the skill level rises. The risk of automation is particularly elevated among low-skilled workers with 34 per cent at high risk. A further 48 per cent are at high to mid risk of automation. Although only a very small proportion of those in middle-skilled occupations are at high risk of automation, almost 40 per cent of middle-skilled workers are in occupations which are at mid-to-high risk of automation. It is important to remember however that the lack of data on caring roles in the methodological approach means that automatability for those in caring occupations is over-estimated. Those in high skilled occupations which tend to require professional training and high levels of educational attainment and include teaching, management and health professionals have the lowest risk of jobs to automation, and it seems at least for now are protected against the risks posed by automation technologies.

In terms of gender, females are working in jobs which are at a higher risk of automation than is the case for males - 9 per cent of females are at high risk of job loss from automation technologies, compared to 6 per cent of males. That said, females (20 per cent) are much less likely to be at mid-to-high risk of automation than males (42 per cent) which would suggest that males may be more vulnerable to change going forward.

Young people are most at risk (11 per cent at high risk), followed by older workers (6 per cent at high risk). However, the results in Table 3 show, the risk of automation by age group is mediated by occupational skill level. Younger adults in low skilled occupations are more likely to be at high risk of automation than those who are middle aged or older. Younger workers often rely on being able to combine study with work in lower skilled occupations such as unskilled labourers, or as customer service representatives in order to obtain necessary resources. In addition, even highly educated younger workers tend to enter the labour market in lower skilled jobs which are at higher risk to automation. These results point to the need for new ways to be found to ensure that labour market entry does not become a particularly problematic issue for younger workers seeking employment.

Table 3: Risk to jobs from automation

	High	High-Mid	Mid-Low	Low	Not classified
Industrial Sector					
Production	0.8	15.4	10.7	5.5	67.6
Manufacturing	2.9	51.1	23.0	7.6	15.3
Construction	1.8	62.8	19.5	8.7	7.2
Distribution, hotels, restaurants	26.8	46.0	13.1	3.1	11.0
Transport & storage	4.0	67.9	13.5	2.8	11.8
Banking, finance, insurance etc.	5.6	24.8	38.3	7.5	23.8
Public administration, education & health	0.4	12.0	38.5	28.1	21.1
Other Services	2.8	23.9	19.6	11.3	42.4
Occupational Skill Level					
High skilled	0.0	3.1	35.9	44.4	16.6
Medium skilled	0.8	39.7	32.4	2.2	24.8
Low skilled	33.7	48.8	0.0	0.0	17.5
Gender					
Male	5.7	41.9	22.1	11.3	19.0
Female	8.7	20.3	31.7	14.5	24.9
Age					
18-34	11.1	36.2	21.6	10.1	21.0
35-54	4.5	27.9	30.5	15.5	21.6
55-64	6.0	32.4	26.3	10.8	24.4

Note: High skill = Managers, directors, and senior officials; Professional occupations. Medium skill = Associate Professional and technical occupations; Administrative and secretarial occupations; skilled trades occupations; caring leisure and other service occupations; process plant and machine operatives. Low skill = sales and customer service occupations; elementary occupations.

4. THE NEED TO MOVE BEYOND THE RECENT SOLE FOCUS ON JOB LOSS AND TECHNOLOGICAL UNEMPLOYMENT

Recent studies concerned with the impact of technology and automation for employment have tended to focus primarily on the ability of technology to substitute for human labour, and the subsequent risk of technological unemployment. However, often overlooked is the fact that while technology does indeed substitute for labour, it can also have a displacement effect by way of changing the character of jobs rather than destroying them. Indeed, the evidence presented in this paper would support the contention that job loss is a risk posed by automation technologies. However, it would also support the contention that the bigger challenge which automation technologies present for the future of work is in terms of how the tasks involved in different jobs will change, the types of jobs available, and indeed what those jobs pay. Furthermore, as has been the case in past technological revolutions, implementation of automation technologies has the potential to raise output in ways that augment demand in the economy and so in turn, have a labour creation effect.

Autor *et al* (2003) argue that the first-order effect of automation technologies is the substitution of machines for humans in the carrying out of specific tasks. This has historically been confined to routine, manual tasks. Routine tasks refer to tasks that follow explicit, codifiable rules which computers have become vastly proficient at carrying out. Many occupations whose core tasks involve repetitive, manual tasks such as moving a part into place on an assembly line fit this description and so are at high risk of automation.

More recently, however, as technology has advanced many tasks associated with middle-skilled occupations such as book keeping and clerical work have become automatable as they follow precise, well-understood procedures which are able to be codified in computer software and performed by machines. This means that increasingly significant shares of the tasks involved in these jobs are at risk of automation. Nevertheless, the tasks involved in these occupations which are non-automatable remain. As automation technologies are increasingly utilised workers will increasingly be required to perform tasks that are either complementary to machines or are non-automatable. *'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'* (Arntz *et al,* 2016: 24). The impact of technology on employment depends on whether workplaces and the economy are able to adjust to the substitution of certain tasks in the production process.

To date, the capability of computers to substitute for workers in carrying out non-routine cognitive or manual tasks has been limited. Indeed, non-routine tasks can broadly be defined as tasks that we understand only tacitly, and for which there is no explicit 'rules' or procedures which can be followed by a computer or a machine to complete the task. This constraint has been referred to as Polanyi's Paradox, following his observation that 'we know more than we can tell' in that there are many tasks that we engage in that we only implicitly know how to perform, which makes it difficult for these tasks to be automated (Autor *et al*, 2003). It is important to note however that as technology continues to advance automation technologies will be increasingly able to undertake non-routine tasks. This is, in large part, due to efforts to turn non-routine tasks into well-defined problems. Still however tasks demanding flexibility, creativity, persuasion, intuition, generalised problem-solving, complex communications, situational adaptability, visual and language recognition, and in-person interactions - do not (yet) lend themselves to computerisation and indeed continue to require humans to carry out these tasks.

It is also worth making the point that evidence of the risk to jobs from automation technologies is often taken to presume that the risk is technological unemployment losses. However, we argue that this is an impetuous conclusion which succumbs to the 'lump of labour' fallacy, as it ignores the broader macroeconomic capacity for adjustment and job creation to counteract the risk of widespread technological unemployment. This synonymising of automation risk for jobs with overall employment losses ignores the fact that while technology may substitute for certain tasks and indeed jobs it has the potential to alter the nature of other jobs and also to create demand for labour in new occupations and sectors. In this sense, evidence from several studies would suggest that there has been a decline in jobs with predominantly routine and thus automatable tasks, and indeed the evidence presented earlier in this paper would support the contention that the overall structure of the labour market is already adjusting with growth in sectors which are less susceptible to automation.

5. RECOGNISING THE IMPORTANCE OF CONSTRAINTS TO JOB AUTOMATION BEYOND TECHNOLOGICAL POSSIBILITY

To date, much of the discussion around the impact which automation technologies will have for the future of work has tended to focus on technological possibility. However, in order, to have a discussion about the future of work there is a need to take into account and give due consideration to other factors, such as the particular economic, social, political and legal /regulatory environment.

The economic viability of implementing automation technologies is fundamental to the discussion. In this sense, when thinking about whether or not it would be economically attractive from a business point of view to invest in automation technologies there is a need to give careful consideration to the relative cost and productivity of such technologies and the incentive to substitute labour. For example, Northern Ireland has the highest proportion of workers earning below the real living wage, when compared to any other UK region. It is reasonable to argue that relying on low-paid workers is a comparatively attractive option for many businesses in Northern Ireland than incurring the potentially large up-front costs of technology investments and all of the risks that this entails. We already know that investment in capital is chronically low in Northern Ireland, with a number of different estimates find Northern Ireland to have the lowest per population capital investment levels in the UK (Mac Flynn, 2016). Further research is needed to consider whether investment and indeed innovation is being subdued by consequence of the large proportion of our labour force who are low-paid.

Moreover, it is reasonable to expect that with time the cost of automation technologies will decrease, which will in turn lead to more widespread adoption. Thus, whilst it remains highly uncertain if or when the 'tipping point' towards much higher adoption of automation technologies will take place it would be preferable to begin preparations for this eventuality as soon as possible. This would help to limit the exposure of low-paid workers in the future. Thus, rather than feeling insulated from the risks of automation because a large proportion of workers remain cheaper than the labour-saving alternative, preparations need to be made for the day when automation technologies are the cheaper alternative so that workers are not faced with technological unemployment or having to accept lower wages to compete against machines for jobs.

There may also be ethical or legal obstacles which are also likely to slow down the utilisation of new technologies. This can be illustrated via the range of legal and ethical challenges being brought to the fore in the case of the autonomous car, and how an algorithm should/could make different decisions in different scenarios (Bonnefan *et al*, 2015; Thierer and Hagemann, 2015). Similar legal and regulatory issues emerge in the case of drone technologies, because of the existence of strict rules that govern the use of physical airspace and the risks that flying robots pose.

What is more, another fundamental aspect which impacts strongly on the utilisation of technology but is given relatively little attention in debates is the fact that there is a strong societal preference for the provision of certain tasks and services by humans, rather than by robots or machines. An example of this can be seen from the case of the supermarket chain Morrisons who in 2015 removed self-service check-outs and returned to the traditional approach of having staff on tills for check-out. Commenting on this, the CEO of Morrisons said that the reverse in policy was a business decision as 'It turns out that people quite enjoy their everyday interactions with the smiling, familiar checkout operator; advice from a knowledgeable shop assistant; or just bumping into a friend in the local supermarket queue.' (Retail Gazette, 2018). Similarly, the care and hospitality sectors provide further examples of where people attach social value to humans providing the service. Additionally, experts tend to overestimate the potential of new technologies to substitute for tasks carried out by humans. The comparative advantage of machines over workers is typically exaggerated for tasks involving common sense, power of judgement, flexibility and empathy (Pfeiffer and Suphan 2015).

6. CONCLUSION

Estimations of job risk to automation have been thought of in two ways in the literature. The first is widely referred to as the `occupation-based` approach to quantifying job risk from automation technologies. This approach assumes each occupation has a standardised structure of tasks and so the risk of automation is classified at occupation level. The short-comings of this methodological approach were discussed throughout this paper. It was argued that the occupation-based approach serves to over-estimate or at least, misrepresent the way in which automation technologies are likely to impact on work. Thus, in seeking to quantify the risk to jobs from automation, this paper utilised what has been termed the `task-based` which accounts for differing task structures within occupations and across firms and geographical areas, and allows for the idea that the risk from automation depends on the tasks which workers perform within occupations. This is important because, for example, one receptionist might only greet customers, another might also carry out administrative duties and operate a switchboard. In taking into account their differing task structures in the estimation of both of these jobs to automation we obtain a more tentative estimate.

In utilising this 'task-based' approach the data showed that, for the year 2016-2017, 7 percent of all jobs in Northern Ireland were at high risk of automation and 58 percent are at risk of substantial change over the medium term owing to automation technology advancements. The risk to jobs from automation however is greatly dependent upon the occupation or industrial sector in which a worker is employed, as well as the sociodemographic and socioeconomic characteristics of the worker. For example, over one in four of those in the *distribution, hotels and restaurant* sector are at high risk of automation (26.8 per cent). Furthermore, one in three of low-skilled workers face high risk of automation.

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APPENDIX 1: LIST OF EXPLANATORY VARIABLES

	Explanatory Variable
Worker characteristics	Gender
	Age group
	Education
	Income
	Health status
Skills	Literacy
	Numeracy
Job characteristics	Sector
	Firm size
Workplace tasks	Exchanging information
	Training others
	Presenting
	Selling
	Consulting
	Planning own activities
	Planning activities of others
	Organising Own Schedule
	Influencing
	Negotiating
	Solving Simple Problems
	Solving Complex problems
	Reading instructions
	Reading letters or memos
	Reading newspapers
	Reading professional publications
	Reading books
	Writing articles
	Filling forms
	Calculating shares or percentages
	Complex maths or statistics

APPENDIX 2: RESULTS OF AUTOMATABILITY REGRESSION

Dependent variable: Automatability – Frey and Osborne Index

Qualification match	-0.156***
	(0.017)
Overqualified	-0.076***
	(0.017)
Age - 20-24	-0.081*
	(0.048)
Age - 25-29	-0.006
	(0.047)
Age - 30-34	-0.015
	(0.046)
Age - 35-39	-0.077*
	(0.046)
Age - 40-44	-0.004
	(0.046)
Age - 45-49	-0.020
	(0.047)
Age - 50-54	-0.058
	(0.048)
Age - 55-59	-0.024
	(0.048)
Age - 60-65	-0.154***
	(0.050)
Female	-0.014
	(0.013)
Lower Secondary	0.140***
	(0.035)
Upper Secondary	0.024
	(0.035)
Post-Secondary Non-tertiary	0.034
	(0.036)
Professional Degree	-0.208***
	(0.036)
Bachelor's	-0.424***
	(0.038)
Master's	-0.525***
	(0.040)
Research Degree	-0.797***
	(0.073)
Income - 10-25%	0.096***
	(0.027)
Income - 26-50%	0.067***
	(0.021)
Income - 50-75%	0.007
	(0.020)
Income - 75-90%	-0.196***
	(0.023)
Income > 90%	-0.211***
	(0.026)
Public Sector	-0.305***
	(0.015)
Not for Profit	0.003

	(0.035)
- Less than once a month	0.077**
	(0.033)
- Less than once a week	0.164***
	(0.032)
- At least once a week	0.095***
	(0.025)
- Every day	0.130***
	(0.022)
Training others	
- Less than once a month	0.028
	(0.018)
- Less than once a week	0.066***
	(0.023)
- At least once a week	-0.071***
	(0.021)
- Everyday	-0.139***
	(0.020)
Presenting	
- Less than once a month	-0.215***
	(0.018)
- Less than once a week	-0.126***
	(0.025)
- At least once a week	-0.128***
	(0.028)
- Everyday	-0.412***
	(0.030)
Selling	
- Less than once a month	0.257***
	(0.029)
- Less than once a week	0.106***
	(0.037)
- At least once a week	-0.009
	(0.030)
- Everyday	0.024
	(0.016)
Consulting	
- Less than once a month	-0.020
	(0.026)
- Less than once a week	-0.181***
	(0.028)
- At least once a week	-0.141***
	(0.022)
- Everyday	-0.094***
	(0.020)
Planning Own Activities	
- Less than once a month	-0.118***
	(0.033)
- Less than once a week	0.060*
	(0.034)
- At least once a week	-0.062**
	(0.027)
- Everyday	-0.040*
	(0.022)
Planning activities of Others	

- Less than once a month	-0.024
	(0.025)
- Less than once a week	-0.115***
	(0.026)
- At least once a week	-0.061***
	(0.021)
- Everyday	-0.186***
	(0.018)
Organising Own Schedule	
- Less than once a month	-0.007
	(0.037)
- Less than once a week	-0.208***
	(0.037)
- At least once a week	0.034
	(0.029)
- Everyday	-0.007
	(0.022)
Influencing	
- Less than once a month	0.015
	(0.027)
- Less than once a week	-0.093***
	(0.029)
- At least once a week	-0.144***
	(0.022)
- Everyday	-0.216***
	(0.020)
Negotiating	
Less than once a month	0.020
	(0.024)
- Less than once a week	0.041
	(0.026)
- At least once a week	0.104***
	(0.022)
- Everyday	0.049***
	(0.019)
Solving Simple Problems	
- Less than once a month	0.029
	(0.030)
- Less than once a week	-0.018
	(0.031)
- At least once a week	0.024
	(0.028)
- Everyday	-0.033
	(0.027)
Solving Complex problems	
- Less than once a month	0.106***
	(0.019)
- Less than once a week	0.043**
	(0.022)
- At least once a week	0.082***
	(0.021)
- Everyday	0.071***
	(0.024)
Reading Instructions	
- Less than once a month	0.022

	(0.023)
- Less than once a week	0.007
	(0.027)
- At least once a week	0.010
	(0.022)
- Everyday	0.111***
	(0.019)
Reading letters or memos	
- Less than once a month	-0.052*
	(0.031)
- Less than once a week	0.010
	(0.033)
- At least once a week	0.019
	(0.025)
- Everyday	0.123***
	(0.021)
Reading newspapers	
- Less than once a month	-0.090***
	(0.023)
- Less than once a week	-0.022
	(0.024)
- At least once a week	-0.116***
	(0.020)
- Everyday	-0.015
	(0.019)
Reading Professional Publications	
- Less than once a month	-0.142***
	(0.019)
- Less than once a week	-0.252***
	(0.021)
- At least once a week	-0.246***
	(0.021)
- Everyday	-0.321***
	(0.026)
Reading books	
- Less than once a month	-0.201***
	(0.018)
- Less than once a week	-0.195***
	(0.024)
- At least once a week	-0.221***
	(0.023)
- Everyday	-0.341***
	(0.023)
Writing articles	
- Less than once a month	-0.049**
	(0.022)
- Less than once a week	-0.066*
	(0.036)
- At least once a week	0.058
	(0.056)
- Everyday	0.011
	(0.067)
Filling Forms	
- Less than once a month	0.049**
	(0.021)

- Less than once a week	-0.038*
	(0.023)
- At least once a week	0.100***
	(0.021)
- Everyday	0.041**
	(0.018)
Calculating shares or percentages	
- Less than once a month	0.131***
	(0.024)
- Less than once a week	0.108***
	(0.027)
- At least once a week	0.153***
	(0.020)
- Everyday	0.194***
	(0.016)
Complex maths or statistics	
- Less than once a month	0.057**
	(0.027)
- Less than once a week	-0.203***
	(0.044)
- At least once a week	-0.011
	(0.043)
- Everyday	-0.186***
	(0.041)
Sufficiently challenged	-0.154***
	(0.020)
Does not require more training	0.047***
	(0.014)
- Less than once a month	0.014
	(0.026)
- Less than once a week	-0.070**
	(0.033)
- At least once a week	-0.104***
	(0.024)
- Everyday	-0.130***
	(0.015)
- Less than once a month	-0.051
	(0.037)
- Less than once a week	- 0.098**
	(0.048)
- At least once a week	0.027
	(0.032)
- Everyday	0.0057***
	(0.018)
Literacy	0.002***
	(0.0003)
Numeracy	-0.001***
	(0.0002)
Health status - Very good	0.049***
	(0.014)
Health status - Good	0.051***
	(0.016)
Health status - Fair	0.009
	(0.027)
Health status - Poor	0.246***

	(0.061)
Constant	0.403***
	(0.072)
Note:	*p<0.1; **p<0.05; ***p<0.01

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