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Assessing the employment impact of technological change and automation: the role of employers' practices

Assessing the employment impact of technological change and automation: the role of employers' practices

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Foreword

The lively recent debate on the future of work has been somewhat side-lined by the Covid-19 crisis. It could not be otherwise. The resultant economic crisis forces us to re-evaluate priorities and is likely to change the way we work.

Some of the trends accentuated by the crisis include greater reliance on digital technologies and new digital forms of working. Another trend is an increased shift towards automation, as machines and robots have proved to be a valuable companion in the fight against the coronavirus, given the pressing need for more remote workspaces and fast data analytics.

The fear that robots and artificial intelligence (AI) may result in jobless growth was already prominent before the coronavirus crisis. As the EU economy is likely to shrink markedly this year and with fears that continued social distancing will leave a negative footprint on key sectors and occupations, the Covid-19 crisis is likely to further exacerbate automation concerns.

Even before the corona period, firms had strong incentives to invest in automation to remain competitive in a changing world of work, most of which led to the vanishing of middle-skill occupations, mostly related to vocational education and training (VET). In the post-corona period, such motives will be stronger, as businesses will aim to gain a competitive edge through offering pandemic-proof work environments, services and products. More sophisticated and humanoid robots and the fast development of AI algorithms will result in transformed warehouses and service delivery modes compared with the past.

But the Covid-19 pandemic has also brought to the fore another reality. It is humans and only humans that are capable of keeping our public health systems, economies and societies afloat during a pandemic. It is only because of the efforts of healthcare and other VET-related professionals, who ensure that our basic needs can be met, that we will manage to cope with this crisis.

While the evidence presented in this report predates the current pandemic, a key message is that automation anxiety is unwarranted. While automation may speed up, our labour markets, overall, are unlikely to suffer from a jobless future. The report also highlights how important human-resource practices and social dialogue is for ensuring a smooth transmission of businesses and workers towards a new digital future. We trust that such findings will stimulate our ongoing discussion about how we wish to shape our future of work and skills.

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Executive summary

The impact of technological change on jobs has received a great deal of attention in recent years in both popular media and the policy debate. To better understand the risks and opportunities of ongoing technological advances, Cedefop has set up its new *Digitalisation, AI and future of work* activity. A key output is the recent launch of the Second European skills and jobs survey**,** which will collect new data and provide unique insights into the impact of digitalisation and automation on EU workers' jobs and skills. Cedefop has also deployed artificial intelligence (AI) technologies to collect almost real-time skills anticipation based on online job adverts, which may inform VET policies.

Much of the policy debate and recent work in this area centres on the predictions of Frey and Osborne (2013), who indicated that half of all jobs are susceptible to replacement by machines. Recent work has criticised their approach and called into question the reliability of their automation estimates. Automation is typically targeted towards the replacement of certain tasks, as opposed to occupations as a whole. As occupations typically contain a mix of tasks, a lot of which are not automatable, the number of occupations that Frey and Osborne (2013) suggest are fully automatable is likely to be an overestimate. Recent studies that account for task heterogeneity within occupations have shown that the proportion of occupations at high risk of automation is just 9-14% (Pouliakas, 2018; Nedelkoska and Quintini, 2018; Arntz et al., 2016).

McGuinness et al. (2019) also challenge the Frey and Osborne (2013) estimates and indicate that a degree of 'technological alarmism' may have entered the policy debate on jobs and automation. Using Cedefop's European skills and jobs survey (ESJS) data, they found that around 16% of EU workers experienced recent changes to the technology they used at work and simultaneously believed that some of their skills would become outdated in the future. Only 5% of EU employees recently affected by technological change were afraid of losing their job. McGuinness et al. (2019) provide evidence of a positive contribution of automation to the task content and skill complexity of jobs, and show that it is associated with dynamic upskilling of workers.

This Cedefop report examines how occupational change has evolved over time and the extent to which such change is consistent with dominant predictions related to the role of technology. It does so using data from the Irish labour force survey, given that Ireland has experienced higher exposure to digitalisation in the past decade compared with other EU Member States. The study also uses matched employer-employee data to examine whether firms carrying out technological changes in 2008 were more likely to have higher shares of workers in occupations that subsequently declined, as would be claimed by 'technology alarmists'.

Examining available evidence that is five years on from the predictions of machine-learning experts in Frey and Osborne (2013) produces little evidence of occupational decline in the occupations highlighted as being 'fully automatable'. While some of the 'at risk' occupations experienced small occupational decline, a substantial number of them showed an increase over the 2013-2018 period. Almost 40% of the occupations identified as being fully automatable actually increased over this five-year interval. The average occupational change of the 'fully automatable' occupations was just -2%, covering a timeframe that is between one quarter and one half of the total period for which massive job losses due to automation were predicted.

Cedefop's report further highlights the significant role played by organisational and firms' human-resources practices in terms of facilitating the beneficial impact of new technologies for employment growth. Firms that provided employees with information on plans to introduce new technology in 2008 employed workers in occupations that subsequently grew by between 2-3 percentage points more than those that did not provide such information. Similarly, firms that used individual performance-management policies and those with a higher share of workers consulted about decisions on working practices and new technologies had an occupational mix that increased in employment in subsequent years, as opposed to firms without such a consultative culture.

Concerns about automation and its impact on jobs are currently at the forefront of the policy debate and may have even become accentuated as a result of the Covid-19 pandemic. It is not possible to accurately predict the future trajectory of automation and its impact on jobs, and one cannot definitively say that the rate of automation in occupations will not increase at a quicker pace in the future, given rapidly advancing digital technologies such as artificial intelligence. However, Cedefop's analysis raises important questions about policy guidance and the timelines associated with technological disruption. While technological change is often associated with some job destruction over the short to medium term, this report highlights that employee empowerment within firms and social dialogue have a critical role in facilitating non-disruptive adoption of new technologies by organisations and workers.

CHAPTER 1.
Introduction

The impact of technological change on jobs has received a great deal of attention in recent years. Much of the policy debate and recent work in this area centres on the predictions of Frey and Osborne (2013), who indicate that half of all jobs are susceptible to replacement by machines. The Frey and Osborne (2013) estimates are based on a 'training data set' of 70 occupations, which experts assign as being either completely automatable or not automatable. The tasks from these occupations in the training data set are then used to compile an automation risk for occupations that were not included in the expert assessments.

Recent work has criticised the approach taken by Frey and Osborne (2013) and called into question the reliability of their automation estimates. Automation is typically targeted towards certain tasks, as opposed to occupations as a whole. As occupations typically contain a mix of tasks, a lot of which are not automatable, the number of occupations that Frey and Osborne (2013) suggest are fully automatable is likely to be an overestimate (Arntz et al., 2016; Autor, 2015). Recent studies by Pouliakas (2018), Nedelkoska and Quintini (2018) and Arntz et al. (2016) take the Frey and Osborne (2013) data set as a starting point, but account for task heterogeneity within occupations. The resulting estimates of the number of occupations at high risk of automation are just 9-14%, much lower than the Frey and Osborne (2013) estimates.

McGuinness et al. (2019) also challenge the Frey and Osborne (2013) estimates and indicate that a degree of 'technological alarmism' may have entered the policy debate on jobs and automation. Using an employee-level data set for Europe, the European skills and jobs survey (ESJS), they find that about 16% of workers are at risk of skills-displacing technological change (SDT). This is defined as a situation where workers experienced recent changes to the technology they use in work and believe some of their skills will become outdated in the future. The authors provide evidence of a positive contribution of automation to the task content and skill complexity of jobs. Moreover, SDT is associated with dynamic upskilling of workers.

Against the backdrop of this ongoing debate on the impact of technological change, we use Irish data to investigate two issues. First, using the Irish labour force survey, we examine how occupational change has evolved over time and the extent to which such change is consistent with dominant predictions related to the role of technology. We examine whether occupations highlighted by Frey and Osborne (2013) as being at high risk of automation have declined since the predictions were made in 2013. One might reasonably have expected substantial decline in the employment share of fully automatable occupations by 2018, if the predictions of the machine-learning experts were accurate. We carry out the same procedure using the estimates provided by Pouliakas (2018), who takes into account task/skills heterogeneity and allocates an automation risk score to each two-digit International Standard Classification of Occupations (ISCO) occupation.

Secondly, we derive a firm-level measure of expected employment change for the period 2008 to 2018, based on aggregate historical changes in occupational employment, which we regress on a range of firm-level characteristics using a historical firm-level data set from 2008. In doing so, we examine whether firms carrying out technological changes in 2008 were more likely to have higher shares of workers in occupations that subsequently declined, as would be claimed by ‘technology alarmists’.

At this point, it is important to point out the main limitation of the approach. Due to the lack of optimal data, the methodology takes a historical firm-level data set, from 2008, and attaches a measure of expected occupational change based on the occupational mix within that firm at that time-point. However, the measure of expected occupational change is derived from subsequent labour force survey (LFS) data sets (from 2008 to 2018). Thus we are not following the 2008 firm over time, but rather we are predicting whether firms carrying out technological changes in 2008 had higher shares of workers in occupations that subsequently declined or increased. Our approach is useful in that it allows us to examine the association between various historical firm-level measures of technological change and subsequent expected employment change based on the firm’s occupational structure.

Five years on from the predictions of machine-learning experts in Frey and Osborne (2013), little evidence is found of occupational decline in the occupations highlighted as being ‘fully automatable’. While some of the ‘at risk’ occupations experienced small occupational decline, a substantial number of these occupations actually showed a positive increase over the five-year period. While it is not possible to accurately predict the future trajectory of automation and its impact on jobs, our analysis raises important questions about policy guidance and the timelines associated with technological disruption. Ireland’s Expert Group on Future Skills Needs (EGFSN), for instance, published a report in 2018 (EGFSN, 2018) assessing the impact of digitalisation on Ireland’s workforce. The study relied partly on the predictions of Frey and Osborne (2013) to assess the risk for Ireland. One of the key findings that feeds into the policy implications of the EGFSN report states:

'Over the next five years 4% of jobs in Ireland are forecast to be at high risk of disruption from the adoption of digital technologies. When those at medium risk are added the number rises to 43%.'

The report also states:

'While it is expected that the number of jobs lost will increase steadily over the next decade, this report estimates that disruption from the adoption of digital technologies over the next five years will lead to a hypothetical loss of 46 000 jobs when compared to growth predictions for jobs without accounting for the adoption of digital technologies.'

The results of this report would caution against overreliance on such high estimates, especially over such a short term (five years). As mentioned, while one cannot predict exactly how automation will affect jobs in the future, our analysis shows little impact on occupations deemed as 'fully automatable' five years on from these predictions. Moreover, given the criticisms of the Frey and Osborne (2013) approach highlighted by several recent studies, we would also caution against basing policy recommendations for Ireland and other EU countries on the Frey and Osborne (2013) predictions, which may substantially overstate the potential risks of automation in the near future.

The remainder of the report is structured as follows. In Section 2 we describe the data and present some descriptive statistics, including our analysis of how occupational change in Ireland compares to the Frey and Osborne (2013) predictions. In Section 3 we present our econometric results analysing the relationship of firm-level technological adoption and expected occupation-driven employment change. Section 4 concludes.

CHAPTER 2.

Data and descriptive statistics

2.1. Construction of study variables

We use the Irish labour force survey (LFS) data to extract a time series for each two-digit ISCO occupation, to show how the share of employees in each occupation has changed over time. The LFS is a large-scale, nationwide survey of households in Ireland, which is used to produce official labour-force estimates. In Appendix A, we graph the percentage of all Irish employees that are in each two-digit ISCO occupation category over the period 2008 to 2018.

In Table 1, we summarise, for each occupation, the percentage change from 2008 to 2018. The percentage-point change gives the percentage-point change in the share of workers in each occupation from 2008 to 2018. This gives an indication as to the magnitude of the effect for the overall economy, i.e. the number of workers affected. We also show the percentage change, which is the relative change within that occupation. For example, administrative and sales managers made up 2.55% of total employees in 2008 and 2.05% in 2018, giving a 0.5 percentage-point, or 19.5%, decrease. To capture the relative size of each occupational grouping, we also show the percentage of total employment relating to each occupational category in 2008, indicated in the Occupation Size column.

We apply our LFS occupational-change statistics to firm-level data contained in the 2008 national employment survey (NES) to generate a measure of predicted future employment change (2008 to 2018), based on the firm’s 2008 occupational structure. The NES is a sample survey of employers and employees in Ireland. It surveys businesses with three or more employees and includes separate questionnaires for both employers and employees. In this study, we use the 2008 questionnaire as it contains relevant questions relating to technological change in the organisation, which form key variables for our analysis. Note that there is also a 2009 NES, but this survey does not capture many of the important variables for our analysis. The survey was discontinued after 2009.

Table 1. **Occupational change (2008-18)**

Occupation	Occupation size, 2008 (%)	Percentage-point change	% change
Admin and sales managers	2.55	-0.50	-19.54
Agricultural labourers	0.47	0.23	49.48
Assemblers	0.75	0.36	47.70
Building-trade workers	6.13	-2.87	-46.75
Business associate professionals	5.60	-0.37	-6.61
Business professionals	4.14	1.08	26.14
CEOs	0.09	0.13	145.32
Cleaners and helpers	1.71	0.16	9.09
Construction, manufacturing, transport labourers	5.72	-3.00	-52.48
Customer-service clerks	2.79	-0.37	-13.28
Drivers and mobile-plant operators	4.88	-1.17	-23.96
Electrical workers	2.12	-0.68	-31.88
Food-prep assistants	1.06	0.37	35.12
Food processing, and other trade workers	1.31	0.42	32.36
Health associate professionals	0.62	0.27	43.18
Health professionals	3.87	0.92	23.87
ICT professionals	1.44	0.84	58.64
ICT technicians	0.44	0.43	98.66
Legal, social, religious associate professionals	1.92	0.48	25.30
Legal, social, religious professionals	1.76	0.37	21.22
Metal workers and machine mechanics	3.18	-1.03	-32.37
Numerical clerks	1.93	-0.06	-3.15
Office clerks and secretaries	2.37	-0.58	-24.33
Other clerical workers	3.21	-0.21	-6.54
Personal-care workers	4.89	0.58	11.83
Personal-services workers	4.11	1.02	24.82
Plant-machine operators	0.97	0.16	16.73
Printing workers	0.54	-0.19	-35.81
Production and professional services managers	1.71	1.27	74.36
Protective-service workers	1.55	-0.22	-14.06
Refuse workers	1.22	-0.03	-2.32
Retail and hospitality managers	2.12	1.59	74.99
Sales workers	8.01	-0.56	-6.97
Science and engineering associate professionals	1.45	0.34	23.13
Science and engineering professionals	2.72	0.90	33.12
Skilled agriculture	5.88	-1.00	-17.08
Skilled forestry	0.10	0.03	25.75
Teaching professionals	4.34	0.92	21.10

Source: Irish labour force survey (2008 to 2018).

The dependent variable that we use in our analysis relates to the expected employment change within the organisation. We observe the occupational mix in the firm in 2008, as per the NES data. We then apply the expected occupational change statistics from the LFS data, which relates to the observed occupational change that occurred in the subsequent 10-year period. From this, we arrive at a weighted average ‘expected employment change’ based on the observed 2008 occupational structure. An example is useful to illustrate this approach. Consider a firm that was observed in the NES data in 2008, with 50% of employees working as customer-service clerks and 50% working as administration and sales managers. From Table 1, we see that the subsequent occupational change for customer-service clerks and administration and sales managers was -13% and -20% respectively. The weighted average predicted employment change in this organisation would then equal -16.5% ([1]). In addition, we create a binary variable that indicates whether the mix of employees in the firm, on average, had a positive or negative predicted employment change. The variable equals one if the predicted employment change is positive and zero if negative.

We use two questions to capture whether firms introduced, or were likely to introduce, new technology in 2008. The first question asks employers, ‘were your employees regularly provided with information on plans to introduce new technology in 2008?’. Employers answered yes or no and were instructed to answer ‘not applicable’ (N/A) if the business had no such plans in 2008. We use this to create an indicator variable designed to capture firms that were introducing or planning to introduce new technology, versus those that were not.

There are various ways to construct such a variable, based on the responses to this question. We create three related variables. The first, which we call *NewTech1*, equals one for firms that answer yes or no, and zero for firms that answer N/A. This is done on the basis that the ‘yes’ firms were planning on introducing new technology and communicated this to employees. The way the question is phrased implies that the ‘no’ firms may also have been planning to introduce new technology but did not communicate this to employees. The N/As therefore capture the firms that had no plans to introduce new technology, as indicated in the questionnaire responses.

We also create a variable called *NewTech2*, which equals one for firms that answer yes and zero for firms answering no or N/A, as well as a *NewTech3* variable that equals one for firms answering yes and zero for firms answering

([1]) That is 0.5(-13) + 0.5(-20) = 16.5.

N/A. We examine the robustness of our findings to all three variables and find little difference.

The second question that we use for capturing technological change asks employers whether 'technological advances in your line of business' generated pressure for change in their company. The employer indicates the level of pressure: high, medium, low, or not applicable. We generate a variable called *TechChange* that equals one for firms indicating high or medium pressure and zero for firms indicating low pressure or not applicable. In terms of the distribution of firms across categories, 35% indicated that technological advances generated medium to high pressure for change in their organisation, whereas 65% indicated that this was not the case.

We use the NES to create other variables that are related to technological change and are therefore relevant to the analysis. We create a variable called *TechAccept*, which is based on a question that asks employees how acceptable they would find 'an increase in the level of technology involved in your work'. Employees respond either 'acceptable', 'unacceptable' or 'no opinion'. The variable *TechAccept* captures the percentage of employees in the firm who indicate that they would find an increase in technology acceptable.

We also create a variable called *ConsultTech* that captures the percentage of employees in the firm who say that they were 'consulted about decisions which affected your work, for example the introduction of new working practices and new technologies'. For convenience, in Table 2, we list our main variables of interest, as described above, along with a brief description.

Table 2. **Description of main variables**

Variable	Description
NewTech1, *NewTech2*, *NewTech3*	Indicator of whether the business provided employees with information on plans to introduce new technology in 2008
TechChange	Indicator of whether technological advances generated pressure for change within the organisation
TechAccept	Percentage of employees in the firm that would find an increase in the level of technology involved in their work acceptable
ConsultTech	Percentage of employees in the firm who say they were consulted about decisions that affected their work, for example the introduction of new working practices and new technologies

Source: 2008 national employment survey (NES).

2.2. Occupational change and automation risk

We examine how the occupations identified by Frey and Osborne (2013) as being automatable have changed over time. Given that the Frey and Osborne (2013) occupation training data set was constructed in 2013, we examine the subsequent change in occupational share among occupations identified as 'fully automatable' or 'not automatable' from 2013 to 2018. Nedelkoska and Quintini (2018) map the Frey and Osborne (2013) occupations to ISCO two-digit occupation categories. We follow Nedelkoska and Quintini (2018) and allocate each of the occupations in the Frey and Osborne (2013) training data set to their appropriate ISCO category. We can then plot the subsequent occupational percentage change, as derived from the Irish LFS data from 2013 to 2018, for the ISCO occupations identified as being automatable or not automatable by Frey and Osborne (2013).

It is important to highlight some limitations to this approach. First, we are taking detailed occupations from the Frey and Osborne (2013) data set and applying them to our two-digit ISCO occupation groups. Therefore, some of the Frey and Osborne (2013) occupations may be more specific than the two-digit ISCO categories. Thus, when we allocate a Frey and Osborne (2013) occupation to an ISCO category, the ISCO category may be capturing a broader range of occupations than the one identified in their data set.

For example, the Frey and Osborne (2013) data set identifies 'sheet metal workers' as being fully automatable. We categorise these into the ISCO 72 category – 'metal, machinery and related trades workers'. Therefore, while the ISCO category is directly relevant to the Frey and Osborne (2013) occupation, it will also include some detailed occupations not specifically identified by them as automatable. Nevertheless, the occupations covered in each two-digit ISCO category will have a high degree of commonality. Therefore, the ISCO occupations that are not directly aligned with the Frey and Osborne (2013) occupations are likely to share many of the same characteristics.

However, many of the occupations are precisely matched. For example, Frey and Osborne (2013) identify 'electrical and electronic equipment assemblers' as a fully automatable occupation. This is categorised into the ISCO 82 occupation of 'assemblers', which primarily consists of the occupations identified by Frey and Osborne (2013). Moreover, for many ISCO occupations we can be more certain that we are accurately capturing the Frey and Osborne (2013) predictions. The Frey and Osborne (2013) data set highlights four separate occupations as being fully automatable, all of which fall into the ISCO category of 83 – 'drivers and mobile plant operators'. Likewise, they identify six separate occupations as non-automatable, all six of which fall into the ISCO 26 category: 'legal, social and cultural professionals'. Therefore, we can be certain that we are capturing a substantial component of these two-digit ISCO categories.

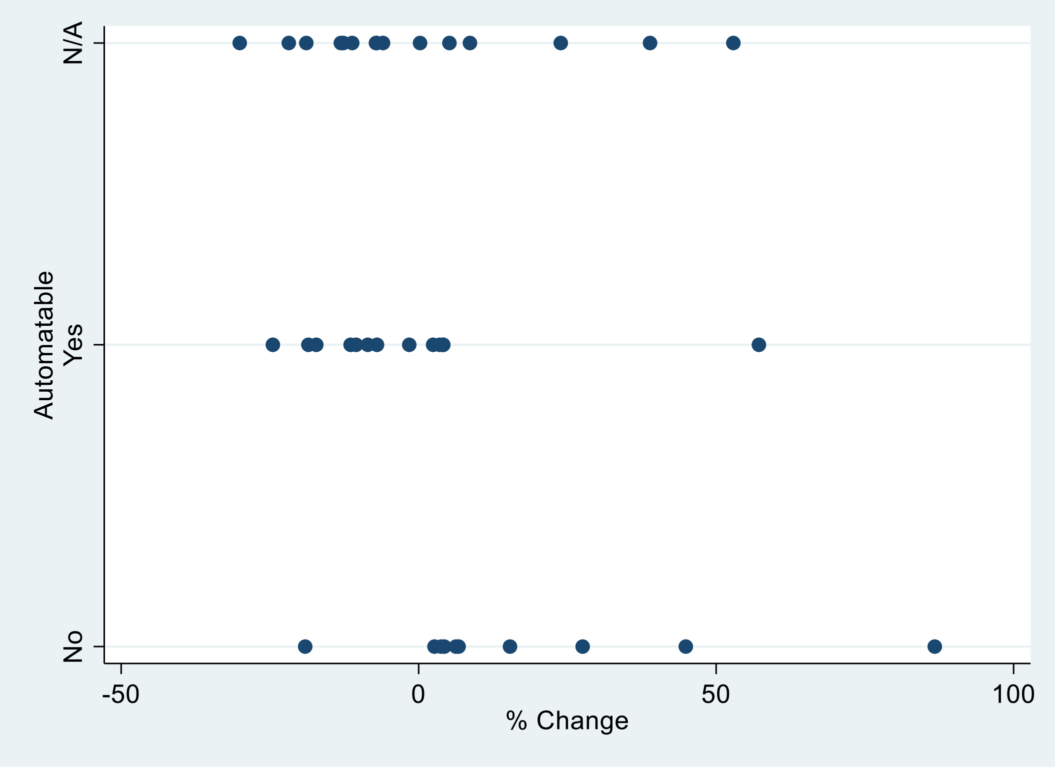
There are some occasions where several Frey and Osborne (2013) occupations map into one ISCO occupation and offer different predictions. For example, seven Frey and Osborne (2013) occupations map into ISCO 21, 'science and engineering professionals'. Six of the seven occupations are non-automatable, whereas just one is considered automatable. In this case, we consider the ISCO group as a whole as non-automatable. Therefore, in these instances, we take most of the Frey and Osborne (2013) occupational predictions as the outcome for the ISCO two-digit group.

Figure 1 plots the percentage change in each ISCO occupation from 2013 to 2018, categorised by whether they are identified by Frey and Osborne (2013) as fully automatable, not automatable, or not identified (N/A). First, we see that the occupations identified as fully automatable were more likely to have declined, or increased by less, than those identified as not automatable ([2]). However, despite this, it is important to note that almost 40% of those occupations identified as being fully automatable actually increased over this time period. Moreover, the average occupational change among these fully automatable occupations was just -2%. This seems particularly striking given that these occupations were highlighted as being 'fully automatable'.

Of course, we cannot say that the rate of automation in these occupations will not increase at a quicker pace into the future, but it is notable that, five years after these predictions, we observe either small negative changes or even positive changes in these occupations. While predicting the timeframe for automation is virtually impossible, Frey and Osborne (2013) indicate that the timeframe could be as soon as one or two decades. Therefore, by examining 2013 to 2018, our analysis is between one-quarter and one-half of the way into this timeframe and finds negligible impacts on most occupations.

([2]) The occupations not covered by the Frey and Osborne (2013) training data set have a wide distribution. Some increased significantly, whereas others decreased.

Figure 1. **Occupational change (2013 to 2018) and the Frey and Osborne predictions**



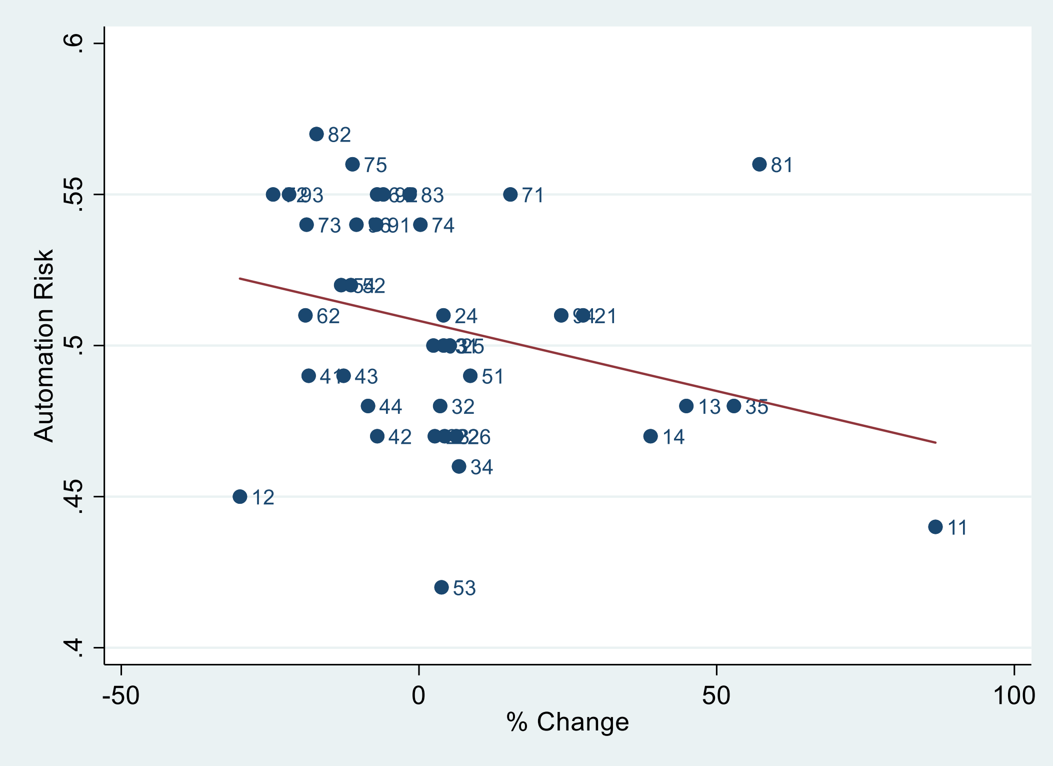
NB: Each dot represents the percentage employment change in each occupation from 2013 to 2018. There are three categories of occupation: those identified as fully automatable by Frey and Osborne (2013), those identified as non-automatable and occupations that did not form part of the Frey and Osborne (2013) training data set.

Source: Irish labour force survey; Frey and Osborne (2013).

Pouliakas (2018) takes the Frey and Osborne (2013) training data set as a starting point, and incorporates tasks and skills needs in jobs to allocate an automation score to ISCO two-digit occupations. We can therefore directly map these automation scores into our two-digit ISCO data set and examine the relationship between predicted automation and actual occupational decline. Again, we focus on the period 2013 to 2018 to coincide with the time-point when the Frey and Osborne (2013) predictions were made and since Pouliakas (2018) uses European skills and jobs survey (ESJS) data collected in 2014.

Figure 2 plots the automation scores against the percentage change in the occupation and overlays a fitted regression line. The slope of the fitted line indicates an inverse relationship; that is, occupations with a lower automation risk were more likely to increase in share. However, as before, the relationship is not definitive. Without the fitted line, and if we remove some of the outliers, it is difficult to visually identify any relationship. Moreover, many occupations with the highest automation risk actually showed a positive increase over this period.

Figure 2. **Occupational change (2013-18) and automation risk**



NB: The Pouliakas (2018) automation risk is plotted against the percentage employment change in each two-digit ISCO occupation.

Source: Irish labour force survey; Pouliakas (2018).

CHAPTER 3.

Adoption of new technologies and occupational change

We combine our LFS measures of occupational change with our main NES variables (described above) to examine the relationship between expected occupational change and preceding firm-level indicators of technological change. As linked employee-employer data are used, we reduce the data set to an employer sample by retaining one line of data per firm that contains all responses from the employer survey and a series of firm-level averages based on the employee sample specific to the firm. Our empirical models take the following general form:

$$Pemp\Delta_i = \alpha + \beta_i Tech_i + X_i'\beta_2 + \varepsilon_i \quad (1)$$

where $Pemp\Delta_i$ is the firm-level predicted employment change based on the occupational structure in firm *i* in 2008. The term *Tech* is used to refer to any of our firm-level measures of technological adoption (described in Table 2) and X_i' is a vector of other confounding firm-level indicators.

First, we regress expected employment change in the firm against our *NewTech* variables, which indicate whether the business provided employees with information on plans to introduce new technology in 2008. We also include sectoral dummies. It is important to add sectoral controls as some sectors, such as construction, will have seen significant changes to their occupational shares over this period due to recession, and which therefore may have been unrelated to technology. The results are shown in Table 3. We report results using our three closely related, but slightly different variations, of the *NewTech* variable: *NewTech1*, *NewTech2* and *NewTech3*. The results indicate that firms that provided employees with information on plans to introduce new technology in 2008 employed workers in occupations that subsequently grew, resulting in a predicted increase in employment of 2-3 percentage points more than firms that did not provide such information, or did not introduce new technology.

In Annex 1 (Table 8), we report the results from the probit model, where the dependent variable takes a value of one for firms with a mix of occupations that, on average, resulted in subsequent predicted employment increases, and zero for those with occupations that subsequently decreased, resulting in negative predicted employment growth. The results are consistent with those in Table 3: firms that provided employees with information on plans to introduce new technology in 2008 were 3-5 percentage points more likely to have an occupational structure that subsequently resulted in predicted employment growth.

Table 3. **Occupation-driven employment change and new technology**

Variables	(1) NewTech1	(2) NewTech2	(3) NewTech3
NewTech (1-3)	1.816***	2.788***	2.544***
	(0.515)	(0.516)	(0.554)
Sectors (Ref: Public Admin)			
Industry	3.912*	4.274**	4.437**
	(2.009)	(2.007)	(2.055)
Construction	-14.342***	-13.607***	-14.127***
	(2.052)	(2.056)	(2.118)
Wholesale and retail	0.376	0.888	0.568
	(1.978)	(1.979)	(2.024)
Transport	-9.607***	-9.168***	-9.490***
	(2.341)	(2.339)	(2.424)
Accommodation and food	6.797***	7.481***	6.600***
	(2.095)	(2.098)	(2.166)
ICT	11.258***	11.303***	11.520***
	(2.323)	(2.319)	(2.374)
Finance	2.523	2.674	2.175
	(2.220)	(2.217)	(2.267)
Professional	8.185***	8.510***	8.541***
	(2.081)	(2.079)	(2.134)
Admin	2.753	3.206	2.596
	(2.229)	(2.228)	(2.307)
Education	12.256***	12.589***	11.943***
	(2.607)	(2.604)	(2.697)
Health and social	11.689***	12.082***	11.696***
	(2.142)	(2.140)	(2.198)
Arts and entertainment	5.572**	5.970***	5.809***
	(2.164)	(2.162)	(2.223)
Constant	3.540*	2.932	3.395*
	(1.948)	(1.940)	(1.984)
Observations	4 974	4 974	4 240
R-squared	0.155	0.158	0.160

NB: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

While these results indicate a positive association between technology adoption and predicted employment growth, we cannot make definite causal statements that technology causes employment growth. It is possible that what we are capturing, at least to some extent, is the existence of a consultative or employee involvement culture in firms. For example, it could be that firms which provide information to employees about various factors, including technology, are the same firms that employed workers in occupations that subsequently increased. We explore this further by examining the relationship between predicted employment change and other consultation-related variables. In addition to providing information on new technology, employers were asked if they provided employees with information on the following factors: the level of competition faced by the firm; new product introduction; firm reorganisation; work practices; sales information. The results are shown in Table 4. We see that, like the introduction of new technologies, all of these consultation-related variables are positively associated with predicted occupationally driven employment growth ([3]).

Table 4. **Occupation-driven employment change and worker consultation variables**

Variables	(1) Competition	(2) New products	(3) Re-organisation	(4) Work practices	(5) Sales info
Consultation variable	1.839***	3.221***	1.630***	0.881*	3.157***
	(0.558)	(0.508)	(0.504)	(0.504)	(0.529)
Sectors (Ref: Public Admin)					
Industry	1.840	3.293*	3.449*	3.579*	1.902
	(2.375)	(1.990)	(2.009)	(2.011)	(2.449)
Construction	-16.480***	-14.357***	-15.335***	-15.039***	-15.788***
	(2.403)	(2.028)	(2.045)	(2.051)	(2.474)
Wholesale and retail	-1.810	-0.164	-0.158	-0.069	-1.568
	(2.345)	(1.957)	(1.978)	(1.982)	(2.420)
Transport	-11.399***	-9.801***	-10.247***	-10.099***	-11.205***
	(2.662)	(2.325)	(2.343)	(2.342)	(2.732)
Accommodation and food	4.630*	6.254***	6.125***	6.178***	5.090**
	(2.439)	(2.070)	(2.092)	(2.094)	(2.513)

([3]) The consultation variables are correlated. Therefore, we do not include a specification that includes all consultation variables together.

Variables	(1) Competition	(2) New products	(3) Re-organisation	(4) Work practices	(5) Sales info
ICT	9.231***	10.276***	10.745***	11.041***	9.183***
	(2.658)	(2.309)	(2.329)	(2.331)	(2.725)
Finance	0.338	1.537	1.798	2.001	-0.176
	(2.559)	(2.203)	(2.220)	(2.219)	(2.637)
Professional	6.431***	7.956***	7.806***	7.965***	6.694***
	(2.437)	(2.061)	(2.081)	(2.084)	(2.507)
Admin	0.581	2.407	2.279	2.401	1.215
	(2.561)	(2.209)	(2.228)	(2.228)	(2.631)
Education	10.360***	11.709***	11.758***	11.593***	11.477***
	(2.933)	(2.581)	(2.602)	(2.614)	(3.052)
Health & social	9.950***	11.241***	11.261***	11.064***	10.646***
	(2.504)	(2.121)	(2.142)	(2.142)	(2.572)
Arts and entertainment	3.406	5.015**	5.133**	5.116**	3.762
	(2.510)	(2.140)	(2.162)	(2.163)	(2.581)
Constant	5.376**	3.426*	4.429**	4.637**	4.992**
	(2.299)	(1.904)	(1.925)	(1.938)	(2.365)
Observations	4 864	4 977	4 982	4 976	4 838
R-squared	0.152	0.161	0.157	0.154	0.159

NB: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

Given that the *NewTech* (1-3) variables could be confounding firms' propensity to adopt new technologies with factors intrinsic to their personnel policies, we next regress occupation-driven employment change on our alternative *TechChange* variable, which equals one for firms that indicated technological advances were generating pressure for change in their organisations, and zero otherwise.

In Table 5 we report the results from our ordinary least squares (OLS) regression with our continuous occupational change dependent variable, as well as the probit results using our binary dependent variable. The OLS results show that firms in which technological advances were driving changes in their organisation had a mix of occupations that subsequently increased in predicted employment by 2.5 percentage points more than other firms. The probit model shows that firms experiencing such technological-related pressure were around four percentage points more likely to have an occupational mix that, on average, led to subsequent predicted employment growth.

Table 5. **Occupation-driven employment change and technological change**

Variables	(1) OLS	(2) Probit
TechChange	2.473***	0.038***
	(0.533)	(0.014)
Sectors (Ref: Public Admin)		
Industry	3.332*	0.003
	(2.003)	(0.052)
Construction	-14.850***	-0.313***
	(2.039)	(0.058)
Wholesale and retail	-0.032	-0.058
	(1.972)	(0.054)
Transport	-10.004***	-0.272***
	(2.331)	(0.068)
Accommodation and food	6.468***	0.148***
	(2.083)	(0.042)
ICT	10.552***	0.131***
	(2.325)	(0.048)
Finance	2.235	-0.008
	(2.218)	(0.059)
Professional	7.632***	0.086*
	(2.075)	(0.048)
Admin	2.835	-0.007
	(2.226)	(0.059)
Education	11.908***	0.247***
	(2.612)	(0.031)
Health and social	11.487***	0.217***
	(2.137)	(0.033)
Arts and entertainment	5.260**	0.113**
	(2.155)	(0.047)
Constant	4.194**	
	(1.915)	
Observations	4 965	4 973
R-squared	0.158	

NB: Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

Pouliakas (2018) examines the employee characteristics associated with higher automation risk in the European Union (EU). He finds that jobs characterised by high automation risk tend to be predominantly occupied by males, as they sort into high-risk occupations and sectors and perform jobs with more ‘automatable skills’. Other characteristics found by Pouliakas (2018) to be associated with higher probability of being in a high-risk occupation include: longer job tenure, being in the private sector, limited promotion prospects, lower levels of job-related training and digital skills deficiencies.

While we do not directly examine the link between automation risk and employee characteristics in this paper; we explore a related question by examining the relationship between expected occupation-driven employment change and the average characteristics of employees in firms. Our main covariate of interest is *TechAccept*, which captures the percentage of employees in the firm that would find acceptable an increase in the level of technology involved in their work. We also include the following covariates: average weekly employee earnings; percentage of male employees; the percentage of employees with a tertiary education; average training costs per employee; average age; average tenure; percentage of staff undertaking supervision duties; percentage of staff undertaking shift work; percentage of staff in trade unions; percentage of staff that are members of professional bodies ([4]).

The results are shown in Table 6. In the first specification, Column (1), the results show that firms with more employees accepting technological change were more likely to have an occupational structure in 2008 that led to increased predicted employment. Specifically, comparing firms in which all employees accepted technological change with those where none did, the former had an occupational mix that resulted in a subsequent predicted employment increase of, on average, around three percentage points more than the latter.

Notice that in this specification we do not include weekly earnings and high education as additional explanatory variables. This is because our analysis highlighted that the *TechAccept* variable was correlated with education and earnings: firms with a high percentage of employees amenable to technology also had high numbers of well-paid and highly educated workers. We thus first show the *TechAccept* results without the inclusion of these variables ([5]).

([4]) To find out the average training costs per employee, the following question was asked: 'What were the costs incurred by the enterprise in the provision of training courses in 2008'. This is divided by the total number of employees.

([5]) Including the *TechAccept* variable alone produces a coefficient of 5.072***.

Table 6. **Occupational change and employee characteristics**

Variables	(1) occ_change	(2) occ_change	(3) occ_change	(4) occ_change
TechAccept	3.195***	-1.634	-1.660	-2.008*
	(1.223)	(1.207)	(1.152)	(1.176)
Male	-9.088***	-7.719***	-1.752*	-1.967**
	(0.812)	(0.846)	(0.910)	(0.924)
Weekly earnings		0.004***	0.005***	0.006***
		(0.001)	(0.001)	(0.000846)
High education		16.618***	11.057***	10.79***
		(0.997)	(1.008)	(1.023)
Training costs	0.000***	0.000	0.000	4.77e-05
	(0.000)	(0.000)	(0.000)	(3.57e-05)
Age	0.045	0.129***	0.075*	0.0785*
	(0.043)	(0.041)	(0.040)	(0.0409)
Tenure	0.093	0.199***	0.153***	0.137**
	(0.061)	(0.059)	(0.058)	(0.0588)
Supervise staff (%)	10.906***	8.303***	9.563***	9.702***
	(1.163)	(1.135)	(1.099)	(1.116)
Shift work (%)	6.954***	10.375***	5.203***	5.130***
	(1.022)	(1.008)	(1.066)	(1.078)
Trade union (%)	-7.042***	-6.725***	-7.000***	-7.074***
	(1.061)	(1.030)	(1.067)	(1.087)
Professional body (%)	14.500***	3.453**	5.575***	5.828***
	(1.393)	(1.462)	(1.473)	(1.502)
Sectors (Ref: Public Admin)				
Industry			4.516**	4.046**
			(1.983)	(2.007)
Construction			-13.372***	-13.37***
			(2.042)	(2.069)
Wholesale and retail			1.054	0.831
			(1.981)	(2.007)
Transport			-9.546***	-9.708***
			(2.303)	(2.322)
Accommodation and food			5.932***	5.864***
			(2.161)	(2.187)
ICT			6.669***	6.131***
			(2.302)	(2.330)
Finance			-1.241	-1.447
			(2.198)	(2.229)
Professional			2.771	2.374

Variables	(1) occ_change	(2) occ_change	(3) occ_change	(4) occ_change
			(2.112)	(2.137)
Admin			2.749	2.651
			(2.204)	(2.236)
Education			10.313***	10.00***
			(2.484)	(2.543)
Health and social			10.095***	10.21***
			(2.113)	(2.147)
Arts and entertainment			5.162**	4.914**
			(2.136)	(2.160)
TechChange				1.709***
				(0.513)
Constant	0.164	-7.781***	-8.299***	-8.159***
	(1.992)	(1.966)	(2.728)	(2.767)
Observations	5 081	5 081	5 081	4 934
R-squared	0.086	0.150	0.239	0.240

NB: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

In Column (2) we include earnings and education and in Column (3) we add in sectoral controls. Once education and earnings are included, the *TechAccept* variable is no longer significant. In Column (4) we add our *TechChange* variable as a covariate. The *TechChange* variable is positive and significant, and indicates that, even controlling for a range of firm-level employee characteristics, firms that experienced organisational pressure due to technological change were more likely to have employees in occupations that subsequently increased, resulting in positive predicted employment growth. However, the *TechAccept* and *TechChange* coefficients are also correlated, which explains why the *TechAccept* coefficient turns negative and marginally significant in this specification.

The results also show that firms with a higher percentage of male workers were less likely to have an occupational mix that subsequently led to increased predicted employment. While Pouliakas (2018) finds that males are more likely to be in occupations at a high risk of automation, it is important to restate that we cannot make such claims, as we are linking employee characteristics to expected subsequent occupational change as opposed to directly linking them to automation risk. Earnings, age, education, tenure, supervision responsibilities and being a member of a professional body are also positively associated with expected occupational increases and predicted employment growth. This indicates that firms with highly skilled, experienced workers were more likely to employ people in occupations that subsequently expanded. A higher share of employees doing shift work is also associated with expected occupational and employment increases. However, it is more difficult to associate this variable with any particular skillset. For example, while many jobs requiring shift work may be highly skilled, a lot of routine, lower-skilled jobs also involve shift work. Finally, firms with a higher percentage of trade union members were less likely to employ workers in occupations that subsequently increased in share.

Finally, we examine the relationship between expected occupation-driven employment change and several human-resource management variables. These include dummy variables indicating whether the firm had systems in place for the competency development of managers, individual performance management and team performance management. We also include variables to indicate the presence of policies relating to dispute resolution and diversity and equality. Our main variable of interest is *ConsultTech*, which captures the percentage of employees who indicated they were consulted about decisions affecting their work; for example, the introduction of new working practices and new technologies.

The results are shown in Table 7. In Column (1) we include the HR/personnel-related variables only. In Column (2) we add in the employee characteristics from the previous analysis as additional covariates. In Column (3) we add in our *TechChange* variable. It is found that firms that used individual performance management policies employed workers in occupations whose share subsequently increased by more than firms with no such policies. There is no statistically significant effect for team performance management, competency development of managers, dispute resolution or diversity policies.

There is a strong positive association between occupation-driven employment increase and the share of workers consulted about decisions on working practices and new technologies. Specifically, a firm in which all workers were consulted about working practices and new technology had an occupational mix that, on average, increased predicted employment by between four and eight percentage points more than firms where all workers were not consulted. When the *TechChange* variable is added, in Column (3), both the *TechChange* and *ConsultTech* coefficients remain positive and statistically significant.

Table 7. **Occupational change and personnel/HR management**

Variables	(1) occ_change	(2) occ_change	(3) occ_change
Individual PM	4.055***	1.208*	1.270*
	(0.724)	(0.665)	(0.670)
Team PM	0.666	0.455	0.330
	(0.781)	(0.698)	(0.706)
Comp. development	1.046	-0.223	-0.270
	(0.786)	(0.709)	(0.715)
Dispute resolution	1.892**	0.482	0.181
	(0.862)	(0.780)	(0.788)
Diversity	-0.951	-0.426	-0.409
	(0.827)	(0.741)	(0.747)
ConsultTech	7.797***	4.461***	4.439***
	(1.052)	(0.966)	(0.977)
Male		-1.857*	-1.921**
		(0.950)	(0.959)
Weekly earnings		0.005***	0.005***
		(0.001)	(0.001)
High education		10.076***	9.833***
		(1.050)	(1.062)
Training costs		0.000*	0.000*
		(0.000)	(0.000)
Age		0.076*	0.077*
		(0.042)	(0.042)
Tenure		0.182***	0.159***
		(0.060)	(0.061)
Supervise staff (%)		7.891***	8.222***
		(1.165)	(1.179)
Shift work (%)		5.576***	5.391***
		(1.112)	(1.121)
Trade union (%)		-7.426***	-7.407***
		(1.140)	(1.153)
Professional body (%)		6.118***	6.307***
		(1.527)	(1.552)
Sectors (Ref: Public Admin)			
Industry		4.267**	3.808*

Variables	(1) occ_change	(2) occ_change	(3) occ_change
		(2.091)	(2.107)
Construction		-11.962***	-12.404***
		(2.169)	(2.187)
Wholesale and retail		1.415	1.061
		(2.096)	(2.113)
Transport		-8.911***	-9.176***
		(2.406)	(2.420)
Accommodation and food		6.601***	6.384***
		(2.282)	(2.301)
ICT		6.990***	6.372***
		(2.403)	(2.424)
Finance		-1.036	-1.317
		(2.306)	(2.324)
Professional		2.770	2.399
		(2.220)	(2.237)
Admin		2.499	2.169
		(2.326)	(2.348)
Education		10.069***	9.928***
		(2.629)	(2.656)
Health and social		10.305***	10.317***
		(2.233)	(2.257)
Arts and entertainment		5.734**	5.404**
		(2.257)	(2.273)
TechChange			1.188**
			(0.533)
Constant	-1.925**	-12.884***	-12.463***
	(0.927)	(2.783)	(2.807)
Observations	4 684	4 684	4 606
R-squared	0.035	0.235	0.237

NB: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

CHAPTER 4.
Conclusion

In this study, Cedefop examined how occupations, identified in previous work as being at high risk of automation, changed over time in Ireland. The case study of Ireland is interesting due to its high exposure to digital technologies and high concentration of technologically intensive sectors in its economy. Moreover, the Irish Expert Group on Future Skills Needs (EGFSN) published a report on the short-term impacts of automation in Ireland (EGFSN, 2018), which draws on the predictions of Frey and Osborne (2013). Assessing whether the Frey and Osborne (2013) predictions have manifested in the data, since the time the predictions were made, is a necessary task for testing whether such predictions are useful in short-term forecasts relating to the impact of automation not only for Ireland, but the whole of the EU.

The study first focused on the occupations identified in Frey and Osborne (2013) as being fully automatable. Cedefop confirmed that these occupations were more likely to have declined, or increased by less, than those identified as non-automatable. However, despite this, almost 40% of these occupations actually increased over time. The average occupational change among all of these fully automatable occupations was just -2%.

These findings raise a number of important points. Since these occupations were identified as being 'fully automatable', potentially within one or two decades, it is notable that, five years following the predictions, most of these occupations either declined by a very small margin or increased in share. However, it is also important to state that, while Cedefop examined the occupational change in the five-year period since the Frey and Osborne (2013) predictions (2013 to 2018), it is possible that the rate of automation, or its associated impacts, may change in the future.

An additional caveat about Cedefop's analysis of the Frey and Osborne (2013) occupations is that we attempted to map their detailed occupational categories into two-digit ISCO occupations. Thus, in some cases, our occupational aggregation may be broader than the Frey and Osborne (2013) list. As a means of corroborating our analysis, Cedefop looked at recent work by Pouliakas (2018), who deals with some of the recent criticisms of Frey and Osborne (2013) by accounting for tasks and skills needs using data from the European skills and jobs survey (ESJS). In doing so, Pouliakas (2018) allocates an automation score to ISCO two-digit occupations on the basis of a highly disaggregated training set comprised of occupations matched to the Frey and

Osborne (2013) list. Cedefop directly mapped these automation scores into its occupation groups. While occupations with a lower automation risk were more likely to increase in share, the pattern is far from conclusive. As with the Frey and Osborne (2013) predictions, many occupations with high automation risk actually showed a positive increase over time.

An additional contribution of this Cedefop study has been to apply the occupational change data to a historical firm-level data set in Ireland, which contains several variables relating to technological change in firms. A key limitation of the data and approach used in the paper is that we apply actual occupational change statistics from 2008 to 2018 to a historical cross-section of firms in 2008. Thus we do not follow these firms over time, but rather examine the characteristics of those that employed workers in occupations that were subsequently found to increase over time. Therefore, we are looking at associations between firm-level characteristics and measures of expected occupation-driven employment change.

Cedefop finds that firms that provided employees with information on plans to introduce new technology in 2008 were more likely to have positive predicted employment growth. While this may specifically relate to plans for introducing new technology, it could also be capturing a broader indicator of a ‘consultative culture’ in the firm. Cedefop finds that other measures of consultation around, for example, new products are also associated with expected occupational increase.

We also find a positive association between expected occupation-driven employment increases and firms reporting that technology was generating pressure for change in the organisation in 2008. Regarding employee characteristics, having a higher percentage of employees amenable to technological change is also associated with expected occupation-driven employment growth.

Finally, we examine a range of personnel and human-resource management variables. There is some evidence that firms with individual performance management policies were more likely to employ workers in occupations that subsequently increased. There is a strong positive association between net occupational employment increase and the share of workers consulted about decisions on working practices and new technologies. Specifically, firms that consulted all workers about working practices and new technology had an occupational mix that, on average, increased predicted employment by between four and eight percentage points more than firms that did not.

Concerns about automation and its impact on jobs are currently at the forefront of the policy debate and may have even become accentuated as a result of the Covid-19 pandemic. While it is not possible to predict accurately, automation and technological change will affect future labour markets. However, while the focus of the policy debate often exclusively rests on the negative aspects of technological change, such as job loss, it is probable that automation will bring substantial positive change; for example, through improved productivity and the creation of new jobs.

Cedefop's analysis cautions against an overly negative policy focus when it comes to automation. The Irish EGFSN, which advises government on future labour-market issues, published a 2018 report highlighting quite substantial risks over the short term (five years) relating to technological change. In arriving at the prediction that 43% of jobs in Ireland are at high or medium risk from automation over the next five years, the report drew, to a certain degree, on the predictions of Frey and Osborne (2013).

However, numerous subsequent studies have indicated that the Frey and Osborne predictions are likely to substantially overstate the short-term effects of automation. Moreover, Cedefop's analysis has shown that, five years on from the predictions of Frey and Osborne (2013), there was little evidence of substantial negative effects on the occupations highlighted as 'fully automatable'. Therefore, while it is advisable for policy to continue to focus on and monitor the impact of technology and automation on the labour market, it is important that the policy narrative does not descend into technological alarmism (McGuinness et al., 2019), especially in the absence of strong evidence of negative effects.

Abbreviations/Acronyms

AI	artificial intelligence
Cedefop	European Centre for the Development of Vocational Training
EGFSN	(Irish) Expert Group on Future Skills Needs
EU	European Union
LFS	(Irish) labour force survey
NES	(Irish) national employment survey
OLS	ordinary least squares
SDT	skills-displacing technological change
VET	vocational education and training

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Annex 1. Occupational change and new technology

Table 8. **Occupational change and new technology (probit specification)**

Variables	(1) NewTech1	(2) NewTech2	(3) NewTech3
NewTech (1-3)	0.034**	0.054***	0.049***
	(0.014)	(0.014)	(0.015)
Sectors (Ref: Public Admin)			
Industry	0.021	0.028	0.042
	(0.051)	(0.051)	(0.051)
Construction	-0.295***	-0.279***	-0.272***
	(0.059)	(0.059)	(0.062)
Wholesale and retail	-0.043	-0.032	-0.030
	(0.053)	(0.053)	(0.053)
Transport	-0.254***	-0.244***	-0.245***
	(0.068)	(0.068)	(0.071)
Accommodation and food	0.160***	0.169***	0.161***
	(0.040)	(0.039)	(0.040)
ICT	0.142***	0.143***	0.153***
	(0.046)	(0.046)	(0.044)
Finance	-0.005	-0.002	-0.008
	(0.058)	(0.058)	(0.059)
Professional	0.097**	0.102**	0.112**
	(0.047)	(0.046)	(0.046)
Admin	0.004	0.013	0.024
	(0.058)	(0.057)	(0.058)
Education	0.253***	0.256***	0.254***
	(0.029)	(0.028)	(0.028)
Health and social	0.225***	0.229***	0.226***
	(0.031)	(0.031)	(0.031)
Arts and entertainment	0.122***	0.129***	0.134***
	(0.045)	(0.045)	(0.044)
Observations	4 981	4 981	4 246

NB: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Source: 2008 national employment survey (NES); Irish labour force survey (2008 to 2018).

Annex 2.
Graphs of occupational change for 2-digit ISCO occupations

Graphs showing the change in share of employees in 2-digit occupations over time in Ireland (2008-18). *Source*: Irish labour force survey (2008 to 2018).

Figure 3. **Administrative and sales managers**

Figure 4. **Agricultural labourers**

Figure 5. **Assemblers**

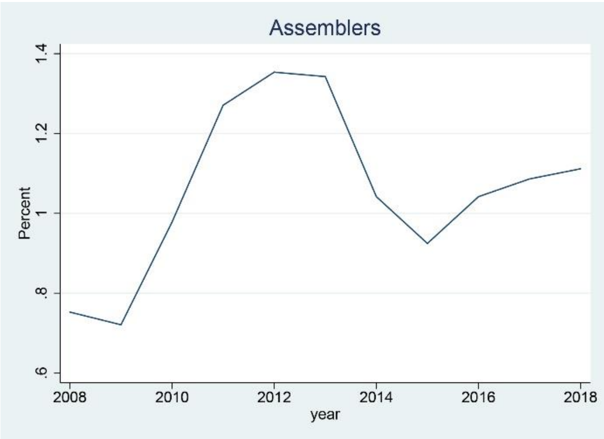

Figure 6. **Building trade workers**

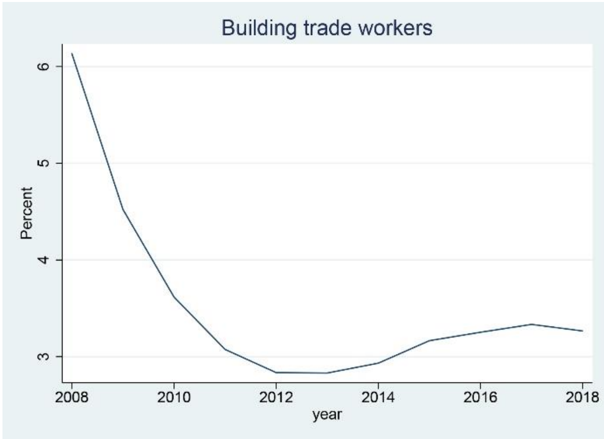

Figure 7. **Business and associated professionals**

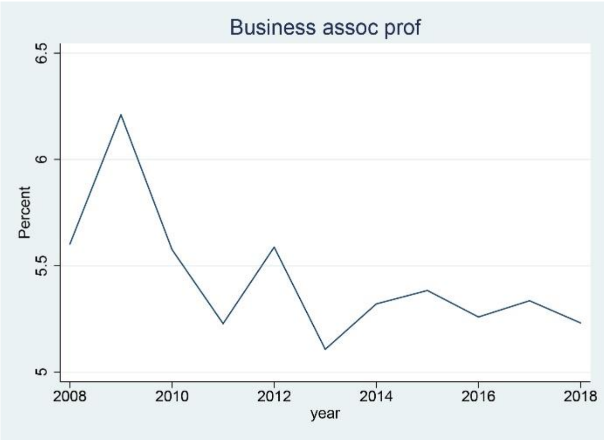

Figure 8. **Business professionals**

Figure 9. **CEOs**

Figure 10. **Cleaners and helpers**

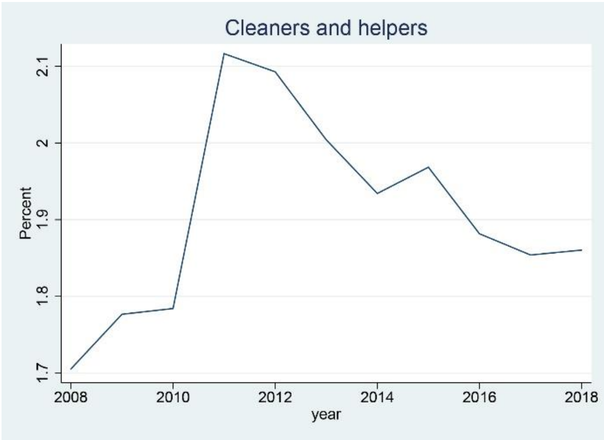

Figure 11. **Customer service clerks**

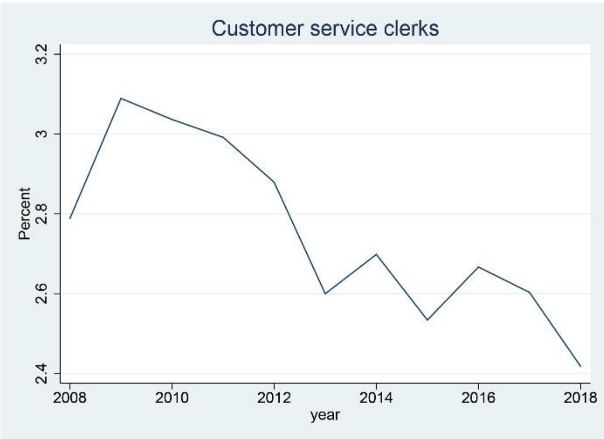

Figure 12. **Drivers and mobile plant operators**

Figure 13. **Electrical workers**

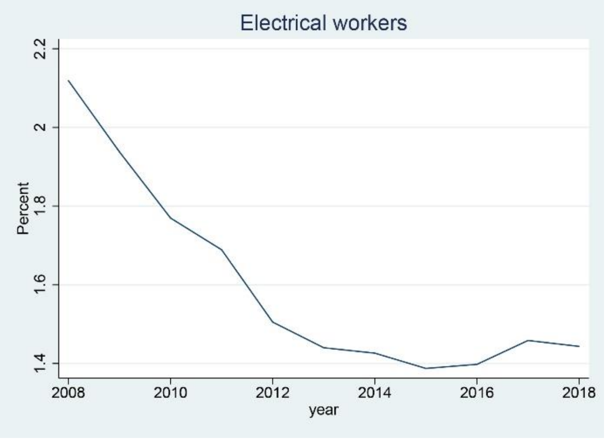

Figure 14. **Food preparation assistants**

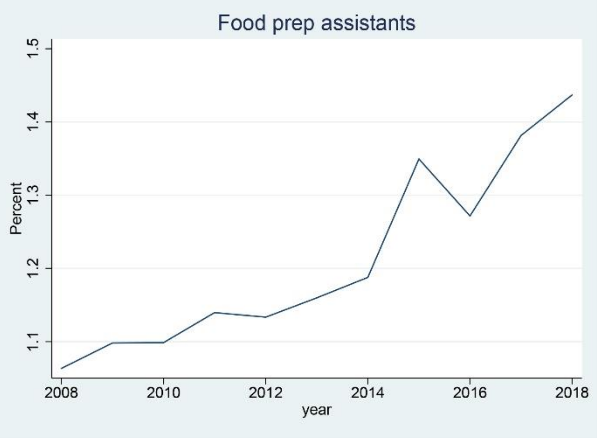

Figure 15. **Food processing and other trade workers**

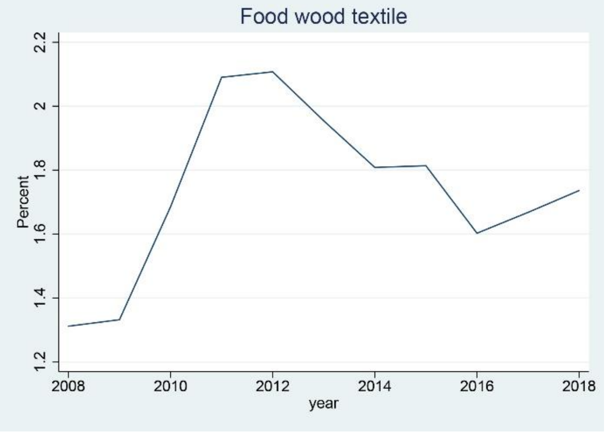

Figure 16. **Health associate professionals**

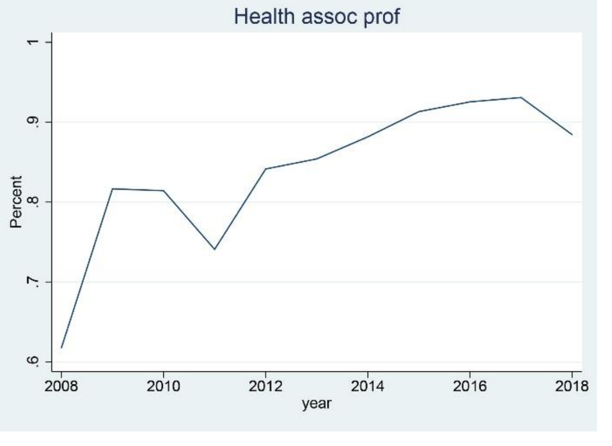

Figure 17. **Health professionals**

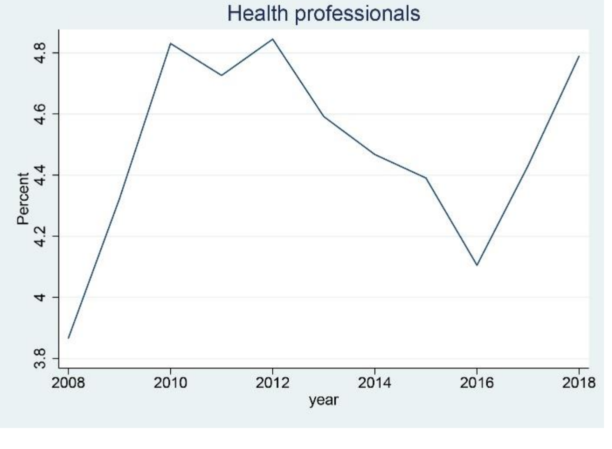

Figure 18. **ICT professionals**

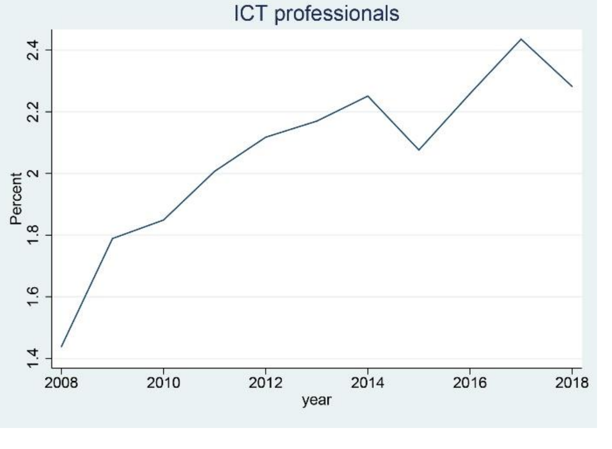

Figure 19. **ICT technicians**

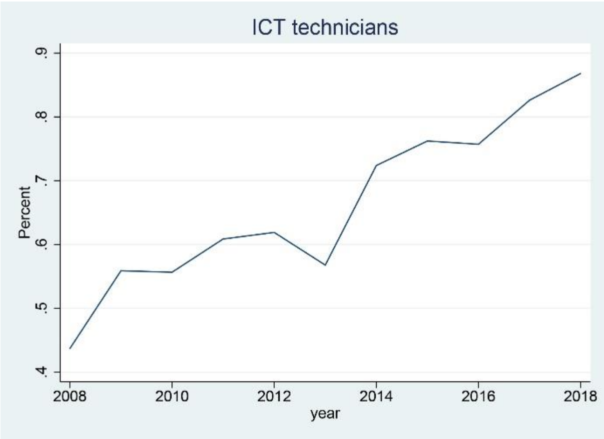

Figure 20. **Construction, manufacturing, transport labourers**

Figure 21. **Legal, social, religious associate professionals**

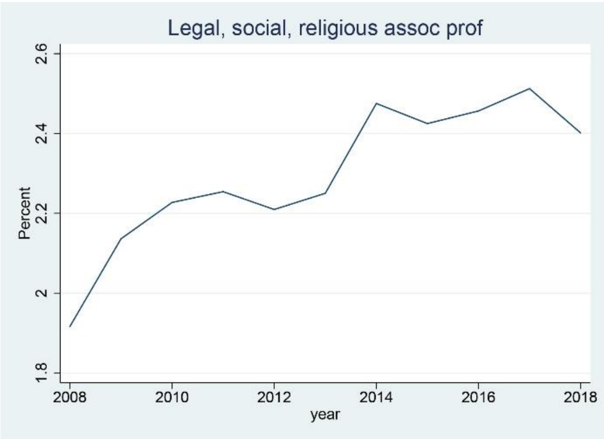

Figure 22. **Legal, social, religious professionals**

Figure 23. **Metal workers and machine mechanics**

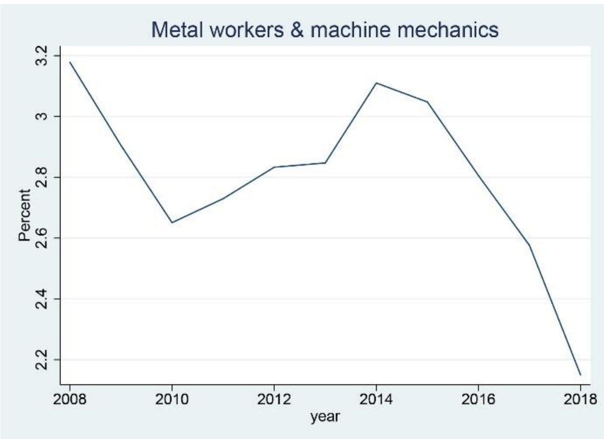

Figure 24. **Numerical clerks**

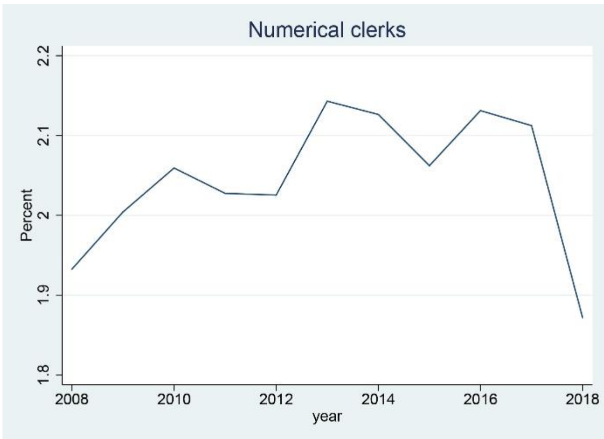

Figure 25. **Office clerks and secretaries**

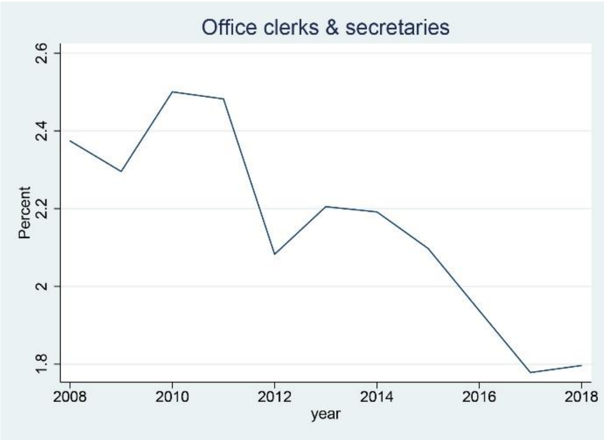

Figure 26. **Other clerical workers**

Figure 27. **Personal care workers**

Figure 28. **Plant machine operators**

Figure 29. **Printing workers**

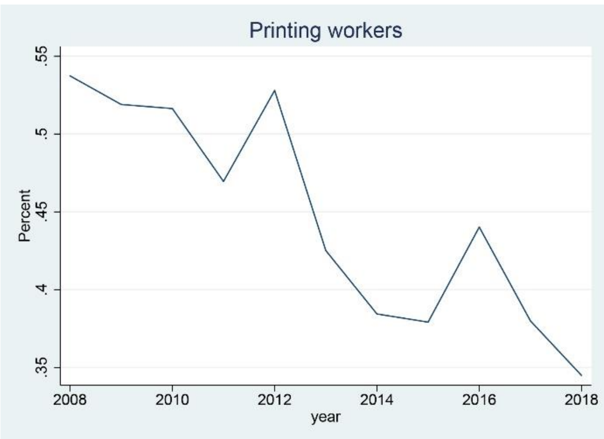

Figure 30. **Production and professional services managers**

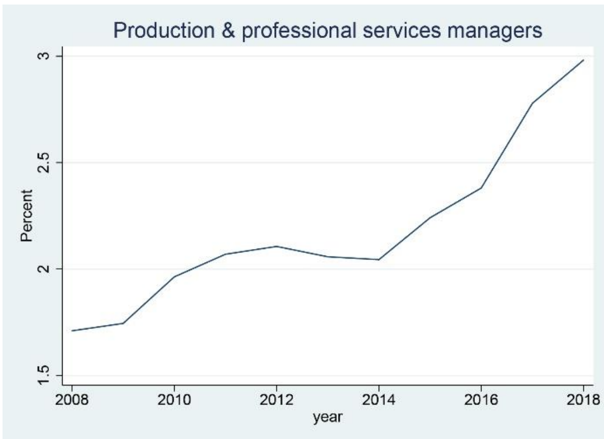

Figure 31. **Protective service workers**

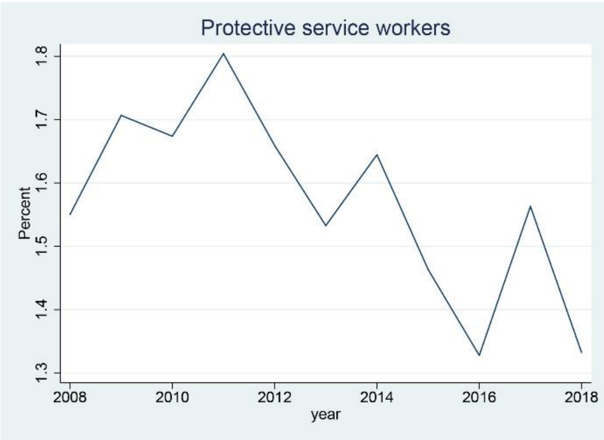

Figure 32. **Refuse workers**

Figure 33. **Sales workers**

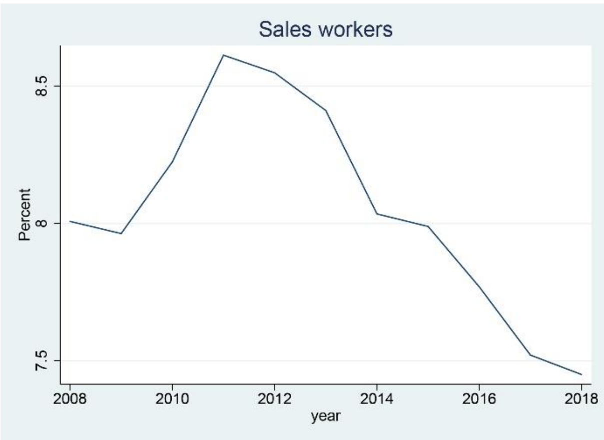

Figure 34. **Science and engineering associate professionals**

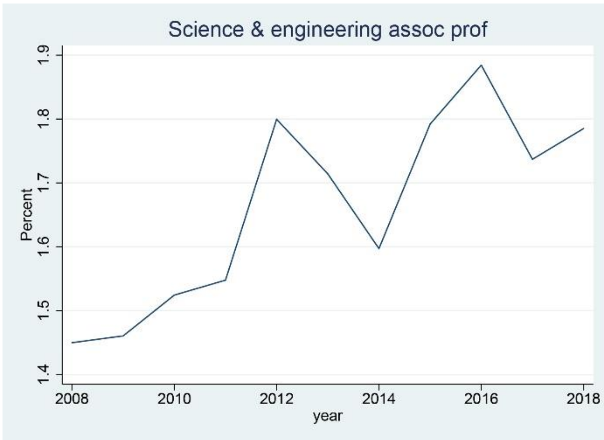

Figure 35. **Science and engineering professionals**

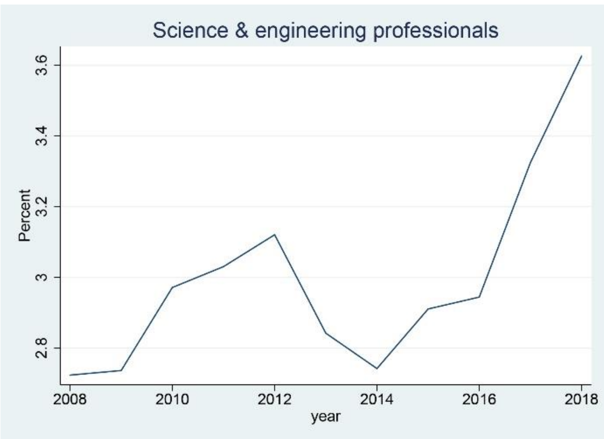

Figure 36. **Retail and hospitality managers**

Figure 37. **Skilled agriculture**

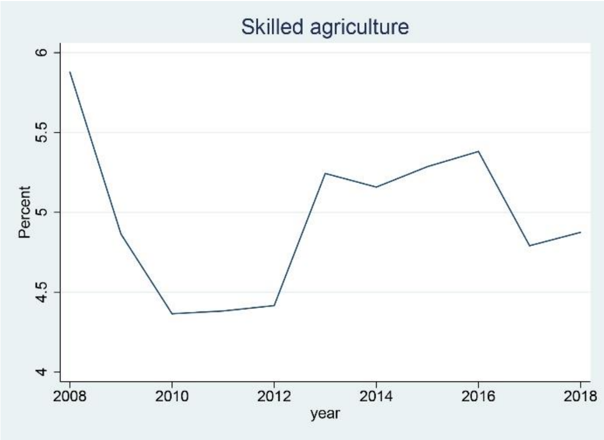

Figure 38. **Skilled forestry**

Figure 39. **Teaching professionals**

Assessing the employment impact of technological change and automation: the role of employers' practices

5579 EN - TI-BC-20-004-EN-N - doi:10.2801/173340

This Cedefop paper examines how employment in occupations identified previously as being at high risk of automation has changed over time. It also uses information from a matched employer-employee data set from Ireland, an EU country with relatively high exposure to digitalisation, to examine the relationship between employment change and organisational practices.

The paper shows that among occupations previously identified as fully automatable, though more likely to experience slower or negative employment growth than the non-automatable, almost 40% saw an increase in the five-year period since predictions were made. The average rate of decline was just -2%.

By correlating a measure of expected occupational change from 2008 to 2018 with various measures of technological change, it is found that firms that introduced new technology or indicated that technology was generating pressure for change in 2008, were more likely to employ workers in occupations with positive future employment change. Having a greater share of employees amenable to technological change, and being consulted about decisions on working practices and new technologies, are associated with higher predicted employment growth.

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