Roinn an Taoisigh
Department of the Taoiseach

IGEES
Irish Government Economic & Evaluation Service

Technical Paper

Automation and Occupations: A Comparative Analysis of the Impact of Automation on Occupations in Ireland

Irish Government Economic and Evaluation Service
April 2018
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Executive Summary

Key Messages:

The Frey and Osbourne (F&O) method and the Nedelkoska and Quintini (N&Q) method produced significantly different scales of estimates regarding the proportion of jobs that were classified as having an automation risk of 70% or more. Nevertheless, both also produced broadly similar estimates of average automation risk for Ireland.

Regarding the sectoral employment impacts of automation, despite variations in the estimates, both models identified broadly the same set of sectors that were most at risk and least at risk.

Employment trends over the last decade indicates that there is already a shift in jobs away from the most exposed sectors towards the sectors with the lowest automation risks.

The regional distribution of automation risk seems to reflect the existing disparities between regional labour markets as Dublin has the lowest exposure, whereas the regions most impacted by unemployment during the economic crisis seems to also have the greatest exposure to automation.

There is a strong relationship between the risk of automation of occupations and the level of education of people in those occupations. Higher levels of education tend to be associated with lower automation risks and vice-versa.

Main Findings:

- Approximately, two out of every five jobs in Ireland are likely to be substantially impacted by automation: 48.3% under the F&O model and 44.9% under the N&Q model.
- The F&O method found that 33.4% of jobs had a high risk/probability of automation (70% or higher) and 19% were at risk of a significant level of automation (between 50% and 70%). The N&Q method found that 15.3% of jobs were at high-risk and 25.5% at significant risk.
- Both methods identified that over half of employment in the *Transportation and storage*; *Agriculture, forestry and fishing*; *Wholesale and retail*; and *Construction* sectors are facing a risk of automation of 50% or higher.
- Under the F&O model the sector with the largest amount of jobs at high risk of automation, was *Transportation and storage* (61.7%). Under the N&Q model, the top sector in terms of high-risk exposure was *Agriculture, forestry and fishing* (24.9%).
- The sectors least exposed to automation under both models were *Education*; *Human health and social work activities*; and *Information and communication.*
- Over the last decade, the *Wholesale and retail* sector saw a reduction in employment of -7.5%; the *Industry* sector declined by -6.2%; and the *Transportation and storage* sector fell by -0.5%. In contrast, the *Information and Communications* increased by +35%; *Education* increased by +20.6%; and *Human health and social work activities* increased by +16.8%.
- Regarding regions, both models identified that the *South-East* and *Border* regions had the highest risk profile while *Dublin* had the lowest risk level.
- Under both models, there was evidence of an inverse relationship between the degree of automation risk and level of education attainment.

Automation and Occupations: High-level Analysis of Impact of Automation of Occupations in Ireland

Introduction

This study is a high-level assessment of how automation is likely to affect the occupation profile of the workforce in Ireland. In recent years there have been several international studies investigating the impact of automation on occupations over the next two decades. This study adapts methodologies of these studies to the Irish labour market.

The study incorporates the estimates produced by Frey and Osbourne (2013) and Nedelkoska and Quintini (2018) studies. The first study was the first substantive attempt to measure the potential impact of automation on labour markets and has been the jumping off point for much of the subsequent research in this area. The estimates produced by Frey and Osbourne study have been the subject of much debate and are widely seen as representing the higher bound of the potential impact of automation. The second paper, published by the OECD in 2018, reflects the most recent attempt at measuring the impact of automation and incorporates a number of refinements of the Frey and Osbourne methodology. Nedelkoska and Quintini, using their refined model, found lower estimates than in the original study. This study compares both sets of estimates and applies them to the Irish labour market.

By using both sets of estimates, this paper attempts to provide as best an assessment as possible of the risk horizon facing occupations in Ireland. The paper further supplements this analysis by also examining the effects at a regional and sectoral level as well as the relationship with educational attainment. This study is not exhaustive, and importantly does not attempt to foresee the creative power of automation, which will undoubtedly create new innovative jobs. For this reason, this paper overestimates the negative impact on jobs using both methodologies.

The rest of this paper is structured as follows: Section 2 will review the existing literature on the relationship between technology and employment; Section 3 details the estimation methodologies; Section 4 examines the impact of technology on occupations and decomposes these impacts by region, sector and educational attainment. Finally, Section 5 draws out some conclusions from the findings.

Developments in Automation and Employment

In this paper, we define automation as the creation and application of technology in order to control and monitor the production and delivery of goods and services. This is, intentionally, a broad definition, which intends to capture the many tasks and sectors that may be impacted by automation. It covers the typical forms of automation – for example robotics in factories that replace human assemblers. It also describes advances in the ICT sector through software, which tests a program and produces a report. This definition, therefore, is broad enough to encompass the many methods of automation, and combinations thereof. For example, in retail, it covers automation through computers fitted with sensors that provide self-service options to customers.

This section will discuss advances in technology that has led to the automat-ability of a wide variety of jobs. It includes a discussion of the massive increase in data, coupled with developments in artificial intelligence and machine learning. It highlights how these developments are increasing the pace of automation, and finally discusses how better sensors and a reduction in price is increasing demand for robotics.

Big Data, Artificial Intelligence and Machine Learning

In recent years, the rise of 'Big Data' and ever more powerful computing technology has led to significant progress in the method and frequency of data generation, processing and storage. These advancements have facilitated the development and dissemination of computerisation and Artificial Intelligence (AI) across an ever increasing range of economic domains and activities. Enhancements in processing power and availability of connected devices has drastically increased the amount of data produced through increased digital communication – not just between people but also increasingly between devices. It has been estimated that there were 8.4 billion connected devices worldwide in 2017 – up 31% from 2016 – and this is forecast to rise to over 20 billion by 2020 (Gartner, 2017). While it is unclear whether this rate of advancement will continue, we can expect continued development in digitisation and computing as well as the discovery of novel applications (Future of Work Commission, 2017).

AI can be defined as machines that can perceive their environment and take actions they decide will be most likely to achieve pre-determined goals (Future of Work Commission, 2017). There is a clear distinction between narrow AI (what is primarily discussed in this paper) and general AI. The term 'narrow' is not literal; instead, it defines machines, which have been given concrete tasks with clear (often commercial) applications. Examples of narrow AI range across industries and functions including self-driving cars, translation systems, and medical diagnoses. General AI, in comparison, is defined as intelligent and analytical behaviour by machines. This type of AI has not yet been achieved and there is uncertainty about the consequences of such a development. A White House report under the Obama administration stated that narrow AI should be the focus of public policy (White House, 2016).

Translating the processing power of AI and vast data sources into useful activities that could replace human labour has depended on the ability of programmers to sufficiently specify criteria for success. However, developments in AI and the production of data has in turn broadened the capabilities of programmers. Machine Learning (ML), a sub field of AI, has provided specific tools to utilise data generation to find rules and patterns through fields such as data mining and computation statistics. This allows powerful predictions that incorporate a very large number of variables. The massive amounts of data available permits these developments in specification, which allows non-routine tasks to be turned into well-defined problems. The rules and patterns discovered through ML can be learned directly from the data, rather than explicitly specified by a human designer. For example, relatively recent developments in handwriting recognition technology could only be developed and tested with the availability of large quantities of handwriting samples due to the large variation in handwriting (Plötz and Fink, 2009).

AI and Automation

The developments discussed above have allowed an increasingly large number of complex cognitive tasks to be automated. There are clear advantages of computerisation over human labour, two of which are accuracy and scalability. Computers can manage the calculations necessary for the analysis of very large datasets efficiently and unrelentingly, without human bias nor the human need to perform certain tasks (e.g. eating and sleeping) to function. For this reason, enterprise has been quick to adopt these technologies. Examples of applications include relatively recognisable uses such as personalised product recommendations or fraud detection (which is now almost completely automated – see Phua *et al.*, 2010). It is now increasingly being used for medical, financial and manufacturing purposes. For example it has been used in personalised cancer treatment (Kantarjian and Yu, 2015), medical diagnoses (Susskind and Susskind, 2015), pre-trial research in law firms (Markoff, 2011), the stock exchange, banks, manufacturing firms and NASA (Kaelbling and Lozano, n.d.).

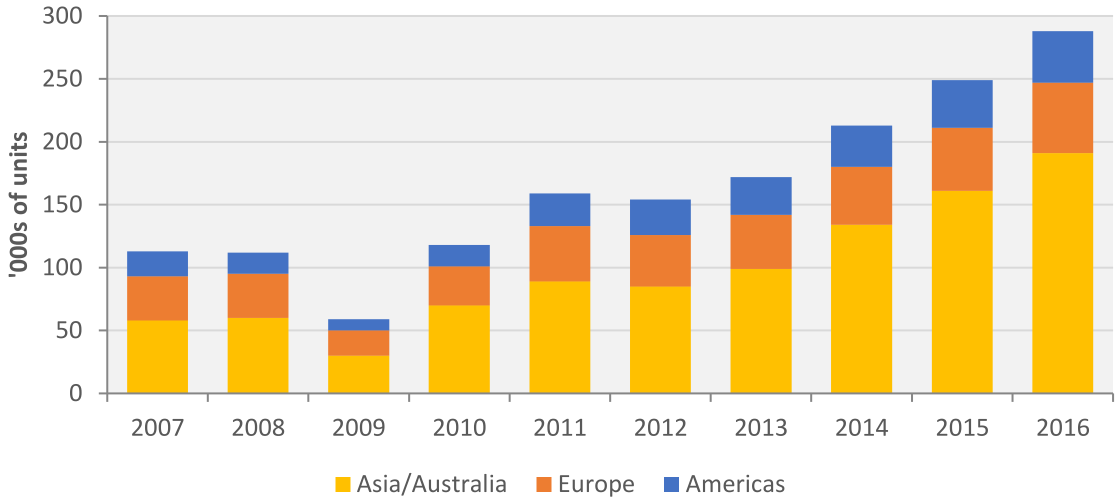
The use of increasingly adept sensors – and the data they produce – coupled with AI and ML systems have allowed many tasks to be computerisable. Condition monitoring sensors have allowed for technological substitution for closed-circuit TV (CCTV) operators and clinical staff monitoring patient's vital signs (Frey and Osbourne, 2013). Improvements in user interfaces have allowed computers to respond directly to human requests, for example the proliferation of 'digital assistants' such as Alexa, Siri and Google. Applications in industry abound including the monitoring of aircraft engines (King *et* *al.,* 2009) and water quality (Osborne *et al*, 2012). It has been estimated that algorithms could substitute for 140 million full-time knowledge workers worldwide (MGI, 2013).

Robotics and manual tasks

The idea of replacement of human labour for robotics is not new, and the introduction of robotics in industry happened decades ago. Indeed, robotics is advancing at a slower pace than computing, as systems struggle to overcome unpredictable obstacles presented by the physical world. Nonetheless, by harnessing big data, AI, and enhanced sensors and manipulators, robotic technology has made significant progress in recent years. Modern robotics can perform complex tasks in uncertain environments – e.g. climbing wind turbines for repairs or performing high-risk medical operations (Robotics VO, 2013). The evolution of advanced sensors and manipulators has also driven developments in robotics across sectors. For example, the Spanish food processor El Dulze uses robots to assess lettuce heads against company standards based on density, discarding those that do not meet those standards (IFR, 2012). The use of big data allows AI to compare current conditions (e.g. snowfall or roadworks) to previous incidents and to submit an appropriate response even if the current conditions are unprecedented (Churchill and Newman, 2012; Mathibela *et al.*, 2012). Self-driving cars, previously thought to be too unpredictable and non-routine to be adequately specified, are now close to mass production (Heineke *et al.*, 2017).

Cost is as important for potential labour market disruption as technical capability in robotics as there must be a positive economic trade off to prompt adoption. The McKinsey Institute found that the price of robotics is falling by 10% per year (MGI, 2013). Since 2010 demand for industrial robots has accelerated, with sales increasing at 12% per year between 2011 and 2016 (IFR, 2017). Figure 1 below shows estimated shipments of industrial robots. Each region in the chart below has seen double digit percentage growth in shipments between 2011 and 2016, with Asia/Australia showing the largest demand and growth at 53%. The Americas saw 37% growth with Europe slightly lower at 21% – albeit from a higher base than the Americas.

Figure 1: Estimated worldwide annual shipments of industrial robots by regions



Source: IFR, 2017

Box 1: Case study of automation drivers in e-Commerce

Automation will be driven and transmitted into enterprise through various channels. A case study of the relatively familiar area of e-Commerce reveals the drivers of automation and how the majority of disruption is still to come.

E-commerce is growing fast. Total e-Commerce sales in the US increased by 15% in 2016. UK internet sales are now 15.3% of total sales, and over 23% when only non-food items are considered. Indeed, e-commerce share gains are accelerating. However, there are indications that most of the disruption is still to come, both in demand and supply.

Demand for online retail has not yet reached its full potential. A recent study by Citi-Group found that once people begin to shop online, online purchases increase (Citi-Group, 2017). As broadband and mobile device penetration continues, demand in e-Commerce will increase. Furthermore, according to Eurostat, the age cohort currently between 25 and 34 make the highest proportion of their purchases online. Demand for online sales will likely increase as this cohort enters into 'peak spending years' (usually 45-54).

As e-Commerce grows, there are likely to be far ranging impacts. For example, real estate will be impacted in two ways: a decline in the highstreet and shopping malls, coupled with shop fronts moving towards more experiential offerings (which is already being felt). Secondly, there will be an increased need for warehousing near urban areas as delivery time becomes more important (see the growth in same day delivery as an example).

This demand-led growth in e-Commerce is the main driver of warehouse and delivery automation. However, technology is not yet a cost effective replacement for human labour in order fulfilment, and further development and commercialisation of sensors, data and software as well as in robotics and drones, is necessary before the full impact of disruption in retail is felt.

While large e-Commerce companies – notably Amazon – have driven advancements in automated order fulfilment, the hand eye coordination, dexterity and flexibility of human labour cannot yet be replaced. Despite various drives to automate warehousing, an Amazon warehouse facility can employ ~5,000 people during peak season. Although human labour is more cost effective for now, there are indications that labour availability may become an issue in logistics.

Wide ranging solutions to transportation logistics are being developed. These include developing real-time information data for truckers and delivery drivers to avoid traffic, the proliferation of automated vehicles, and current pilot programmes in drone delivery. However, these are yet to be rolled out to a substantial extent, and some – most notably drone delivery – have faced challenges. The regulatory environment for drone delivery will probably not be in place until 2025.

The pace of technological development, coupled with demographic change and increasing internet usage, means that automation trends, when demand driven, are likely to only increase.

Estimation Methodology

Overview of Recent Studies

Over the last 15 years, a number of studies have been conducted which try to estimate the risk of automation on current occupations, and consequently the impact of automation on employment. Autor *et al.* created a probabilistic model that depended on a two-by-two matrix with routine versus non-routine tasks on one axis and manual versus non-manual on the other (2003). They used this matrix to identify the automatability of certain tasks, finding for example that routine, manual (e.g. record-keeping and repetitive customer service) and non-manual tasks (e.g. repetitive assembly) would have substantial substitution impacts, while non routine manual tasks (e.g. truck driving and janitorial services) would have limited opportunities for substitution. It is noteworthy that over the short decade between Autor *et al.* and Frey and Osbourne's work in 2013, technology had advanced to make non-routine manual tasks automatable (e.g. driverless cars). This shows the unpredictable nature and speed of technological progress.

Frey and Osbourne built on this model by incorporating modern developments in AI and Machine Learning that has allowed for the automation of non-routine tasks (2013). The study focused on the US labour market, and suggested that 47% of all persons employed in the US were working in occupations that were at risk of automation over the next two decades (their methodology is discussed in more detail in the next section). Their methodology has been used in further research (in a similar way to this paper) to extrapolate their findings onto other countries and regions (e.g. Pajarinen and Rouvinen, 2014; Brzeski and Burk, 2015; Bowles, 2014).

Frey and Osbourne's work has been questioned by researchers, most notably by the OECD (Arntz, Gregory and Zierahn, 2016). They query the focus on occupations rather than tasks, as the former consists of many heterogeneous tasks, only some of which are automatable, and the composition of which can change from person to person within the same occupation (Autor and Handel, 2013). They build on Frey and Osbourne's work for OECD countries by focusing on specific tasks and find that the share of jobs at risk of automation was between 6% and 12% across OECD countries – much lower than Frey and Osbourne's estimation (Arntz, Gregory and Zierahn, 2016).

In 2018, Nedelkoska and Quintini used the Frey and Osbourne methodology, while developing the task based approach set out in Arntz, Gregory and Zierahn. Their data allowed the model to account for a broader range of occupations including jobs that do not involve using a computer. The study found that close to half of jobs are likely to be significantly affected by automation. 14% of jobs are highly automatable (probability of automation higher than 70%), while an additional 32% of jobs have a risk between 50 and 70%. The latter points towards the possibility of significant change in the way these jobs are carried out because of automation.

They also found large variation across countries. Jobs in Anglo-Saxon, Nordic countries and the Netherlands are generally less automatable than jobs in Eastern-European countries, South European countries, Germany, Chile and Japan. This variation across countries is explained better by differences in how tasks are organised within occupations, rather than by cross-country differences in the sectoral structure of the economy. This may reflect the extent to which automation has already taken place and resulting occupation adaptation. According to this theory, countries where the adoption of labour-substituting technologies has not yet taken place would show a structure of job tasks more prone to automation.

In this study, the probability of automation in Ireland was below the OECD average. This was due to the difference in how tasks are organised, while the sectoral structure of the economy counteracted this. For example we have a relatively large proportion of people employed in the agriculture sector, which in general has a high probability of automation. Overall, the Irish sectoral structure acts as a force to increase automatability of jobs overall. However, the way that tasks are structured within occupations – i.e. what tasks a skilled agricultural worker in Ireland performs compared to Slovakia – means Ireland is less automatable relative to the average OECD countries.

The authors also argue that AI puts more low-skilled jobs at risk than previous waves of technological progress, which generally replaced middle-skilled jobs creating labour market polarisation (increase in higher and lower skilled jobs).

In this paper, we have chosen to use both Frey and Osbourne's and Nedelkoska and Quintini's methodologies in order to build up as comprehensive a picture as possible of the risk frontier facing the occupational make-up of the Irish labour market. This paper does not attempt to estimate the impact on employment of automation *per se*, as advances in technology will continue to create new occupations, and the occupations that already exist may change in the composition of tasks as a response to automation – as has been seen in computerisation to date (Spitz-Oener, 2006). However, by focusing on the risk profiles, we can identify those occupations – and the sectors, regions and levels of education – that are more at risk and which therefore implies a lower level of labour demand in the future.

The timeline of automation, and its related impact on employment, has also been discussed. Frey and Osbourne viewed their probability model of estimation as a rough timeline for automation. They interpreted their results, which were clustered at high and low risk of automation, as two waves of computerisation separated by a 'technological plateau'. The first wave would affect logistics, transportation, office and administrative support workers, and production occupations. The second wave would then depend on overcoming certain engineering problems associated with automating more complex and 'human' tasks such as originality and persuasion (Frey & Osbourne, 2013).

More recently, PWC identified three overlapping waves of automation. First, the 'algorithm wave' – already underway – which would automate computational tasks of structured data in areas such as finance, information and communications. The second 'augmentation wave' would automate repeatable tasks like robots in warehouses, form filling, and providing information through technological support. This wave is also underway, but is likely to peak in the 2020s. Finally, the 'autonomy wave' would automate physical labour, manual dexterity and problem solving. These technologies are in development, but are likely to be introduced to the market in 2030 (2018).

Outline of Estimation Method

Frey and Osbourne concentrated their research on US occupations and associated employment. Understanding that due to advances in machine learning and Artificial Intelligence, non-routine as well as routine tasks may be subject to automation, Frey and Osbourne created a model based on 'engineering bottlenecks' where the rate of automation was slower than other tasks. The bottlenecks identified were a) perception and manipulation; b) creative intelligence, and; c) social intelligence (see Table 1 for more information). Therefore, the presence of engineering bottlenecks in an occupation would result in a lower probability of automation. They then used O*NET[1] data to objectively rank occupations according to the skills, abilities and knowledge required and then subjectively categorise the occupations based on the variety of tasks involved. See Table 1 below which shows the identified engineering bottlenecks and associated O*NET variables. They matched O*NET data to six digit US SOC 2010 occupations, (which included the associated employment levels of each occupation)

[1] A key aspect of O*NET data is that it defines key features of occupations as standardised and measurable variables, and also provides open-ended descriptions of specific tasks.

excluding those occupations without O*NET data. They then used a combination of subjective and objective labelling to prescribe probabilities of automation to each occupation.

> Subjective: hand labelled a selection of 70 occupations assigning a 1 if automatable and 0 if not. The occupations that were included were only those for which the authors had confidence in their labelling.
>
> Objective: fitted a probabilistic model using the variables in Table 1 to assign probabilities to all 702 occupations.

The results of both were then cross-checked for variation. This approach minimised the dual issues that a) O*NET data was not collected to measure automat-ability and b) possible subjective biases held by researchers in hand labelling.[2]

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, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative Intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or 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 and Caring for Others	Providing personal assistance, medical attention, emotional support or other personal care to others such as co-workers, customers or patients.

Source: Frey and Osbourne, 2013, p. 31

According to Frey and Osbourne's methodology, this represents the probability of each associated occupation of being automated over an unspecified number of years – they indicate two decades. The associated probabilities can also be interpreted as a possible timeline, with higher numbers indicating occupations that are likely to be substituted by computer capital relatively soon.

[2] For full details of Frey and Osbourne's methodology see: Frey and Osbourne, 2013, pp. 22-36.

Nedelkoska and Quintini built on the 2016 OECD study, using a task-based approach, while integrating Frey and Osbourne's methodology. Using the Survey of Adult Skills (PIAAC), they identified tasks associated with the engineering bottlenecks, linked to the 70 original occupations hand labelled by experts in Frey and Osbourne. The coefficients for automation associated with these tasks (using Canadian data at the four-digit ISCO level due to sample size) were used to estimate the risk of automation in occupations across OECD countries. Unlike O*NET, PIAAC does not include questions about tasks that relate to caring for and assisting others, which means that the automat-ability of some occupations that involve social intelligence may be overstated. However, the PIAAC data identifies occupations (and tasks associated) which explicitly do not use computers, and provide automation probabilities (unlike the Frey and Osbourne paper).

This paper matched the estimation results of both the Frey and Osbourne paper and the Nedelkoska and Quintini paper to the 2016 Census occupation data. Using Census data allowed us to have a full and up-to-date picture of employment in Ireland, with 2,006,641 people in employment. For some sections of the analysis (e.g. region and education) the data includes all those in the labour market (i.e. both employed and unemployed persons) – a total of 2,304,037 people. In these analyses those currently looking for work were categorised by their previous occupation. There were 125,914 in employment who did not state an occupation leaving 1,880,727 people. Within the labour force, there were 233,084 people who did not state an occupation, and a further 31,434 who were unemployed and looking for their first job, leaving 2,039,519 people.

For the Frey and Osbourne data we first matched UK SOC 2012[3] with US SOC 2012 occupations using an unofficial crosswalk[4] (available on request). Some UK occupations did not have a directly comparable US occupation, while some US occupations did not have probabilities of automation in the Frey and Osbourne paper (generally due to lack of O*NET data on certain occupations). These occupations were excluded from the analysis (see Appendix 1 for all excluded data across both methodologies). It is important to note that the US SOC 2012 is much more detailed than the UK SOC 2012 (and by association the CSO occupation categorisation). Frey and Osbourne labelled 702 occupations, while the Irish Census data contains 326 occupations. Therefore, multiple US codes often represented a single occupation in the Census. Where multiple US SOC 2010 codes were used to represent a single CSO occupation code, the mean of the available probabilities was taken. In total

[3] Irish census occupation data is based on a variation of the UK SOC 2012. As some occupation groups in the census data are not included in the UK SOC 2012, they are excluded from the analysis. See Appendix 1 for more details.

[4] A crosswalk is simply a table that shows equivalent fields – in this case occupations – across more than one database classification system.

1,730,481 jobs (2,164,178 people in the labour force) associated with 287 Census occupations were analysed with the Frey and Osbourne methodology.

To match the Nedelkoska and Quintini methodology to Irish data, we received (confidentially) the breakdown of Irish-specific automation risk by two-digit ISCO occupation (missing data listed in Appendix 2). We used an official crosswalk between ISCO 2 digit occupations and detailed UK SOC 2012 to match the occupations, excluding those that did not have a definite match (listed in Appendix 1). However, as the categorisation was only at the 2 digit ISCO code, the matching was much more complete with only 13,259 jobs (14,000 people in the labour force) excluded for these reasons. In total, 1,867,468 jobs (2,025,519 in the labour force) were analysed with the Nedelkoska and Quintini methodology.

These occupations, and associated probabilities, were then assessed by intermediate occupation level, sector, region and educational attainment. For presentation purposes, the occupations are classified in the following categories by probability of automation:

- High Risk: a probability score of 70% or over;
- Significant Risk: a probability score of 50% or over, but less than 70%; and
- Low Risk: probability scores of less than 50%.

Along with the methodological and data issues of both papers discussed, there are advantages and disadvantages within both methodologies as applied to Ireland. The Frey and Osbourne probabilities are specific to the US, and are based on occupations that may not have the same task structure in Ireland. Therefore, there is an inherent assumption that the risk of automation is comparable across countries – i.e. the share of jobs at risk is driven by the composition of occupation rather than any underlying differences between the same occupations in different countries.[5] In comparison, the Nedelkoska and Quintini estimations are task-based with Irish data, but we are only provided with an average probability of automation at the two-digit ISCO level due to sample size. This assumes that, for example, Chartered and certified accountants and Management consultants and business analysts have the same probability of automation (41%), while the Frey and Osbourne methodology shows very different estimates (94% for the former, .08% for the latter).

This paper also contains some other implicit assumptions. First, it only discusses the destructive power of automation. It does not attempt to foresee the creative power of automation, which will undoubtedly create new innovative jobs. For this reason, this paper overestimates the negative impact

[5] As discussed earlier, N&Q showed that cross-country variation in automation risk was driven by the variation of task structure within occupations rather than structural differences in a countries' economy.

on jobs using both methodologies. Secondly, the risk of automation is based on the technical capability of automation and does not consider substitution costs, the ability of firms to absorb new technologies or behavioural responses to automation (e.g. according to the Frey and Osbourne methodology barbers have a high risk of automation, but there may be human reluctance to adopt this technology).

Analysis of Occupations in Ireland

Occupational Distribution

To contextualise the results of the mapping exercise, it is first useful to identify the broad occupation structure of the Irish labour market. Figure 2 below details the number of jobs in 2016 associated with each of 24 intermediate occupation groups as classified by a CSO variation of UK SOC coding. The top three occupations in terms of numbers of jobs were *Administrative occupations*, accounting for 176,833 jobs; *Elementary administration & service occupations*, accounting for 135,553 jobs; and *Business & public service associate professionals* representing 120,525 jobs (See Appendix 3 for occupation groups). Together these occupational groups accounted for 21.6% or one in five of all jobs in 2016.

Figure 2: Numbers Employed by Intermediate Occupation Group (UK SOC Codes), 2016

Change in Occupations

This section will discuss trends in occupation composition in Ireland over the past ten years. Overall, there is little difference in the total number of people employed in these two years, with 2,232,900 people employed in Q4 2007 and 2,231,000 employed in Q4 2017 – a change of -0.1%. However, over the intervening period, because of the recession, employment levels underwent a major contraction, falling to a low of 1,863,200 in Q1 2012 before gradually recovering. In addition, the composition of the employed population by occupation changed drastically over that period.

Figure 3 below shows the change on a proportional basis. The occupational groups that have seen growth over the last ten years were *Managers, directors & senior officials* occupations, increasing from 143,400 to 192,300 (+34.1%); *Professional occupations*, increasing from 345,800 to 446,100 (+29%); *Caring, leisure & other service* occupations, increasing by 34,400 to 190,300 (+22.1%); and *Associate professional & technical* occupations which increased by 43,100 to 262,500 (+19.6%) (see Appendix 3 for breakdown of occupation groups).

The remaining occupation groups have all seen reduction in employment. *Process, plant & machine operative* occupations reduced from 171,000 to 167,000 (-2.3%); *Sales & customer service occupations* reduced from 198,500 to 181,600 (-8.5%); *Administrative & secretarial* occupations reduced from 257,000 to 215,600 (-16.1%); *Elementary* occupations reduced from 299,700 to 243,700 (-18.7%); and the *Skilled trades* occupations had the greatest fall in employment over the period from 435,200 to 318,300 (-26.9%).

These trends indicate there has been movement up the value chain in terms of skills in the labour market although part of this may be attributed to cyclical factors, as the period analysed covers the recession which was dominated by a fall in construction. Nevertheless, the overall picture suggests that lower skilled occupations are shrinking as a share of overall employment. Furthermore, the trend seen in the last decade is distinct from the decade before. Between 1998 and 2008, all occupational groups grew (due to cyclical factors), however the largest growth was in *Personal & Protective services* (77%), followed by *Sales* (68.7%). In comparison, the occupations with the lowest growth were *Plant & machine operatives* (10.6%) followed *by Managers & administrators* (18.4%).[6]

This change in occupation composition over the last decade indicates that structural change in the labour market is already occurring.

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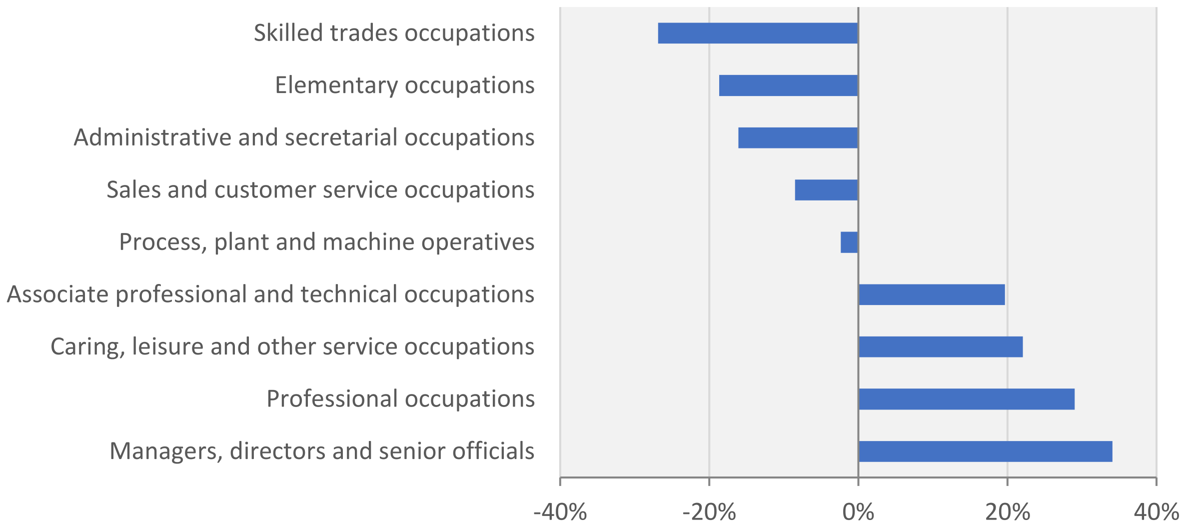
[6] This analysis used archived tables of the Quarterly National Household Survey, and occupational groups are not directly comparable to those in the last decade.

Figure 3: Change in Employment Q4 2007 to Q4 2017 (UK SOC Broad Occupation Group)



Source: CSO, LFS Q4 2017

Risk of Automation

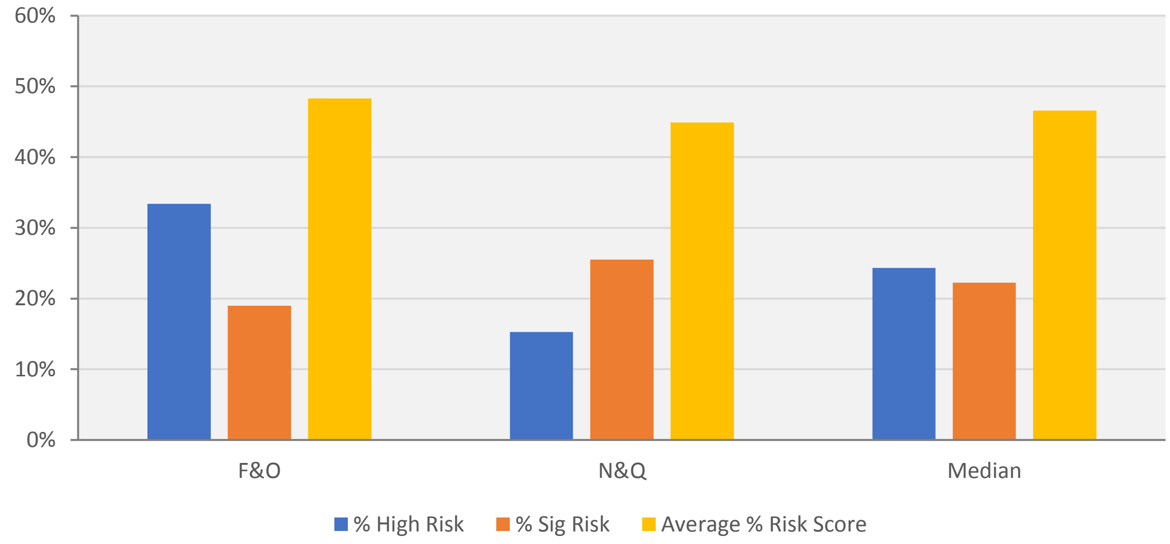
Figure 4 below details the comparative estimates of automation risk for each of the two methodologies and includes the average of both. The average overall risk of automation estimates produced by both studies indicates that more than two in every five jobs in Ireland will be impacted by automation in some way. The Frey and Osbourne method produced an average automation risk of 48.3% compared to a 44.9% risk from the Nedelkoska and Quintini method.

There were notable differences in the proportion at high risk of automation. The Frey and Osbourne method found that 33.4% of jobs had a probability of automation of 70% or higher. In contrast, the Nedelkoska and Quintini method found that less than half that proportion, 15.3% were in the high-risk category. When the estimates for the significant automation risk category were compared, the pattern was reversed. The Frey and Osbourne method found that 19% were at risk of a significant level of automation (between 50% and 70%), whereas the Nedelkoska and Quintini found 25.5%.[7]

When the average of both studies was calculated, the median level of risk was 46.6% with the high-risk category accounting for 24.3% of employment and 22.2% faced a significant risk of automation.

[7] According to N&Q, this difference is due to sample size and associated degrees of freedom – see Nedelkoska and Quintini, 2018 p. 48 for more details.

Figure 4: Proportion of Employment by Risk Category by Methodology



Breakdown of Risk by Occupations

To explore the impact of automation in detail, this section breaks down the automation risk estimates by individual occupation categories. As discussed earlier, the two studies use different occupation codes. The F&O study uses the UK's Standard Occupational Classification system (SOC) and the N&Q study uses the ILO's International Standard Classifications of Occupations (ISCO). Due to these definitional differences, the results at occupation level for each method are presented separately.

Figure 5 below details the F&O estimates for the SOC intermediate occupation groups in terms of the proportion of occupations that classified as at high, significant or low risk of automation[8]. There were eight occupation groups in which over half of jobs had an automation risk of 70% or over. Amongst these, the occupations with the highest proportions of jobs at risk of automation it was found that more than four out of five jobs were automatable. These included *Secretarial & related occupations* for which 100% of jobs had a high automation risk; *Process, plant & machine operatives* occupations where 91.3% of jobs were in the high-risk category; 87.4% of *Sales occupations* were in the high-risk category; and 80.5% of *Transport & mobile machine drivers & operatives* (see Appendix 3 for breakdown of occupation categories). When the significant risk category is included, 13 of the 25 occupation groups were expected to experience substantial change due to automation.

The least at risk occupation groups included: *Corporate Managers & directors,* of which 89.6% were categorised as in the low risk group; *Leisure, travel & related personal service occupations,* where

[8] Occupations within the intermediate occupation groups have been excluded where there was no probability score available to map to.

89.2% of jobs were low risk; and *Science, research, engineering & technology professionals;* and *Health professionals*, which in both cases, 88.1% of jobs were in the low risk category.

Figure 5: F&O Risk Estimates by SOC Intermediate Occupation Group

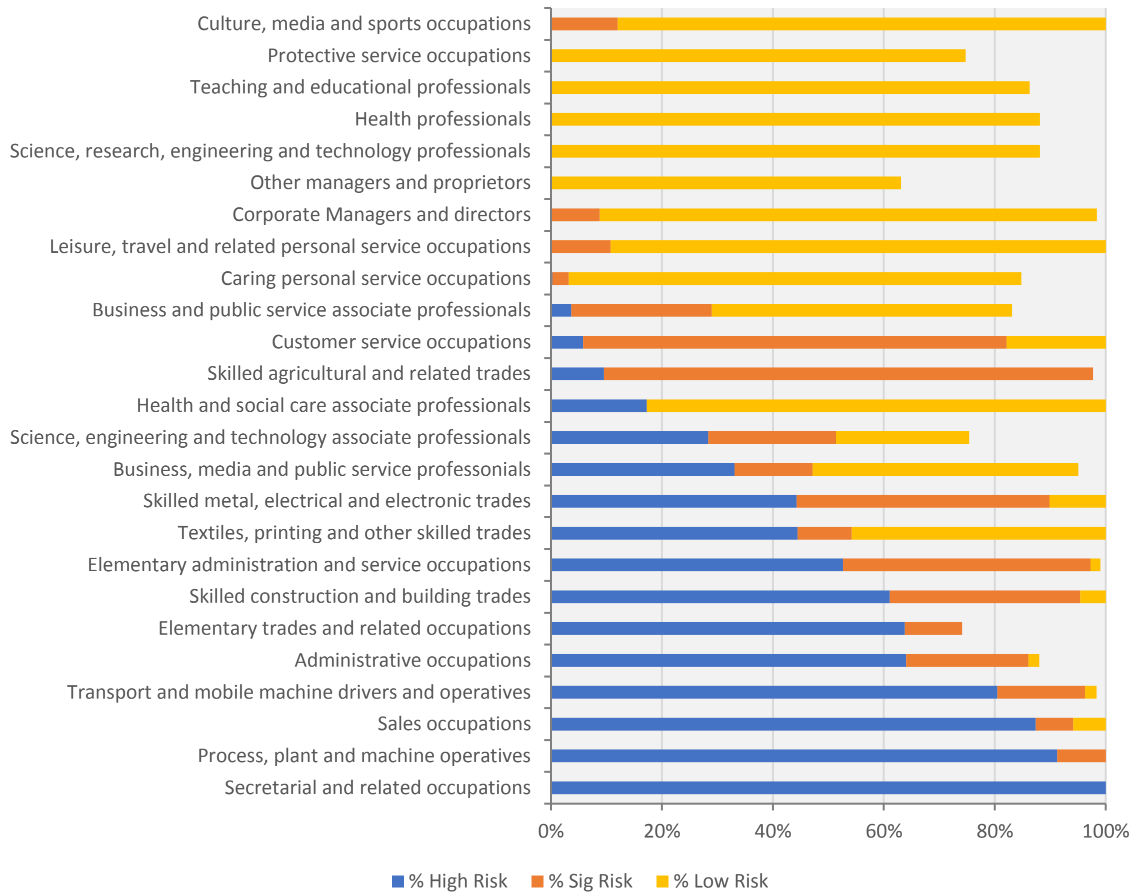
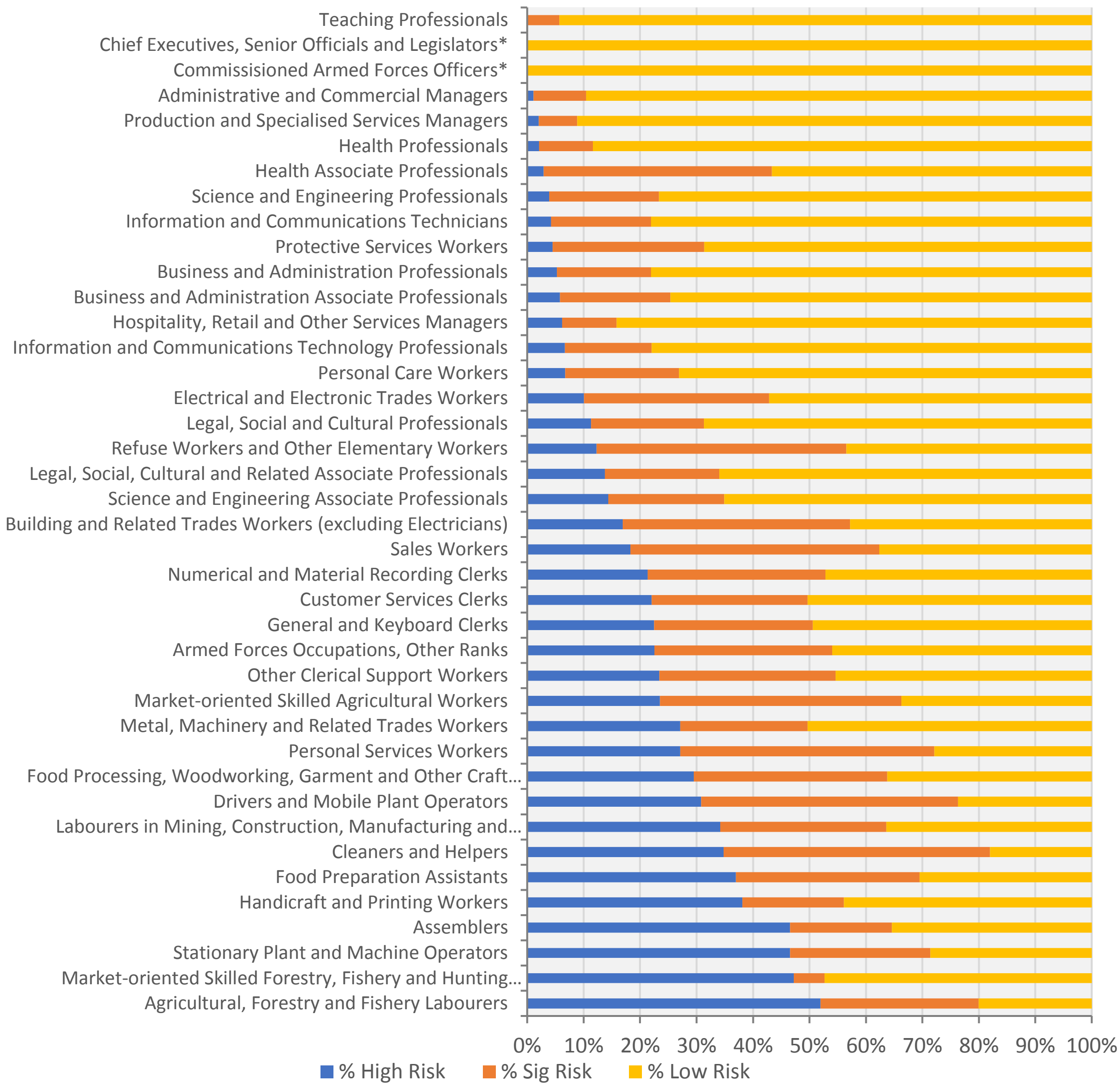


Figure 6 details the N&Q estimates for the ISCO occupation codes (see Appendix 4)[9] in terms of the proportion of occupations that are classified as at high, significant or low risk of automation. Only one occupation group under this methodology was found to have more than half of jobs in the high-risk category. It was estimated that 52% of jobs relating to *Agricultural, Forestry & Fishery Labourers* had a risk of automation of 70% or higher. The next largest proportion of jobs in the high-risk category was estimated for *Market-oriented Skilled Forestry, Fishery & Hunting Workers* at 47.2%, followed by *Stationary Plant & Machine Operators*; and *Assemblers* where in both cases 46.6% of jobs were categorised as having a high risk of automation.

[9] The International Standard Classification of Occupations, or ISCO, was developed by the International Labour Organisation to allow comparison of occupation structures across countries. As it is intended to cover all countries, it is more detailed than the CSO version of UK SOC 2012, which was developed for the Irish labour market. For more information, see: http://www.ilo.org/public/english/bureau/stat/isco/isco08/

When the high risk and significant risk categories were added together, the most at risk occupation group was the *Cleaners & Helpers*, where 82% of jobs related were predicted to experience substantial changes due to automation. The next most at risk group was *Agricultural, Forestry & Fishery Labourers* at 80%; and *Drivers & Mobile Plant Operators* where 76.3% of jobs were likely to experience substantial change due to automation. The occupations with the highest proportion of jobs in the low category were *Commissioned Armed Forces Officers;* and *Chief Executives Senior Officials & Legislators*, which both had 100% of jobs in the low risk category, followed by *Teaching Professionals;* and *Production & Specialised Services Managers* with 94.3% and 91.1%, respectively.[10]

Figure 6: N&Q Risk Estimates by ISCO Occupations



* Based on less than ten observations.

[10] Please note that the results for these two occupation categories are based on less than ten observations in the N&Q methodology.

As discussed earlier, the two studies use different occupation codes. The F&O study uses the UK's Standard Occupational Classification system (SOC) and the N&Q study uses the ILO's International Standard Classifications of Occupations (ISCO). To get a better sense of how both models perform comparatively, this section breaks down the automation risk estimates at the broadest level of both classification systems. While the occupation categories are not directly comparable, it is instructive to note the trends across each model.

Figure 7 details the F&O estimates for the SOC occupation codes. *Process, Plant & Machine Operatives* were found to have the largest proportion of jobs at substantial risk of automation (high risk plus significant risk) at 98.2%. Indeed, 86.1% of these type of occupations were in the high-risk category. The next largest in terms of proportion of jobs at risk was the *Elementary Occupations*. Under the F&O model, 54.9% were in the high-risk category and 37.6% were in the significant risk category. The result overall indicated that 92.5% had a greater than 50% of automation within the next two decades. *Sales & Customer Service occupations* were also found to have a similar proportion of jobs with a 50% of greater risk of full automation. However, in this case 73.3% were at high risk compared to 18.8% at significant risk. The least at risk of automation under the F&O model were *Caring, Leisure and Other Service occupations* at 5.6%; *Managers, Directors & Senior Officials* at 6% and *Professional Occupations* at 12.2%. Furthermore, in the case of *Managers, Directors & Senior Officials*, the proportion of jobs at high risk is negligible.

Figure 8 details the results for the N&Q model. In this case, the occupation group with the largest proportion of jobs with a risk of automation of 50% or more was *Plant & Machine Operators and Assemblers* at 73.6%, with 38.2% at high risk of automation. This was followed by *Elementary Occupations* at 69.1%, with 33.4% in the high risk category; and then *Skilled Agricultural, Forestry & Fishery Workers* at 65.3%, with 24% at high risk. The occupations with the smallest proportion of jobs at risk were *Managers* at 11.8%; *Professionals* at 17.8%; and *Technicians & Associate Professionals* at 29.7%. In each of these occupation groups, less than 10% were in the high-risk category.

Figure 7: F&O Risk Estimates by SOC Occupations

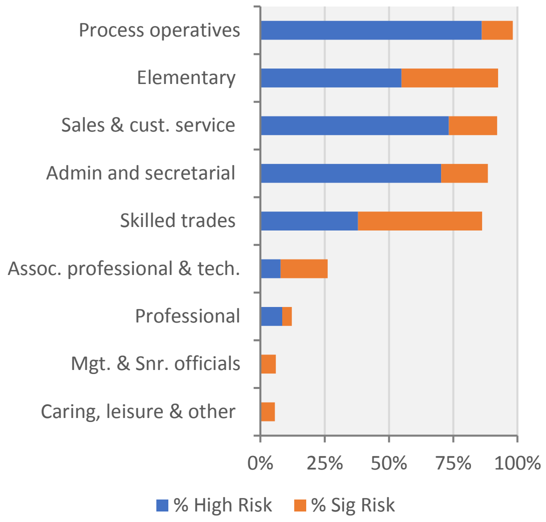
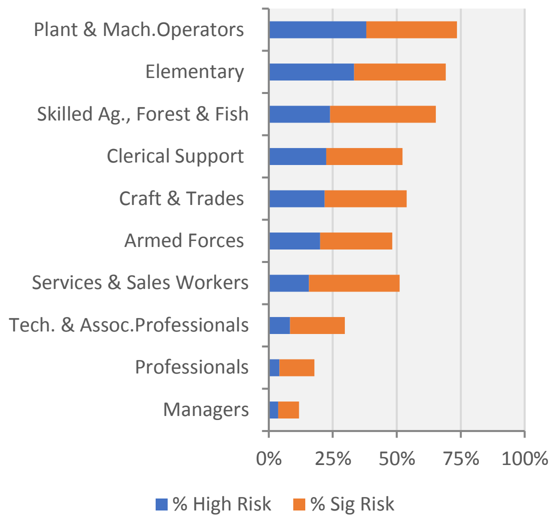


Figure 8: N&Q Risk Estimates by ISCO Occupations



On the face of it, there was a high degree of commonality regarding the type of occupations most and least at risk, despite the differences in the estimates of risk, across both models. Routine and elementary type occupations were found to be most at risk in both models, while management occupations and professions were the least at risk.

However, a notable difference concerned sales occupations. Under the F&O model, *Sales & Customer Service* occupations had the second highest proportion of jobs in the high-risk category of 73.3%. In contrast, under the N&Q model, the proportion of jobs at high risk was 15.6% in the *Services & Sales Workers* occupation group. While these two occupation groups are not directly comparable, the results nevertheless are instructive. A further difference concerned the inclusion of Caring, leisure and other service occupations in the F&O model and not the N&Q model. Note that these type of occupations were found to have amongst the lowest risk profile of occupations.

These differences can be explained in part by methodological differences between the models. The F&O model does not account for occupations that do not involve significant use of a computer, which may lead to over-estimating in the case of sales occupations, as many sales occupations still involve significant human input, especially regarding bespoke goods and services. The lack of data on caring roles in the N&Q model prevent it from estimating results for that sector. This is a significant disadvantage as labour demand is growing in this area as noted in the previous section.

Supplementary Analysis

Using the occupation data it is possible to explore the impact of computerisation across a number of additional dimensions in order to get a sense of the wider implications on the economy. This section links the occupation to the CSO's NUTS 2 Regions codes and the NACE Rev 2 economic sector codes as well as educational attainment data to examine the impact of computerisation of different sectors, regions and level of education.

Automation and Sectors

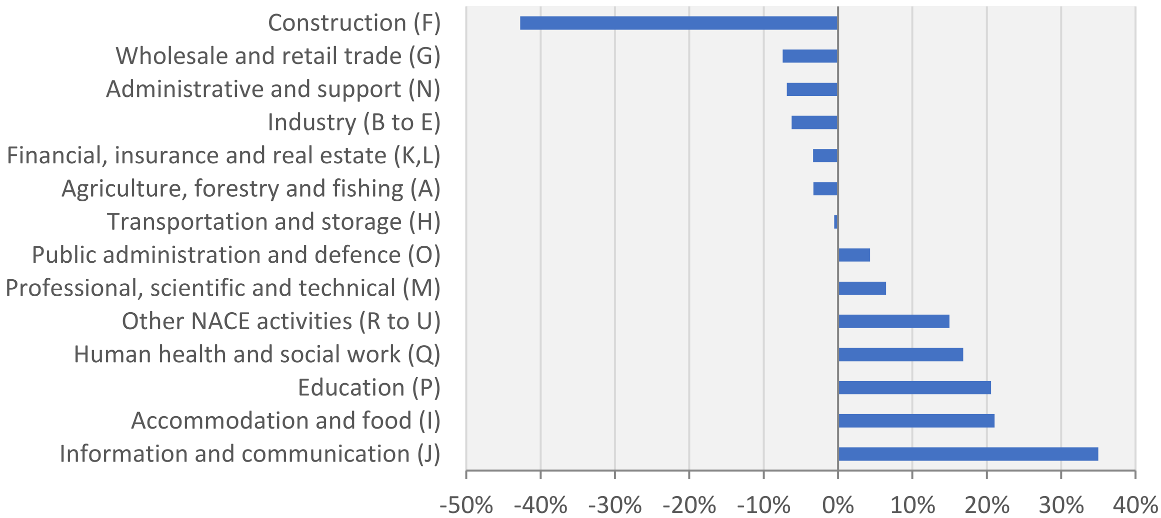
The impact of computerisation will have a variable impact across industrial sectors but all sectors are expected to experience some level of change because of technological advancements. Figure 7 details the number of jobs associated with each NACE 2 Rev Industrial Sector.

Sectoral Employment

There has been significant change in the sectoral distribution of employment over the last decade, in part driven by the recession, but also the changing nature of the economy. The *Construction* sector experienced the largest losses in employment over the period 2007 to 2017, witnessing a fall of -42.7% to 133,200. This is primarily due to cyclical factors. The *Wholesale & retail* sector saw the second largest reduction in employment of -7.5% to 308,900. These were followed by the broad *Industry* sector which saw reductions of -6.2% to 282,300 and the *Transportation & storage* sector which saw a marginal reduction in employment over the period of -0.5% to 95,200. These four sectors together accounted for more than one third (36.9%) of total employment in Ireland in Q4 2017.

The *Information & Communications* sector saw the largest increase of 35% to 116,500 people employed. *Education* saw increases of 20.6% to 167,600 over the period, while *Human health & social work* increased by 16.8% to 281,000. These sectors comprised just over one quarter (25.4%) of total employment in Ireland in Q4 2017. These trends suggest that sectors traditionally associated with lower skills such the *Wholesale & retail* sector and the *Transportation & storage* sector are shrinking relative to higher skilled areas and/or human services such as *Information & Communications* and *Human health & social work*.

Figure 9: Percentage change in employment by sector Q4 2007 to Q4 2017



Source: CSO, LFS Q4 2017

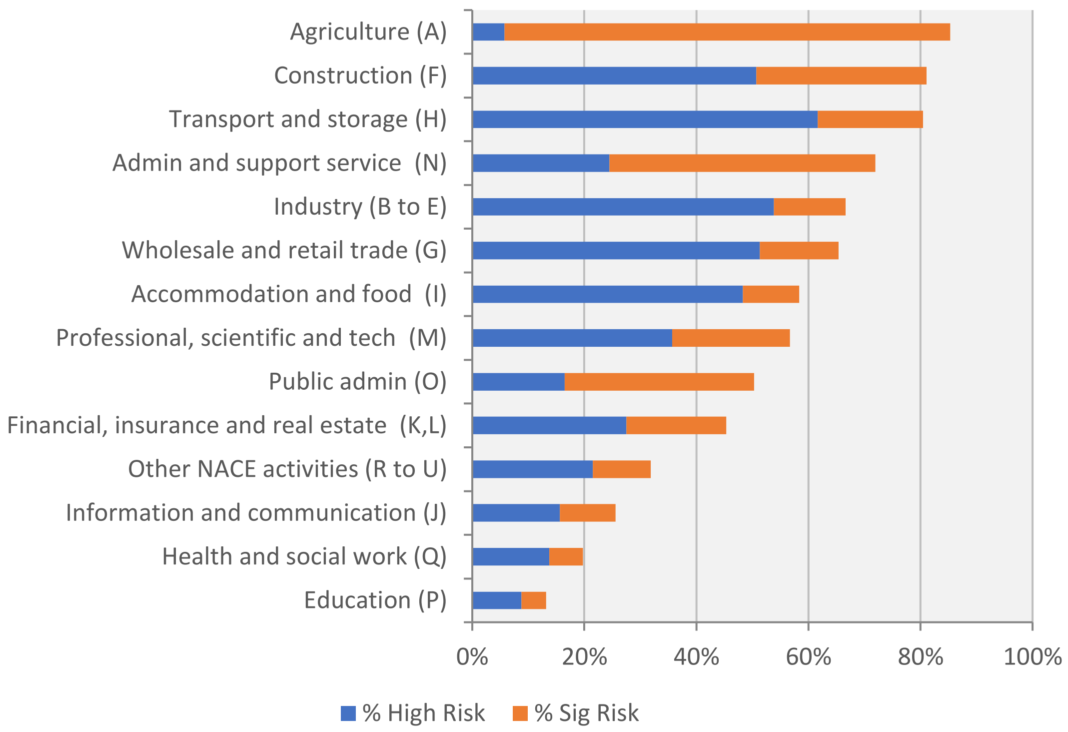
Sectoral Risk

This section examines the automation risk profile in terms of sectors under each model. Figure 8 shows the distribution of risk under the F&O model. Under this method over half of employment in four of the 14 of the NACE 2 industry sectors were classified as high risk. The sector with the largest proportion of jobs at high risk of automation was *Transportation & storage*, with 61.7% of jobs with a risk profile of 70% or over. This was followed by the Broad *Industry* sector, with 53.8% of jobs at high risk of automation; and then the *Wholesale & retail* sector with 51.3%; and *Construction* with 50.7%.

When jobs in the significant risk category are included, the sectors with the highest proportion of jobs at risk were *Agriculture, forestry & fishing* with a total of 85.3% of all jobs with a significant or high risk of automation; *Construction* with 81.8%; and *Transportation & storage* with 80.4%.

The sectors with the lowest risk of automation were *Education* with 13.2% of jobs at high and/or significant risk of automation; *Human health & social work activities*, at 19.8%; and *Information & communication* with 25.8%.

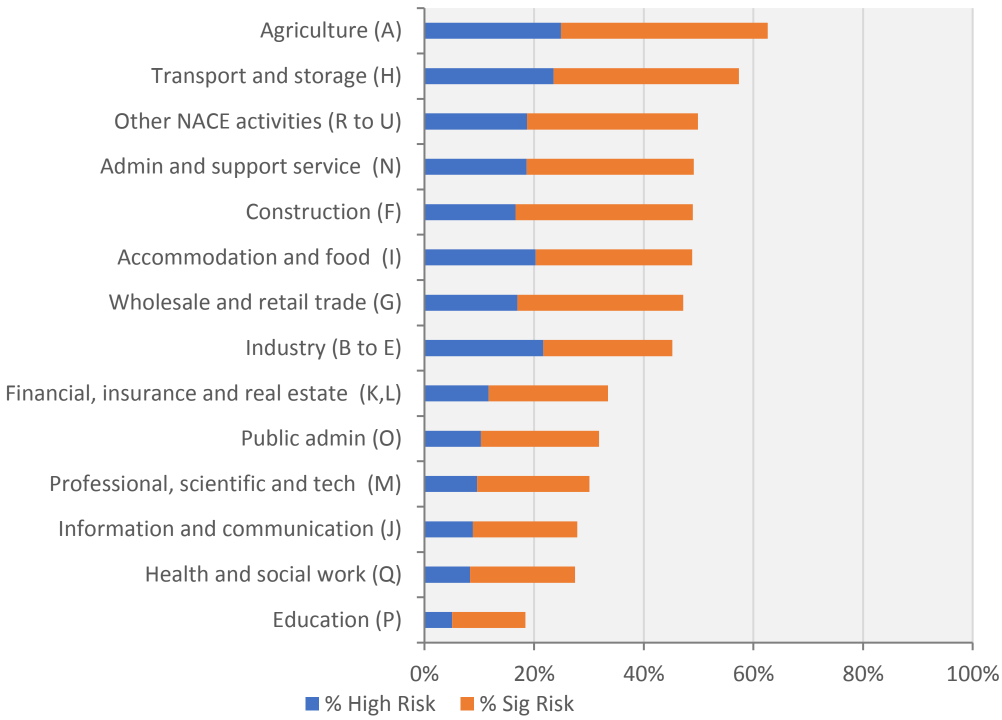
Figure 10: Automation Risk by Sector, F&O Method



Under the N&Q model (see Figure 11), the sector with the greatest proportion of jobs in the high-risk category was *Agriculture, forestry & fishing* at 24.9%. This sector also had the largest proportion of jobs in the significant risk category at 37.7%, meaning overall almost two-thirds of jobs in this sector (62.6%) were predicted to experience substantial change due to automation. The next most at risk sector was *Transportation & storage*, with 57.4% expected to experience substantial change from automation (23.6% at high risk and 33.8% at significant risk). *Other NACE activities* and *Administrative & support service activities* followed with 49.9% and 49.2% of jobs likely to experience substantial change respectively.

The sectors with the lowest risk profiles were *Education*, with only 5.1% of employment in the high-risk category and 13.3% in the significant risk category. The *Human health & social work activities* sector was the second least at risk with 8.3% of jobs at high risk and 19.1% at significant risk of automation. This was followed by the *Information & communication* sector with 8.8% jobs at high risk and 19.0% of jobs in the significant risk category.

Figure 11: Automation Risk by Sector, N&Q Method



While both methodologies provide different estimates for automation by sector, they nevertheless identify the same group of sectors most at risk of automation. Under both models *Transportation & storage*; *Agriculture, forestry & fishing*; *Wholesale & retail*; and *Construction* were found to be amongst the most at risk of automation. Together these sectors accounted for 26.8% of employment in 2016. In addition, both models find that *Education*; *Human health & social work activities*; and *Information & Communications* had the lowest risks of automation.

It is also worth noting from Figure 9, that employment in the most at risk sectors has been declining in recent years, while employment in the least at risk sectors has been growing. This would suggest that the economy is already undergoing structural change that may mean in future the potential exposure to automation related dislocation of workers will shrink.

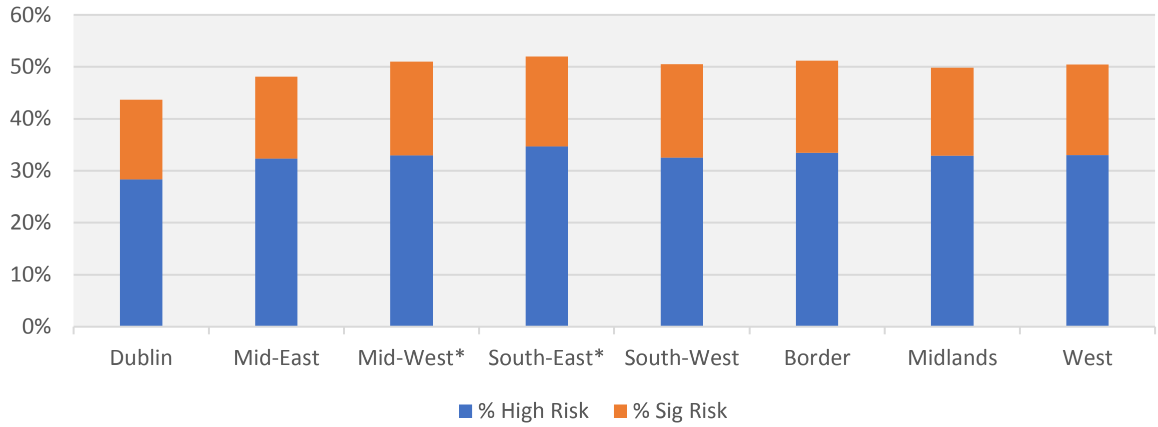
Automation and Geography

The following section explores the risk profile of jobs in terms of each NUTS 2 Region under both the F&O model and the N&Q model.

Figure 12 shows the risk of automation for each region based on the F&O methodology. The analysis indicated that the *South-East* region had the highest proportion of employment in the high risk of automation category at 34.7%; followed by the *Border* with 33.4% at high risk. *Dublin* was estimated to have the lowest proportion in the high-risk category with 28.4%, while the high-risk estimates for the rest of the regions clustered around 32%.

When the proportion at significant risk of automation were included, the pattern remained broadly consistent. The *South-East* and *Border* regions remained the most at risk at 52% and 51.2% respectively. The lowest automation risks (high risk plus significant risk) were in the *Dublin* and *Mid-East* regions, at 43.7% and 48.1% respectively.

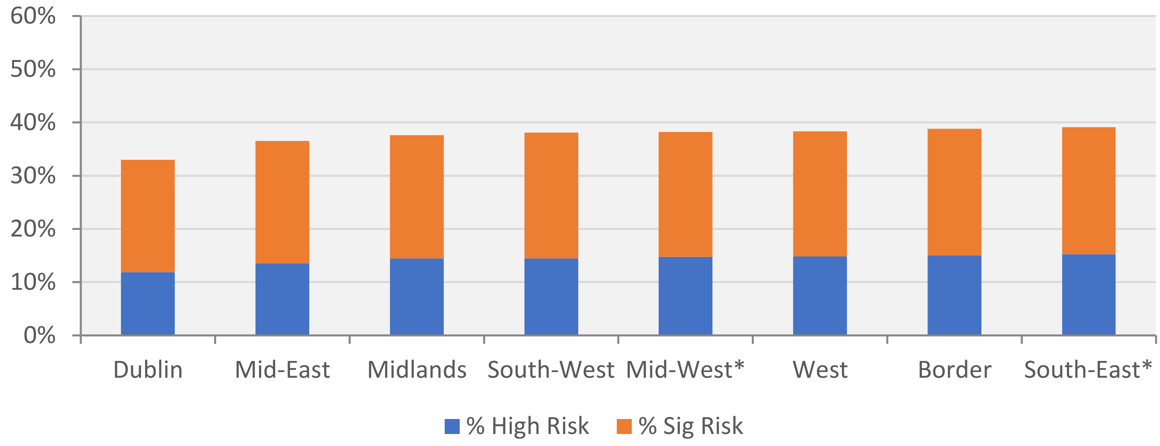
Figure 12: Automation Risk by Region, F&O Method



** Tipperary is counted in the Mid-West Region.*

Under the N&Q model, as shown in Figure 13, employment in most regions faced comparable estimates of automation risk with marginal variations. The *South-East* and *Border* regions were estimated to face the largest impacts from automation in terms of employment. About 15.3% of employment in the *South-East* region was found to be in the high risk category and 23.9% was at significant risk. In the *Border* region, the respective estimates were 15.1% at high risk and 23.7% at significant risk. The regions with the lowest proportions of jobs at risk were the *Dublin* region, where 11.9% were at high risk and 21.1% were at significant risk; and the *Mid-East* region, where 13.6% of jobs faced a high risk of automation and 23% faced a significant risk.

Figure 13: Automation Risk by Region, N&Q Method



** Tipperary is counted in the Mid-West Region.*

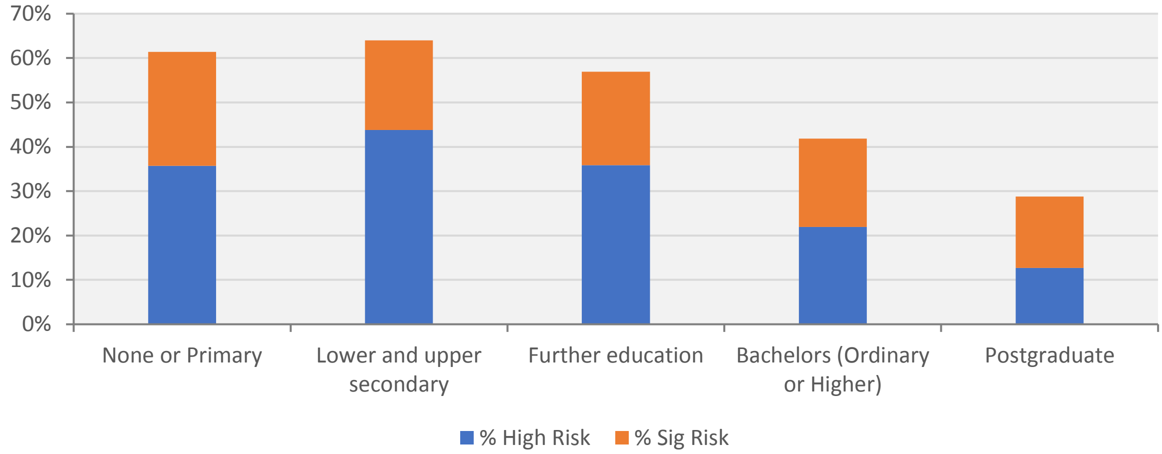
Interestingly, notwithstanding the variance in estimates, both models identify the *Dublin* and *Mid-East* regions as facing the lowest risks from automation and the *South-East* and *Border* as the most exposed regions. This presents a challenge insofar as the regions that are most at risk of automation also experienced the most significant labour market disruptions during the recession. As a result the South-East and Border regions labour markets are relatively weaker and would be less capable of offering alternative opportunities to workers should significant automation of jobs occur.

Automation and Education

This section analyses the relationship between education levels, occupations and the risk of automation. By linking the occupational data to the educational profile of the people employed in those occupations in 2016, it is possible to examine how automation is likely to interact with different levels of education.

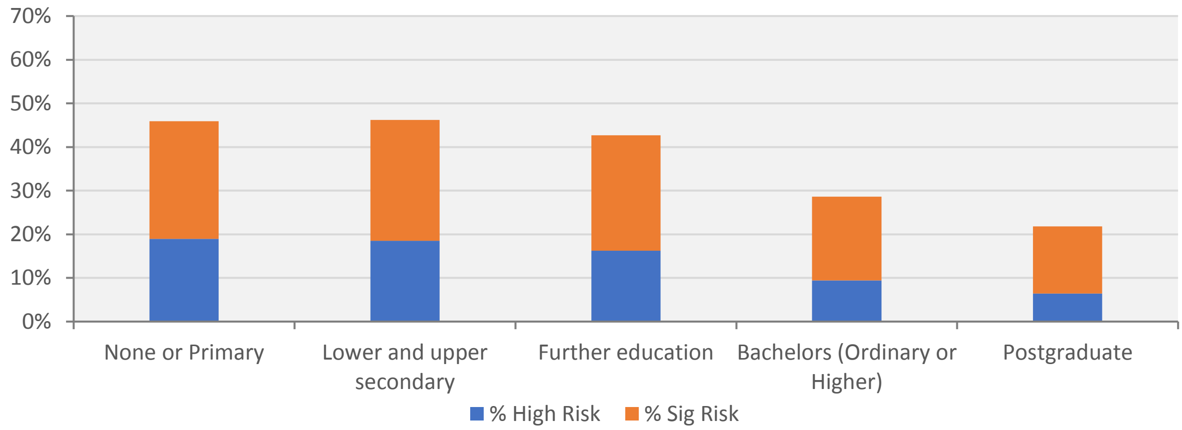
Figure 14 details the relationship between education attainment and automation risk using the results of the F&O method. The estimates for this model indicate that the higher the education level of the person in a certain occupation, the lower the risk of automation within that occupation. The high risk estimate for educational attainment categories *Lower and upper secondary* was the highest at 43.8%; followed by *Further education* with 35.9% and *None or Primary* with 35.7%. Meanwhile the proportion of jobs for people with a *Bachelor's* degree and/or a *Postgraduate* degree in the high-risk category were 22% and 12.7% respectively. This pattern is broadly replicated with the significant risk category is added to the high-risk category.

Figure 14: Automation Risk by Education Attainment, F&O Method



Under the N&Q model, the results, as detailed in Figure 15, clearly show an inverse relationship between risk of automation and level of education attainment. Jobs associated with lower levels of education have the highest automation risk estimates whereas higher levels of education are associated with lower risk estimates. The proportion of jobs in the high-risk category, linked to the *None or Primary* and the *Lower and Upper Secondary* categories of education, were 18.9% and 18.5% respectively. In contrast, the proportion of jobs associated with a *Bachelor's* degree and *Postgraduate* degree in the high-risk category were 9.4% and 6.5% in turn.

Figure 15: Automation Risk by Education Attainment, N&Q Method



The results for both models point to clear relationship between level of education and the risk of automation. Those with higher education levels tend to be in occupations with generally lower risk of automation, while those with low levels of education are likely to be in occupations more at risk of being automated. This suggests that investment in education, including lifelong learning, may mitigate the risk of automation.

Conclusions

These estimates are projections based on different methodologies subject to specific caveats. In particular, the estimates associated with occupations do not account for national variations in the absorptive capacity of enterprise to adopt new technologies and adapt business models to greater levels of automation. If enterprise is quicker to absorb such technology, this would increase the rate of change associated with automation. Furthermore, these estimates cannot anticipate unexpected technological developments. Nevertheless, based on existing knowledge concerning likely development pathways for technology, these estimates highlight that the occupational structure is likely to undergo significant change in coming years.

While it was not possible to examine the individual occupations on a like for like basis with the two methodologies, it was possible to compare the estimates of the overall impact on employment. When compared the F&O and N&Q methods produce significantly different estimates of jobs at high risk. The F&O method estimates that 33.4% of jobs have a risk of automation of 70% or more, while the N&Q method indicated that 15.3% were at high risk. The estimates of significant risk are reversed. The F&O method produced estimates of 19% with an automation risk of 50% to 70%, whereas the N&Q method estimated that 25.5% of jobs fell into the significant risk category. The result of this is that the average automation risk estimates derived from each methodology are relatively comparable. At 48.3% for the F&O method versus 44.9% for the N&Q method, the difference was relatively small at 3.4 percentage points. Interestingly, when average automation risk estimates are compared in terms of sector, region and education, both methodologies also produce similar results albeit the estimates vary.

Concerning sector, both models identified the same sectors as the most at risk in terms of overall average risk. *Transportation & storage*; *Agriculture, forestry & fishing*; and *Administrative & support service activities* had amongst the greatest risk in terms of automation. However, the breakdown by risk category is more varied. For example in the *Agriculture, forestry & fishing* sector under the F&O model only 5.8% of jobs were in the high risk category, however, under the N&Q model it was 24.9%.[11] Similarly, while both methods estimate the *Industry* and *Transportation& storage* sectors as being in the top three in terms of high risk of automation, both models differ on the proportion in the high-

[11] As mentioned earlier, N&Q discuss this variation in their paper, citing the larger sample size when analysis is based on tasks. This means that the distribution of probability is closer to a normal distribution, with more occupations found in the centre. According to this explanation, it will likely create a more accurate estimate. See N&Q, 2018 p. 48 for more details.

risk category. The F&O model estimated that the high-risk category accounted for the larger proportion, 53.8% and 61.7% respectively. In contrast, the equivalent estimates under the N&Q model were 21.7% and 23.6% respectively. Furthermore, the N&Q found that a greater proportion in each case was in the significant risk category, whereas under the F&O model the significant risk category accounted for the smaller share.

When examined by region, both models produce similar results. The *South-East* and *Border* regions were most exposed while *Dublin* and the *Mid-East* had the least exposure. This pattern corresponds with the disparity in economic and employment disparities between regions in Ireland. *Dublin* and *Mid-East* amongst the most economically developed regions, especially *Dublin* which hosts much of the foreign owned high technology industries. In contrast, the *Border* and *South-East* regions have tend to have a higher concentrations of less developed and lower productivity industries with greater prevalence of lower skilled, routine based occupations. This was reflected in the disproportionate impact of the recession and the subsequent recovery on the labour markets in these regions. To date the *Border* and *South-East* regions lag behind the rest in terms of employment.

In terms of education, notwithstanding the differences in the estimates, the results of both models broadly show an inverse relationship between risk of automation and educational attainment. Lower levels of educational attainment were associated with the high-risk category, while educational levels were higher tended to have a lower risk profile.

Notwithstanding the methodological differences, both models suggest that on average two out of every five jobs is likely to be substantially impacted by automation. Whether the impact manifests as the total replacement of occupations by automation or the reconfiguring of the type of tasks associated with the impacted occupations, there will be major implications for workers and the type of skills that they will need to invest in to adapt. It is clear from the analysis of automation risk in terms of education, that investment in higher education will be an important part of the response. Furthermore, while the sectoral analysis indicates that there is already a re-allocation of labour away from the sectors most at risk of automation, the implications of automation will still need to be factored into future education and enterprise development policies. The regional dimension to automation impacts will also need to be taken into account, especially in the context of prevailing regional disparities. The *Border* and *South-East* regions already have weaker labour markets, which means they will likely be less capable of adapting to automation than regions with more robust and diverse labour markets.

Ultimately, the pace of these changes is contingent on many factors, including rate of technological developments, the cost-benefit ratio of employing people over machines, the absorptive capacity of industry to integrate new technologies into production processes, and the regulatory and policy responsiveness of governments to mention a few. That said, even in a conservative scenario, some jobs will be lost and others will change by increasing automation in the workplace. The extent to which workers can adapt to more automation or access new jobs will be determined by how effectively public policy can adapt.

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Appendices

Appendix 1: Occupations excluded from analysis

CSO Code	Occupation	F&O	N&Q	Number Employed
1116	Elected officers and representatives	X		551
1118	Civil and public service Assistant Secretary and above and senior officials	X	X	436
1171	Officers in armed forces	X	X	732
1218	Managers and proprietors in horse-racing and related industries	X	X	289
1224	Publicans and managers of licensed premises	X		4,127
1226	Travel agency managers and proprietors	X		348
1252	Garage managers and proprietors	X		2,133
1254	Shopkeepers and proprietors – wholesale and retail	X		8,432
1255	Waste disposal and environmental services managers	X		643
1258	Civil and Public Service AP & PO and equivalent grades	X	X	3,299
2134	IT project and programme managers	X		4,330
2139	Information technology and telecommunications professionals n.e.c.	X		6,601
2211	Medical practitioners	X		14,122
2311	Further and higher education teaching professionals	X		13,681
2424	Business and financial project management professionals	X		4,398
2435	Chartered architectural technologists	X		454
2449	Welfare professionals n.e.c.	X		15
3116	Planning, process and production technicians	X		3,587
3132	IT user support technicians	X		5,477
3311	NCOs and other ranks	X	X	6,070
3315	Police community support officers	X		5
3537	Financial and accounting technicians	X		1,796
3538	Financial accounts managers	X		13,489
3561	Public services associate professionals	X		5,044
4114	Officers of non-governmental organisations	X		1,633
4124	Finance officers	X		1,071
4151	Sales administrators	X		2,262
5112	Horticultural trades	X		1,113
5118	Skilled workers in horse-racing and related industries	X	X	745
6126	Educational support assistants	X		14,702
6144	House-parents and residential wardens	X	X	171
6146	Senior care workers	X		155
6147	Care escorts	X		787
8215	Driving instructors	X		1,113
9111	Farm workers	X		4,513
9118	Elementary occupations in horse-racing and related industries	X	X	1,517
9119	Fishing and other elementary agriculture occupations n.e.c.	X		2,935
9239	Elementary cleaning occupations n.e.c.	X		105
9271	Hospital porters	X		1,191
	Total excluded in F&O			134,072
	Total excluded in N&Q			13,259

Appendix 2: Probabilities for Ireland from N&Q (Confidential)

ISCO 2	Occupation Group	Average Probabilities
01	Commissioned Armed Forces Officers*	14.9%
03	Armed Forces Occupations, Other Ranks	47.5%
11	Chief Executives, Senior Officials and Legislators*	32.4%
12	Administrative and Commercial Managers	28.1%
13	Production and Specialised Services Managers	26.5%
14	Hospitality, Retail and Other Services Managers	34.6%
21	Science and Engineering Professionals	36.2%
22	Health Professionals	29.0%
23	Teaching Professionals	21.2%
24	Business and Administration Professionals	36.3%
25	Information and Communications Technology Professionals	33.8%
26	Legal, Social and Cultural Professionals	38.7%
31	Science and Engineering Associate Professionals	40.5%
32	Health Associate Professionals	41.6%
33	Business and Administration Associate Professionals	38.3%
34	Legal, Social, Cultural and Related Associate Professionals	40.6%
35	Information and Communications Technicians	40.7%
41	General and Keyboard Clerks	48.5%
42	Customer Services Clerks	50.4%
43	Numerical and Material Recording Clerks	51.2%
44	Other Clerical Support Workers	51.8%
51	Personal Services Workers	57.9%
52	Sales Workers	53.5%
53	Personal Care Workers	35.5%
54	Protective Services Workers	40.4%
61	Market-oriented Skilled Agricultural Workers	56.0%
62	Market-oriented Skilled Forestry, Fishery and Hunting Workers*	48.5%
71	Building and Related Trades Workers (excluding Electricians)	53.1%
72	Metal, Machinery and Related Trades Workers	49.5%
73	Handicraft and Printing Workers	53.0%
74	Electrical and Electronic Trades Workers	43.4%
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	53.5%
81	Stationary Plant and Machine Operators	61.5%
82	Assemblers	56.7%
83	Drivers and Mobile Plant Operators	59.4%
91	Cleaners and Helpers	61.4%
92	Agricultural, Forestry and Fishery Labourers	63.0%
93	Labourers in Mining, Construction, Manufacturing and Transport	55.4%
94	Food Preparation Assistants	60.2%
96	Refuse Workers and Other Elementary Workers	52.1%

* Estimation based on less than 10 observations

Appendix 3: UK SOC 2012 occupation category breakdown with examples

Occupation Category	Occupation Group	Examples
Managers, Directors and Senior Officials	Managers and directors	Chief executives, elected representatives, directors
	Other managers and proprietors	Hotel managers, public service managers
Professional	Science, research, engineering and technology professionals	Physical scientists, mechanical engineers, IT systems designers
	Health professionals	Pharmacists, nurses, occupational therapists
	Teaching and educational professionals	Teachers, school inspectors, education advisers
	Business, media and public service professionals	Chartered accountants, social workers, judges, librarians
Associate Professional and Technical	Science, engineering and technology associate professionals	Laboratory technicians, IT technicians, quality assurance technicians
	Health and social care associate professionals	Housing officers, counsellors, youth and community workers
	Protective service occupations	Police officers, fire service officers, prison service officers
	Culture, media and sports occupations	Graphic designers, sports coaches, authors, AV operators
	Business and public service associate professionals	Aircraft pilots, investment analysts, estate agents
Administrative and Secretarial	Administrative occupations	Government admin occupations, credit controllers, office managers
	Secretarial and related occupations	Personal assistants, secretaries, receptionists
Skilled Trades	Skilled agricultural and related trades	Farmers, groundsmen, landscape gardeners
	Skilled metal, electrical and electronic trades	Welders, pipe fitters, mechanics, electricians
	Skilled construction and building trades	Plumbers, carpenters, painters, bricklayers, plasterers
	Textiles, printing and other skilled trades	Tailors, chefs, butchers, printers, bar managers
Caring, Leisure and Other Services	Caring personal service occupations	Home carers, teaching assistants, pest control officers
	Leisure, travel and related personal service occupations	Hairdressers, housekeepers, air travel assistants, caretakers
Sales and Customer Service	Sales occupations	Sales and retail assistants, window dresser, tele-sales
	Customer service occupations	Call centre occupations, market research interviewers
Process, Plant and Machine Operatives	Process, plant and machine operatives	Assemblers, chemical process operatives, food operatives
	Transport and mobile machine drivers and operatives	Van drivers, taxi drivers, rail operatives, fork-lift drivers
Elementary	Elementary trades and related occupations	Elementary construction occupations, packers, postal workers

	Elementary administration and service occupations	Cleaners, security guards, bar staff, refuse workers

Appendix 4: ISCO occupation categories used in N&Q analysis

Occupation Category	Occupation Group
Managers	Chief executives, senior officials and legislators
	Administrative and Commercial Managers
	Production and Specialised Services Managers
	Hospitality, Retail and Other Services Managers
Professionals	Science and Engineering Professionals
	Health Professionals
	Teaching Professionals
	Business and Administration Professionals
	Information and Communications Technology Professionals
	Legal, Social and Cultural Professionals
Technicians and Associate Professionals	Science and Engineering Associate Professionals
	Health Associate Professionals
	Business and Administration Associate Professionals
	Legal, Social, Cultural and Related Associate Professionals
	Information and Communications Technicians
Clerical Support Workers	General and Keyboard Clerks
	Customer Services Clerks
	Numerical and Material Recording Clerks
	Other Clerical Support Workers
Skilled Agricultural, Forestry and Fishery Workers	Market-oriented Skilled Agricultural Workers
	Market-oriented Skilled Forestry, Fishery and Hunting Workers
	Subsistence Farmers, Fishers, Hunters and Gatherers
Craft and Related Workers	Building and Related Trade Workers (excluding electricians)
	Metal, Machinery and Related Trades Workers
	Handicraft and Printing Workers
	Electrical and Electronics Trades Workers
	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
Plant and Machine Operators and Assemblers	Stationary Plant and Machine Operators
	Assemblers
	Drivers and Mobile Plant Operators
Elementary Occupations	Cleaners and Helpers
	Agricultural, Forestry and Fishery Labourers
	Labourers in Mining, Construction, Manufacturing and Transport
	Food Preparation Assistants
	Street and Related Sales and Services Workers
	Refuse Workers and Other Elementary Workers
Armed Forces Occupations	Commissioned Armed Forces Officers
	Non-commissioned Armed Forces Officers
	Armed Forces Occupations, Other Ranks

For more information and full breakdown of ISCO-08, see here: http://www.ilo.org/public/english/bureau/stat/isco/isco08/