Automation and Irish Towns: Who’s Most at Risk?

Frank Crowley and Justin Doran

Spatial and Regional Economics Research Centre, Department of Economics, University College Cork, Cork

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Spatial and Regional Economics Research Centre
Cork University Business School,
University College Cork

Abstract

Future automation and artificial intelligence technologies are expected to have a major impact on the labour market. Despite the growing literature in the area of automation and the risk it poses to employment, there is very little analysis which considers the sub-national geographical implications of automation risk. This paper makes a number of significant contributions to the existing nascent field of regional differences in the spatial distribution of the job risk of automation. Firstly, we deploy the automation risk methodology developed by Frey and Osborne (2017) at a national level using occupational and sector data and apply a novel regionalisation disaggregation method to identify the proportion of jobs at risk of automation across the 200 towns of Ireland, which have a population of 1,500 or more using data from the 2016 census. This provides imputed values of automation risk across Irish towns. Secondly, we employ an economic geography framework to examine what types of local place characteristics are most likely to be associated with high risk towns while also considering whether the automation risk of towns has a spatial pattern across the Irish urban landscape. We find that the automation risk of towns is mainly explained by population differences, education levels, age demographics, the proportion of creative occupations in the town, town size and differences in the types of industries across towns. The impact of automation in Ireland is going to be felt far and wide, with two out of every five jobs at high risk of automation. The analysis found that many at high risk towns have *at low risk* nearby towns and many *at low risk* towns have *at high risk* neighbours. The analysis also found that there are also some concentrations of *at lower risk* towns and separately, concentrations of *at higher risk* towns. Our results suggest that the pattern of job risk from automation across Ireland demands policy that is not one size fits all, rather a localised, place-based, bottom up approach to policy intervention.

1. Introduction

The process of technological change displaces and replaces existing products and production processes and frees up resources that can be deployed elsewhere. Schumpeter (1942) referred to this process as 'creative destruction' and one which was an 'evolutionary process' and an 'essential fact of capitalism'. Technological change is also identified, both theoretically and empirically as the critical driver of long run growth (Schumpeter 1942; Romer 1990; Baumol 2002). Yet, the process of technological change, and in particular the change associated with job replacement, creates anxiety and angst within societies (Akst 2013; McClure 2017). 72 per cent of adults in the United States are worried of a future where robots and computers can do many human jobs (Anderson 2017). These fears surrounding automation is not a recent phenomenon. During the industrial revolution, many English textile workers (the Luddites) protested that machines and steam engines would destroy their livelihoods (McClure 2017).

Keynes was concerned that technological advancement was happening faster than the creation of new jobs. Keynes (1933:3) famously made reference to the incidence of 'technological unemployment' as 'unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour'. We know today, that at that time, such concerns were unwarranted. Unemployment in the United States is currently at its lowest rate in over fifty years. However, it is argued by some (Brynjolfsson and McAfee 2012, 2014; Ford 2015; Ruta 2018; Wajcman 2017) that it may be different this time around, largely due to the pace of the change and the fact that today's automation technologies are highly intelligent and able to learn (Ruta 2018). The worldwide annual supply of robots has trebled since the start of the century (OECD, 2018). Brynjolfsson and McAfee (2014:11) argue that "there has never been a worse time to be a worker with only 'ordinary' skills and abilities to offer, because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate". Future automation disruptions, like past automation disruptions are likely to have a disproportionate effect on people that have certain skills (Brookings Institute, 2019). Since the 1970's there is also evidence of downward pressure on wages and declining labour shares. (Piketty 2013; Schwellnus, Kappeler, and Pionnier 2017). Recently, Acemoglu and Restrepo (2017), found a large and robust negative effect of robots on employment and wages.

Existing estimates of how automation may impact workers are wide ranging and some predict extreme disruption. The most widely cited work in the empirical examination of automation by Frey and Osborne (2017) estimated that 47 per cent of U.S. current employment is at 'high risk' of being automated in the future. Using the same methodology, Frey and Osborne (2014), estimated that 35 per cent of the jobs across the UK and 30 per cent of the jobs in London were automatable. However, while this national figure provides context for the number of jobs at risk it overlooks the geography of this risk. Indeed, despite the significant research in the area of automation and the risks it poses to employment, there is very little analysis which considers the sub-national implications of automation risk. One significant exception is work conducted by the OECD (2018) which identified that the job risk variation between OECD regions is significant and could be as much as 36 per cent[1]. Given the existing disparities across regions within the OECD, the possible job losses due to automation could exacerbate or attenuate employment inequalities across regions depending upon whether it is leading or lagging regions

[1] It is important to note that the results of Frey and Osbourne (2017) are not directly comparable with the (OECD, 2018) results as there is a difference between the studies in the definition of automation risk and whether the risk is based on tasks and individual characteristics (OECD approach) or jobs (Frey and Osbourne, 2017). In any case, the disruption and spatial variation is stark and still likely to have a disruptive effect.

which are most at risk. Doyle and Jacobs (2018) highlight that this is also the case for Ireland where there are approximately two out of five jobs at risk of automation.

Technological displacements created the existing world order and there is evidence that the concern, fear and uncertainties of what the future holds for people have recently been expressed at the ballot box. The spatial disparities of technological disruptions are increasingly suggested as the underlying drivers of electoral wins for Donald Trump and Emmanuel Macron, Brexit, the recent extreme right-wing and left-wing populist voting patterns in Germany and the recent violent yellow vest protests in France (Rodríguez-Pose 2018). Frey et al. (2017) also found that the support for Donald Trump was significantly higher in local labour markets more exposed to automation.

Despite the impact automation has had on local labour markets and spatial displacement, there is still very little research that examines the spatial implications of future automation shocks. The international debate on artificial intelligence has gained significant momentum in recent years with the G7 ICT Ministers agreeing on the need to facilitate R&D and the adoption of emerging technologies including AI, and to ensure policy frameworks take into account the broader societal and economic implications of such technologies as they are developed (OECD 2018). We have an idea of the impact at a national level due to Frey and Osborne's (2017) paper in the U.S. and further at the county level in the U.S. (Muro et al., 2019). This work has also been complimented by national analysis (Arntz, Gregory, and Zierahn 2016) and an extended analysis at NUTS 2 regional level for OECD countries (OECD 2018). But given the significance of the political and social upheaval that can be caused by technological disruptions, the current literature is insufficient to inform policymaking at a disaggregated level that can assist national and local policymakers to make meaningful local intervention decisions across space in cities, towns, villages and rural areas. There is an absence of an accurate picture of the local automation job risk.

This paper makes a number of significant contributions to the existing nascent field of regional differences in the spatial distribution of the job risk of automation. Firstly, we use the same automation risk methodology developed by Frey and Osborne (2017) at a national level using occupational and sector data and apply a novel regionalisation disaggregation method to identify the proportion of jobs at risk of automation across the 200 towns of Ireland, which have a population of 1,500 or more using data from the 2016 census. Doyle and Jacobs (2018) provide an analysis of automation in Ireland using national and NUTS3 regional data and this paper extends upon their work by considering Irish towns. This methodology is applicable to any dataset which contains broad occupational classifications which can be directly mapped to detailed occupational classifications and could be replicated for countries across Europe or elsewhere to generate imputations of detailed employment risk of automation information at sub-national level. Secondly, in addition to imputing the employment risk of automation across towns we also examine what factors may explain variations in the exposure of Irish towns to automation. In doing so we use an economic geography framework to examine what types of local place characteristics are most likely to be associated with high risk towns while also considering whether the automation risk of towns has a spatial pattern across the Irish urban landscape.

The next section provides a review of the existing literature on the job risk of automation and how this can be linked to the ongoing discussion in economic geography. The precise data used and regionalisation imputation implemented are described in Sections 3 and 4 respectively. Section 5 reports the results and the paper concludes with a conclusion and discussion section.

2. Literature Review

In this section we discuss two aspects of the existing literature and identify our theoretical rationale. The first section discusses the impact of automation on jobs while the second section places this in the context of economic geography.

2.1 *Automation and job risk*

Humans have always developed new and superior products and production technologies to satisfy new wants and needs and to produce greater economic output with less human effort. This is what is meant broadly by technological change and it is a significant catalyst of long run economic growth (Schumpeter 1942; Romer 1990). In this context, the idea of computerisation where job automation is by means of computer-controlled equipment (Frey and Osbourne, 2017) is not new. New technologies (like computerisation) and new markets have replaced and generated new and more productive jobs and will continue to do so in the future (OECD, 2018). Automation technologies have a long history with inventions like the steam engine, electricity, and more recently with information technologies. Some automation developments have been more specialised. For example: mechanized weaving looms; industrial robots; or automated teller machines (Acemoglu and Restrepo 2018). From this perspective, robots have been coming for a long time.

As far back as Simon (1965), the decline of routine jobs was predicted where computers were argued to hold the comparative advantage in "routine" rule-based activities which are easy to specify in computer code. Autor, Levy and Murname (2003) presented a simple theory, which has become referred to as the ALM model, of how the rapid adoption of computerisation by firms is changing the tasks performed by workers at their jobs, which in turn changes the market demand for human skills. For them robots (machines), are substituting 'routine' tasks but will not substitute non-routine tasks that involve problem-solving, complex social and emotional communication activities and tacit knowledge. Non-routine tasks that cannot be substituted by automation are generally complemented by it (Autor 2015). Routine tasks are tasks that follow explicit rules and non-routine tasks cannot be specified in a computer code (Frey and Osborne 2017). Autor (2015) argues that the tasks that can be automatable are bounded by the limits of human knowledge and what he refers to as Polanyi's paradox: Since humans "know more than they know they know" (i.e. know things that are difficult to explain as a matter of codified, programmable steps), there are limits to the substitutability of human tasks. Consequently, there will always be a division of 'human tasks' and 'machine tasks'.

Susskind and Susskind (2015) have identified key weaknesses of the theoretical ALM model where tasks that were considered 'non-routine' in the ALM task based literature have already become 'routine' due to technological changes leading to the likelihood of a more dramatic job displacement reality from current modern computerised technologies. Big data and artificial intelligence are progressing at incredible speed. The rate of the progress will largely be unknown, but nevertheless, Autor's (2015) Polanyi paradox point is still valid: in that the progress of machine tasks is a function of human intelligence. Susskind and Susskind (2015) observations suggests that the findings of Frey and Osbourne (2017) who identified the scope of jobs that could be automatable in the future may actually occur more quickly than is largely accepted in parts of the literature. Frey and Osbourne (2017) identified that 47 per cent of jobs in the U.S. are susceptible to automation. They argue their estimate also aligns closely to the extent of job displacement that has happened in the past. For instance, in 1900, 40 per cent of the U.S workforce was employed in agriculture. Now it is less than 2%.

In general, the grave concern of technological unemployment has been unfounded. One of Kaldor's (1961) stylised fact was the unhinging constant labour share of national income through time, despite significant technological disruptions in transportation, electricity and communications. The process of creative destruction has led to as many new jobs being created in new sectors and hence jobs lost were replaced with often better paid, more highly skilled jobs in their place. Despite the unfounded unemployment concerns of the past, it still created widespread disruption with a greater polarisation in jobs and incomes, as technologies (robots and algorithms) replaced, in particular, middle skilled people based-routines. But the concerns of today around new technologies are similar to the hypotheses of those from Keynes (1933) almost 90 years ago. Schwab (2016) in his piece on the fourth industrial revolution at the economic summit in Davos stated:

> 'We stand on the brink of a technological revolution that will fundamentally alter the way we live, work, and relate to one another. In its scale, scope, and complexity, the transformation will be unlike anything humankind has experienced before. We do not yet know just how it will unfold, but one thing is clear: the response to it must be integrated and comprehensive, involving all stakeholders of the global polity, from the public and private sectors to academia and civil society.'

And, other rather pessimistic predictions have been voiced by Brynjolfsson and McAfee (2014:11) where they expect technological progress 'to leave behind some people, perhaps even a lot of people, as it races ahead'. Further Ford (2015), warns of a 'jobless future' where he argues that most jobs can be reduced to a division of routines. More recently, Acemoglu and Restrepo (2017) found supporting evidence for pessimistic predictions. They identified that one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 per cent. There is also growing evidence that labour as a share of income is declining since Kaldor's (1961) finding, with wages falling by over 10 per cent in Spain, Italy, South Korea and the United States since 1970 (OECD 2018)[2].

2.2 *The economic geography of job risk and automation*

Job displacement, job polarization and technological unemployment are often the most discussed adjustment concerns raised around automation and the rise of artificial intelligence. But an often overlooked implication and possibly a greater problem, is the displacement to places that has been created by technological change. The past century has seen a large migration of the human race from rural to urban areas. By 2050, Eurostat predicts about 80 per cent of the European population will be living in urban areas.

Urban theorists argued that agglomerations are intellectual breeding grounds for new ideas and innovations (Jacobs 1969; Glaeser 1999; Marshall 1890). Urban areas and in particular, cities for a long time have been identified as important in explaining innovation. In particular, face-to-face interaction and transfer of knowledge between individuals for innovation is critical (Porter 1985; Porter 1990; Storper and Venables 2004). Geographical proximity is critical for "fostering, facilitating and nurturing of flows of local knowledge, ideas and innovations" (McCann and Shefer, 2005: 302). In theoretical approaches to knowledge flows and innovation it is assumed that it is easier for knowledge to transfer over shorter distances than longer distances (McCann 2007), or as Glaeser at al. (1992:1126) put it, 'intellectual breakthroughs must cross hallways and streets more easily than oceans and continents'. Given the spikey distribution of prosperity around the world, between countries and within countries, the

[2] It is important to note that there could be a number of reasons for this trend other than just automation. For instance, increased globalization, collective bargaining, labour standards, and unemployment levels could also be determinants (OECD, 2018).

importance of ‘place’ in contributing to economic growth has been a central research topic (McCann and Simonen 2005).

From the literature, it is apparent that urban areas therefore have an important role as creative and intellectual spaces. The ‘tolerant’ and ‘Bohemian’ nature (Florida 2002); the creative spill-overs that are ‘in the air’ (Marshall 1890); the Jacobian diverse economies (Jacobs 1969); and the creative ‘buzz’(Storper and Venables 2004) in urban areas drive innovation and ‘swarms of creative clusters’ emerge in global and capital cities (Chapain et al. 2010). Florida’s thesis of the creative class which varies in their proportions from place to place suggests that innovation will also vary from place to place. Hence, the outcome is a spikey world in terms of economic performance. Educated, creative young people are migrating to urban areas to exploit higher wages and employment opportunities in favourable business environments (Chen and Rosenthal 2008; Moretti 2012). Agglomerations provide an enhanced ecosystem to drive novel combinations of knowledge and ideas which result in sharper geographical divides between the world’s urban hierarchy and between urban and rural areas (Rosenthal and Strange 2004; Organization 2009; Moretti 2012).

The shift from manufacturing to predominantly service driven economies has actually made geography matter more resulting in increased divergence between places (Moretti 2012). There is strong evidence that digital technologies are resulting in greater divisions between large and small urban areas (Muro 2019). In general, urban areas with a more dense critical mass are more productive (World Bank, 2009), more innovative (Carlino et al, 2007), offer more job opportunities (Hendrickson, Muro, and Galston 2018) and higher wages (Wang 2016). 72 per cent of new jobs were created in large US cities (over 1 million) since 2013 (Whiton 2018). A similar trend is occurring in Ireland. 43 per cent of honours degree graduates work in Dublin city (authority 2019) and 60 per cent of the jobs created in Ireland in the past year were in the capital (CSO, 2016). But it is also not just a story of ‘large’ versus ‘small’ and ‘winners’ versus ‘losers’ – a much more complex geographical landscape is emerging with brain hubs, declining manufacturing cities and a number of cities that could thrive or decline (Moretti 2012). It is suggested economic stagnation and a decline of economic and social opportunities in smaller cities, declining regions and rural areas was the force behind recent populist voting patterns in the United States (Hendrickson, Muro, and Galston 2018; Shearer 2016), in France, Germany and the United kingdom (Rodríguez-Pose 2018; Dijkstra, Poelman, and Rodríquez-Pose 2018). In response, many are calling for new strategies and policies to tackle the concerns of lagging areas (Iammarino, Rodríguez-Pose, and Storper 2018; Rodríguez-Pose 2018; Shambaugh and Nunn). We envisage that future automation disruptions will further exacerbate regional and local disparities and that it is necessary to get a better understanding of the spatial disparities that future automation disruptions will create at the sub-national level across Ireland.

3. Data

This section discusses the construction of the data used in this paper. It begins by defining the identification of which sectors are most at risk of automation based on the methodology used by Frey and Osborne (2017) in Section 3.1. Section 3.2 discusses the Irish data and how this is used and applied to the Frey and Osborne (2017) methodology. In Section 3.3 descriptive statistics of the risk of automaton are presented at the national level.

3.1 Frey and Osborne (2017) methodology for identifying at risk occupations

Frey and Osbourne (2017) used machine learning experts to assess the automatability of 70 occupations using detailed task descriptions. Specifically, they asked the experts to assess whether each task for these occupations was automatable given current knowledge on computerisation capabilities and possibilities. They drew on data from O*Net which has detailed data from population surveys of 20,000 unique task descriptions and additional data on the skills, knowledge and abilities possessed by different occupations. They used big data and algorithm applications to assess automatable versus non-automatable tasks of the 70 different occupations. This algorithm was then applied to assess the automatability of another 632 occupations. In total, Frey and Osbourne (2017) were then able to examine a total of 702 occupations that existed for 97 per cent of the workforce in the United States. Tasks linked to perception and manipulation, creativity, and social intelligence are considered to be safe from automation (OECD 2018).

3.2 Converting *Frey and Osborne (2017) US SCO codes to the Detailed Irish Occupational Classifications*

Frey and Osborne (2017) occupational classifications is based on the 2010 version of the US Standard Occupational Codes (SOC). The Irish Central Statistics Office (CSO) bases their occupational classifications on the UK SOC. The US and UK SOC are not directly comparable and there is no direct conversion available (this is further highlighted by Doyle and Jacobs in the Irish case). Therefore, in order to convert the US codes to their UK counterparts (which are approximately identical to the Irish codes used by the CSO) we transform these data using a series of established international classifications. This is accomplished through the use of the International Standard Occupational Classifications (ISOC). The US SOCs can be converted using the Bureau of Labour Statistics official conversion (Bureau of Labor Statistics 2012). The codes used in Frey and Osborne (2017) to identify those sectors at risk of automation are 6-digit US SOCs. When converting these to the ISOC there is not a one to one match. This is due to the ISOC codes being at a higher aggregation level. Therefore, in some instances, two or more of the US SOC codes are combined into one ISOC code. Where this occurs the risk of automation values from Frey and Osborne (2017) are averaged to provide an average risk for the aggregated occupation.

Once the codes are in ISOC format it is possible to convert these ISOC codes to the UK SOC codes using a conversion framework developed by the Office for National Statistics (2010). In doing so, again there are a small number of occupations which have more than a one for one match and therefore there is a need to average the probability of risk associated with these occupations. It is possible, once this process has been completed, to perform an analysis of the risk of automation to occupations in Ireland.

Regarding the exact figures obtained from the match of US SOC codes to UK SOC codes this paragraph provides a summary. To begin with there are 878 US SOC codes. However, for various reasons, Frey and Osborne (2017) provide risks of automation for only 702 SOC codes. For more on this see Frey and Osborne (2017). Therefore, we begin the conversion process with a total of 702 SOC codes out of a possible 878 (no automation data is available for the 176 SOC codes for which Frey and Osborne (2017) do not provide automation risk). When these codes are converted to ISOC 2008 codes this yields a total of 245 ISOC codes. The final conversion of the ISO 2008 to UK SCO 2010 yields a total of 314 occupations. When this is matched with the Irish data on occupations a total of 302 of these occupations are present in Ireland. However, not all have associated risk probabilities. Therefore, our analysis begins with, what the CSO define as, the detailed occupational classifications for Ireland of which we have risk probabilities associated with 273 detailed occupations across 24 intermediate occupation aggregates covering, in total approximately 86% of all jobs in Ireland.[3]

[3] Doyle and Jacobs' (2018) undertake a similar conversion routine using what they term an 'unofficial crosswalk'. There is some variation in the results found by this paper compared with Doyle and Jacobs (2018). This may be due to variations in the matching process across occupations.

3.3 Description of the Irish data

The age old concern with automation and any technological change is technological unemployment (Keynes 1933) and the adjustment disruptions in the labour market. In the past two decades, Ireland experienced one of most substantial transitional change shifts of middle jobs to higher skilled jobs in the OECD. Where, 15.1 per cent of jobs in manufacturing were lost. During this time, the increase in high skilled jobs was 14.4 per cent, with only 0.7 per cent in low skilled jobs. Ireland has experienced over twice the rate of disparity to that observed in the US. According to the OECD (2018), over the same period, the average decline across OECD countries in traditional middle skilled jobs was 7.6 per cent. In turn, the increase in low skilled jobs was 2.3 per cent and 5.3 per cent in high skilled jobs.

Having identified the occupations at risk and converting these to Irish codes we now discuss the availability of Irish data and the application of the Frey and Osborne (2017) methodology to Ireland along with the main difference in our application of this methodology which allows for inferences at a detailed sub-national level.

We begin by describing the Irish occupation data and setting up our imputation approach to disaggregate the data to a sub-national level. The most disaggregated Irish data on occupation, in terms of the scope of occupations, is available at a national level. This is referred to by the CSO as the detailed occupations classifications and covers, in our analysis, 273 occupational classifications. This detailed classification is also available at Regional Authority level of which there are 32 in Ireland. At these levels data is available from the Irish censuses of 2016 on the number of people employed in each detailed occupational classification. Therefore, the exposure of Ireland and the Regional Authorities to automation can be obtained by identifying the number of people employed across different 'probability of an occupation being automated' groupings. The groupings used here are identical to Doyle and Jacobs (2018) where high-risk (>70% probability of an occupation being automated), medium risk (70-50% probability of an occupation being automated), and low-risk (<50% probability of an occupation being automated) to facilitate a comparison with their analysis.

At a national level this yields Figure 1 which shows the breakdown of high, medium, and low risk occupations at a national level. We observe a general U-shaped pattern where jobs in Ireland are mainly susceptible to high or low risk automation potential. This U-shaped pattern is largely in line with the findings of Frey and Osbourne (2017). However, the pattern is skewed in favour of a greater percentage of low risk jobs in Ireland, whereas it was skewed in favour of a greater percentage of high risk jobs in United States. This is in line with the finding of Doyle and Jacobs (2018) for Ireland also.

When breaking this down by the proportion of jobs at risk in each occupation, Figure 3 shows the broad occupational classifications and the associated proportion of jobs in each broad classification at high, medium, and low risk. Certain occupations can be seen to be entirely low risk while others are entirely high risk. The areas expected (in the theoretical and empirical literature) to be the most resilient to automation are in the fields of education, legal and community services, the arts, media, healthcare, computers, engineering and science and the types of jobs at high risk are jobs in office and administrative support, low skilled services, transportation and sales related industries such as telemarketers, waiters, barmen, taxi drivers, accountants, tax preparation and jobs in retail. (Frey and Osborne 2017; OECD 2018). We can identify from Figure 2 that the occupations least and most resilient to automation in Ireland also correspond to the findings in previous studies.

Figure 1: National risk profile of occupations – proportion of jobs at risk

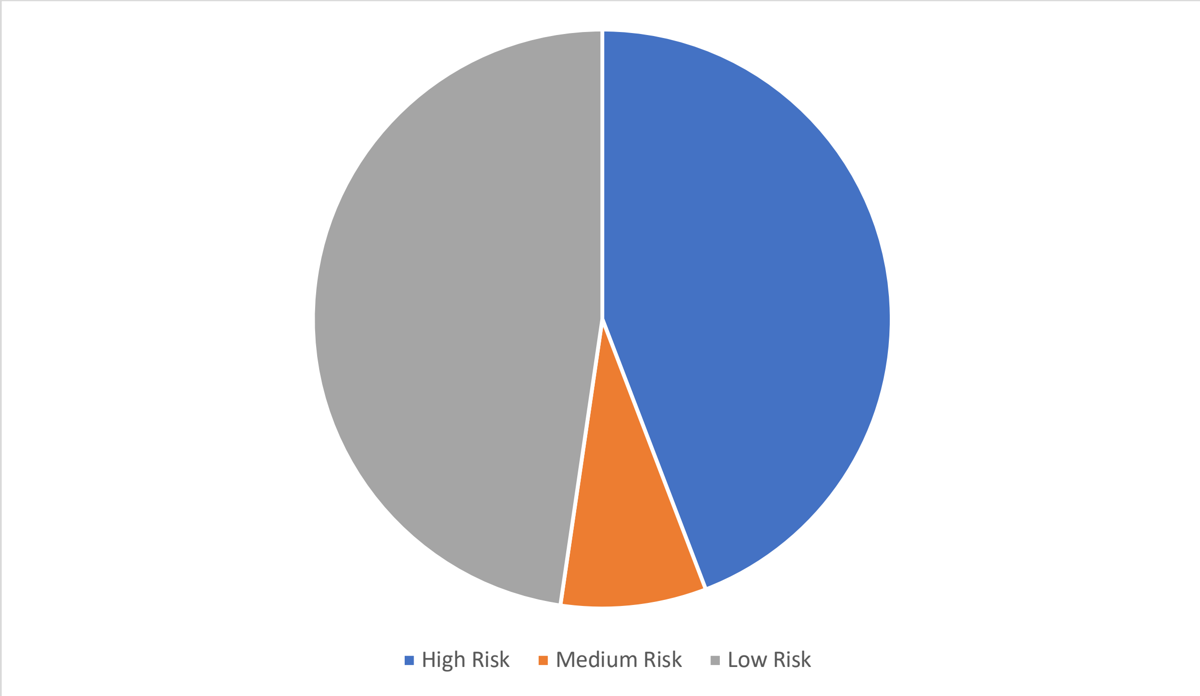
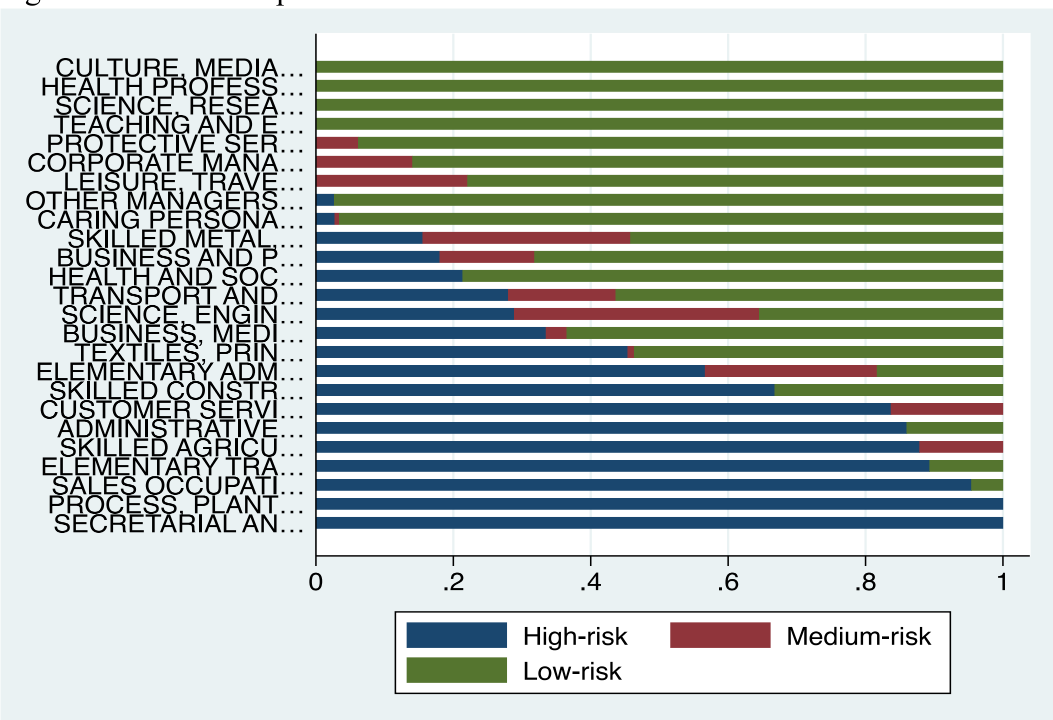


Figure 2: Broad Occupational Classification and Risk



4. Regionalising the analysis

While the national description provided in Section 3 shines some light on the employment risk of jobs across Ireland to automation the aim of this paper is to provide regional estimates of the risk of automation. Using the actual detailed occupational data this is possible at the County and city level of Ireland, of which there are 32 regions available. This analysis can be performed using the detailed occupational classification statistics presented and discussed in Section 3. However, no further disaggregated data is available beyond this point at lower spatial scales, as is consistent internationally, with only intermediate or broad measures of occupational classifications available. In the Irish case occupational classifications for towns with a population of more than 1,500 people is only available at the intermediate occupational classification, of which there are only 24 available (see Figure 2 for details of these classifications). The lack of availability of detailed occupational classification is not limited to Ireland as is common across most countries. Therefore, this paper proposed a method to disaggregate the potential impact of automation to smaller regional levels. In this section this methodology is discussed, and a robustness check of this approach is presented.

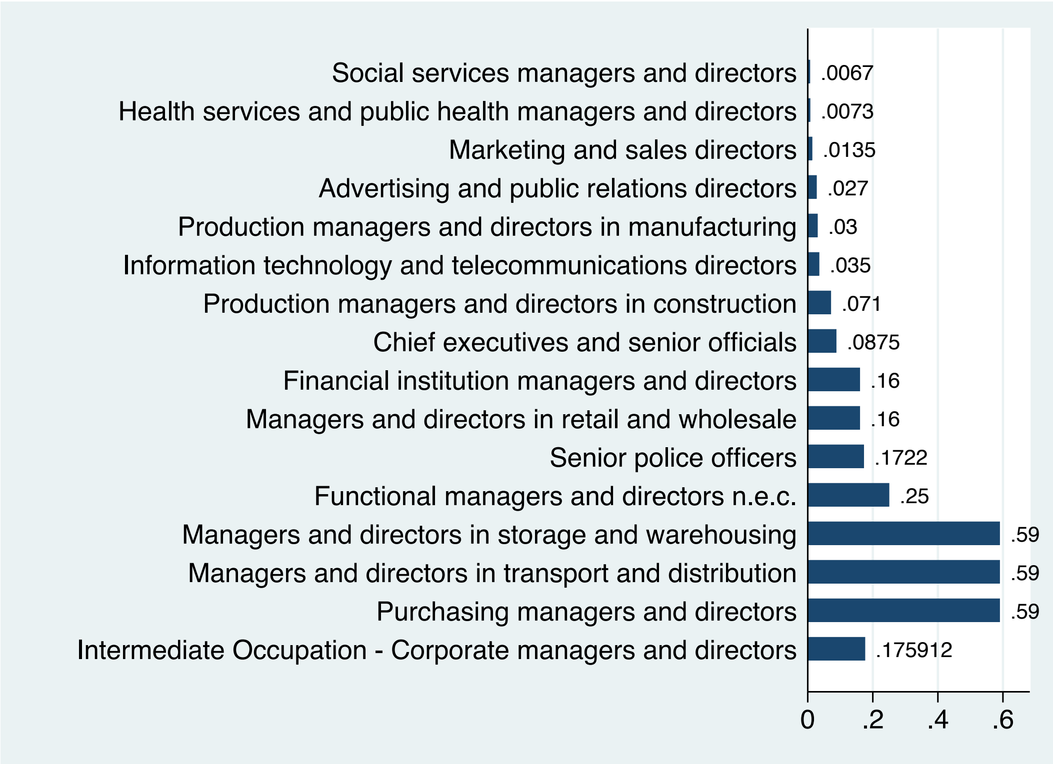
4.1 *Regionalisation methodology*

The regionalisation methodology applied in this paper is based on firstly identifying the automation risk for each detailed occupational classification nationally. Once this risk has been identified (see Section 3 for a discussion of how this is accomplished and the results of the national analysis) the number of individuals in each occupational category is obtained based on the 2016 Irish census. In total there are 274 detailed occupation classifications available. These 274 detailed occupation classifications are aggregated by the Irish CSO across 24 intermediate occupation classifications. These 24 intermediate occupational classifications are available across a far wider range of geographical and social indicators than the 274 detailed occupational classifications. The method of identifying the automation risk within the 24 intermediate occupational categories can be summarized as follows:

1. Identify the risk probability associated with each of the detailed occupational classification
2. Identify the proportion of the national workforce which is employed in each of the detailed occupational classifications
3. Weight each of the risk probabilities of the detailed occupational classifications by the proportion of the national workforce employed in that occupation
4. Sum the weighted risk probabilities of the detailed occupational classifications across the intermediate occupational classification

An example of this is provided for the intermediate occupational classification ‘Corporate managers and directors’. This has 15 detailed occupational classifications within it with risks of automation running from 0.67% to 59%. When these are weighted by the number of individuals employed in each detailed occupational classification and this is then aggregated the intermediate occupational classification (which is comprised of these 15 detailed occupational classifications) has a probability of automation of 17.5% in the Irish national case.

Figure 3: Example of aggregation from detailed occupational classifications to intermediate occupational classifications



Having calculated these 24 new risk of automation values for the intermediate occupational classification based on the 274 detailed occupational classifications weighted by the proportion of the workforce employed in each of these occupations we now turn to regionalising the risk of automation. To do so we obtain the number of people employed in each of the intermediate occupational classifications at the lowest level of spatial aggregation available using our data. The lowest level of aggregation available are towns with a population of 1,500 people or more of which there are 200. We then calculate the number of jobs at risk of automation by identifying the number of people employed in each of the intermediate occupational classification by the risk of automation associated with each of those intermediate occupations based on our constructed risk measure described in points 1 to 4 above. In doing so we can generate a series of measures of the proportion of jobs at high, medium, and low risk of automation across the 200 towns of Ireland which have a population of 1,500 or more.

4.2 *Robustness check of accuracy of regionalisation methodology*

In order to assess whether our regionalisation approach works we first test it at the level of county and cities of which there are 32 in Ireland. The reason for choosing this as our test bed is that data on detailed occupational classifications and intermediate occupational classifications are available at this scale. Therefore, we can compare our imputed intermediate occupational risk values with the outcome of using actual detailed occupational data and access the accuracy of our proposed approach.

We begin by presenting the results of the analysis of counties and cities of Ireland using the actual detailed occupational data. This is displayed in Figure 4. When applying our imputed intermediate occupational classification risk profiles we observe the regional breakdowns of risk displayed in Figure 5.

Figure 4: Regional risk based on actual detailed occupational data

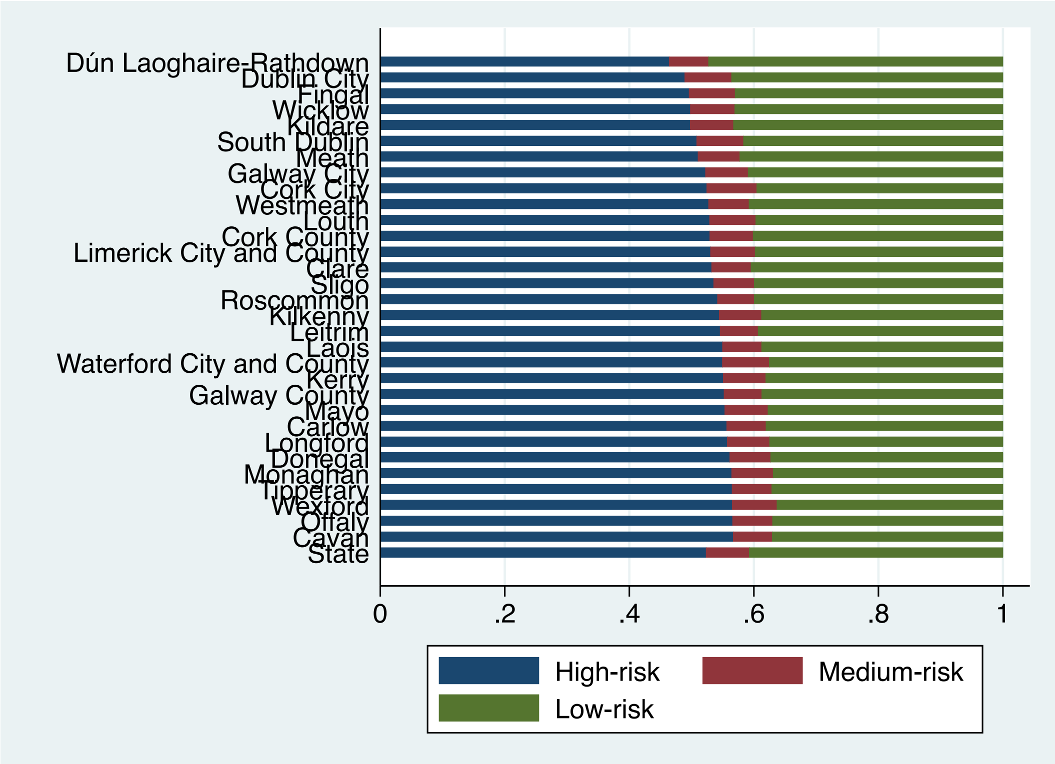
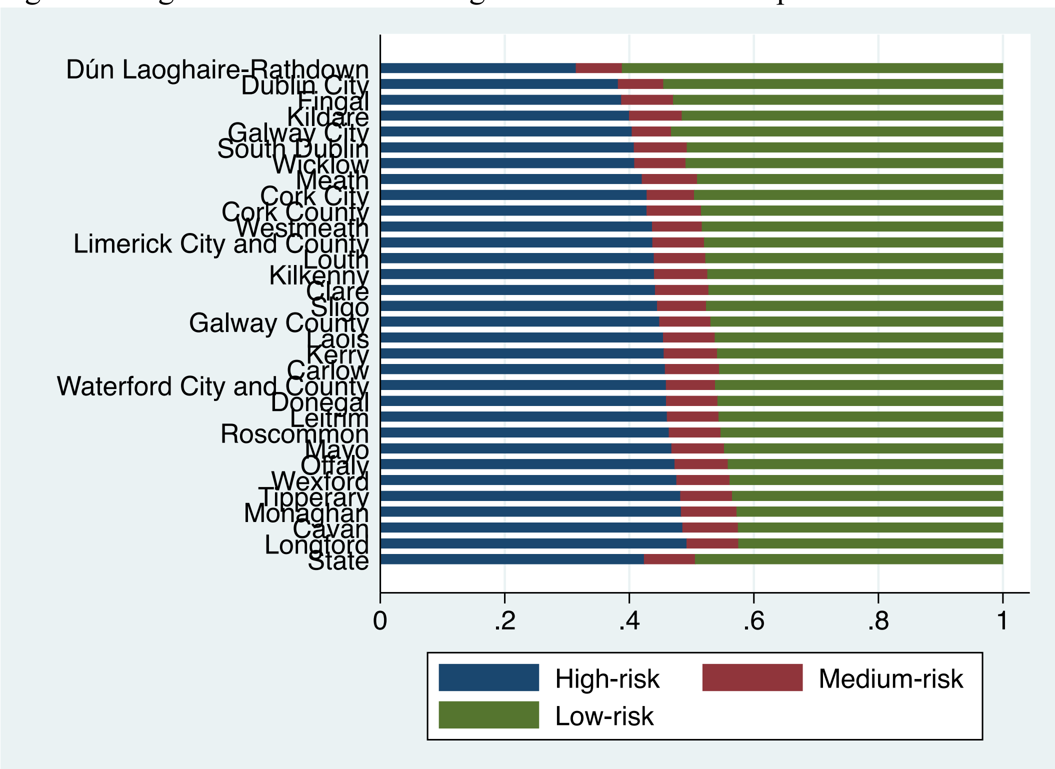


Figure 5: Regional risk based on weighted intermediate occupational data



When comparing the analysis based on the actual detailed occupational classifications with the analysis from the nationally weighted intermediate occupational classifications there is a slight difference in the magnitude of the risk factors. The high-risk category is typically under estimated while the medium-risk category is typically over estimated. However, the ranking of the regions in terms of high-risk remains robust to the alternative specifications. The Spearman's Rank Correlation coefficient between the rankings of the detailed and intermediate occupational groupings for high risk is 0.9776 with an associated p-value of 0.0000. As well as this the correlation between the proportion of jobs in the high-risk and low-risk categories across both methods is 0.9651 and 0.9696 respectively (with associated p-values of 0.0000 in both cases). Medium-risk is the only category with a low correlation of 0.5765 (with an associated p-value of 0.0006). The difference in the values can be explained as the detailed occupations classification data covers 86% of those employed (274 occupations out of 324). While the intermediate occupational classifications cover 100% of those employed. It is not possible to identify which individuals in the intermediate occupation classifications do not have detailed occupational information so they cannot be excluded from our imputed analysis and will therefore always induce some degree of bias to our analysis. However, as can be observed from the significantly high correlation coefficients the correlation between the real and imputed remains extremely high. However, as a robustness measure throughout all our analysis we test both the imputed proportion of jobs at high risk and the ranking of towns based on the imputed proportion of jobs at high risk.

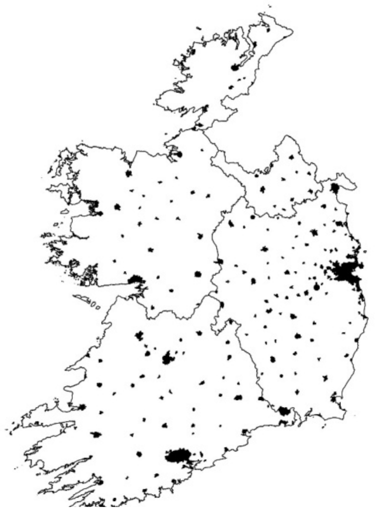
5. The impact of automation on towns in Ireland

We now turn to the analysis of the exposure of Irish towns to automation. In addition, we also identify some of the characteristics of these towns which impacts the extent to which they are at risk.

5.1 Describing Irish Towns

In total we analyse 200 Irish towns and cities with a population over 1,500 people. The distribution of these towns across Ireland is displayed in Figure 6. The largest cities of Dublin and Cork are clearly visible by their footprint with numerous smaller towns being dotted across the remainder of the country.

Figure 6: Map of Irish Towns and Cities



Descriptive statistics for Irish towns are presented in Table 1 below. The average percentage of jobs at high risk of automation across Irish towns is 44.15%, However, there is significant differences in the degree to which the towns are exposed with the lowest proportion of jobs at risk being 26.14% and the highest being 57.79%.

A number of factors are considered including proportion of the population of the town with a third level qualification, the population size of the town, the proportion of the workforce employed in creative occupations, age demographics, the unemployment rate of the town, industrial structure of employment in the town and the level of diversity of the population in the town. Descriptive statistics and all information pertaining to these variables are displayed in Table 1.

Table 1: Descriptive statistics of variables

Variable	Mean	Std. Dev.
Dependent Variable		
Proportion of Jobs at High Risk	*44.15%*	*5.64%*
Independent variables		
Proportion with third level degree or higher	25.73%	6.35%
Age Profile		
Age 19 to 24	6.01%	1.46%
Age 25 to 44	31.29%	3.83%
Age 45 to 64	21.86%	2.97%
Age 65 plus	12.31%	4.19%
Sector		
Agriculture, forestry and fishing (A)	1.52%	1.42%
Mining and quarrying (B)	0.20%	0.29%
Manufacturing (C)	10.84%	4.80%
Electricity, gas, steam and air conditioning supply (D)	0.47%	0.30%
Water supply; sewerage, waste management and remediation activities (E)	0.45%	0.27%
Construction (F)	4.44%	1.42%
Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	12.89%	2.06%
Transportation and storage (H)	3.56%	1.99%
Accommodation and food service activities (I)	6.35%	3.38%
Information and communication (J)	2.81%	1.83%
Financial and insurance activities (K)	2.98%	1.98%
Real estate activities (L)	0.33%	0.20%
Professional, scientific and technical activities (M)	3.75%	1.45%
Administrative and support service activities (N)	2.82%	0.94%
Public administration and defence; compulsory social security (O)	4.27%	1.44%
Education (P)	6.97%	2.08%

Human health and social work activities (Q)	9.13%	2.22%
Arts, entertainment and recreation (R)	1.44%	0.60%
Other service activities (S)	2.08%	0.49%
Proportion Irish	84.44%	6.24%

We begin with presenting the extent of the exposure of Irish towns to the risk of automation by presenting the top 10 and bottom 10 towns in Figure 7a and 7b. Note that these figures are based on imputed values of occupation for towns based. Therefore, the figures are approximate and for illustrative purposes. To emphasise the proportion of the workforce at high-risk of automation calculated is displayed for illustrative purposes. It can be seen that the level of exposure of towns is wide ranging with a low of 26 per cent of the jobs in Bearna at high risk to a high of 58 per cent in Edgeworthstown. These figures are relative to 44 per cent average proportion of jobs at high risk across Irish urban areas. At a county level, these towns span across more than fourteen counties (of a possible 26) and across all the four provinces in Ireland. Hence, the spatial exposure across the country is large.

Figure 6a: 10 Towns at highest risk of automation

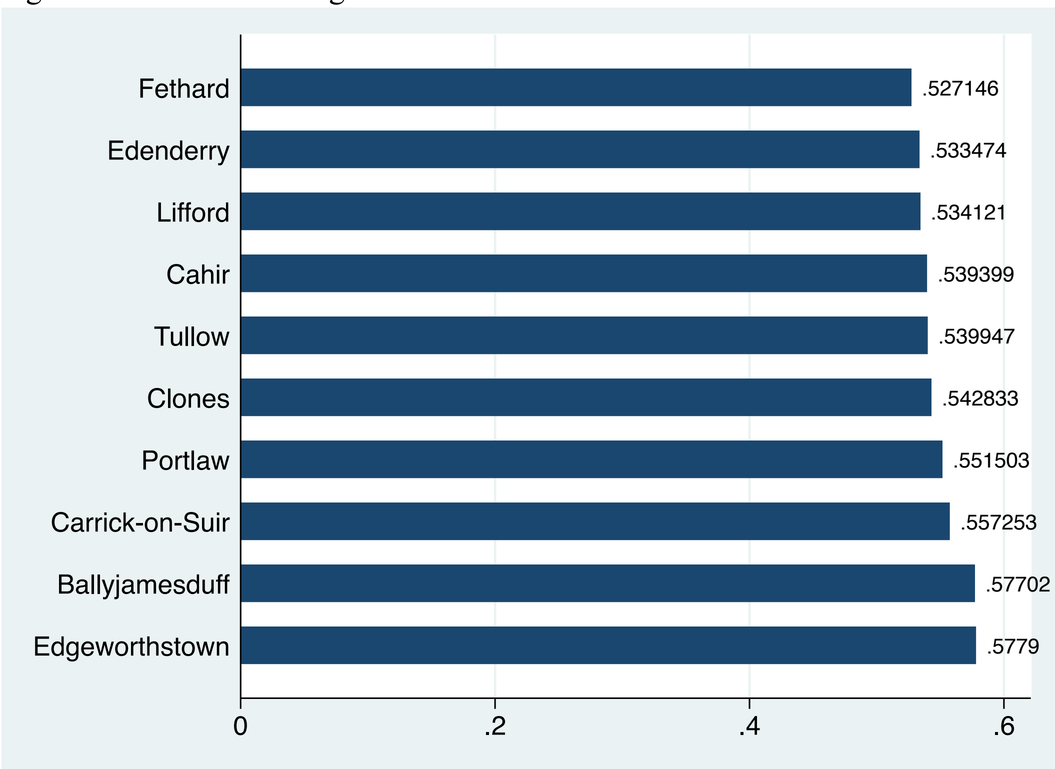
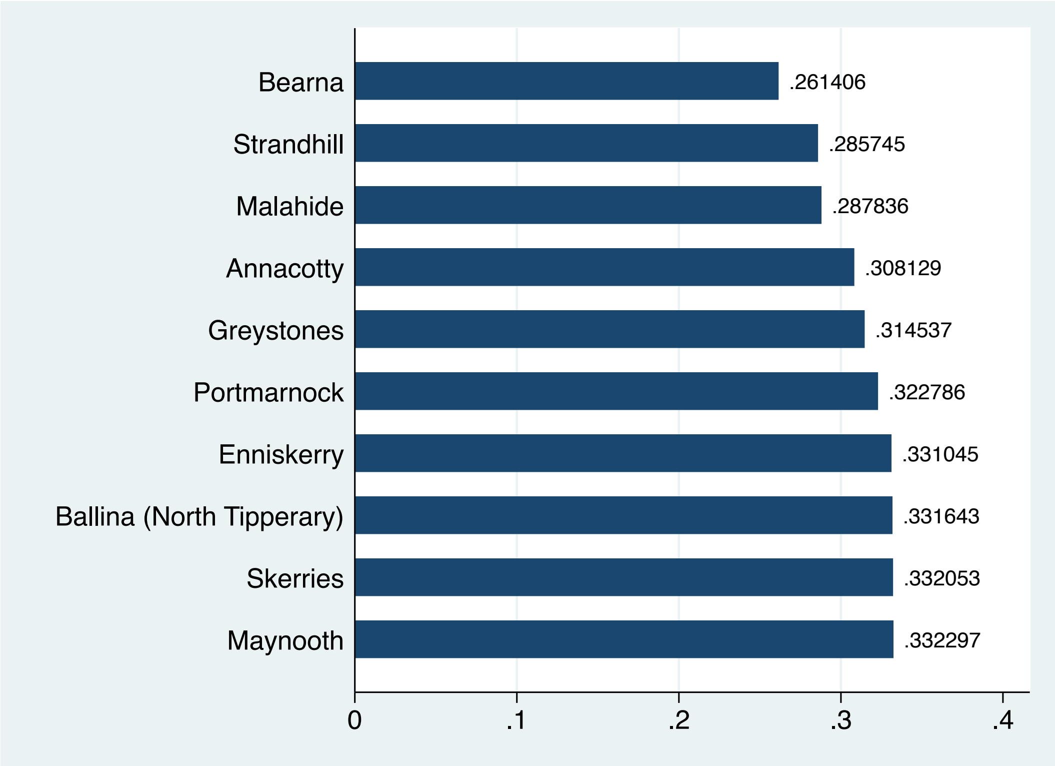


Figure 6b: 10 Towns at least risk of automation

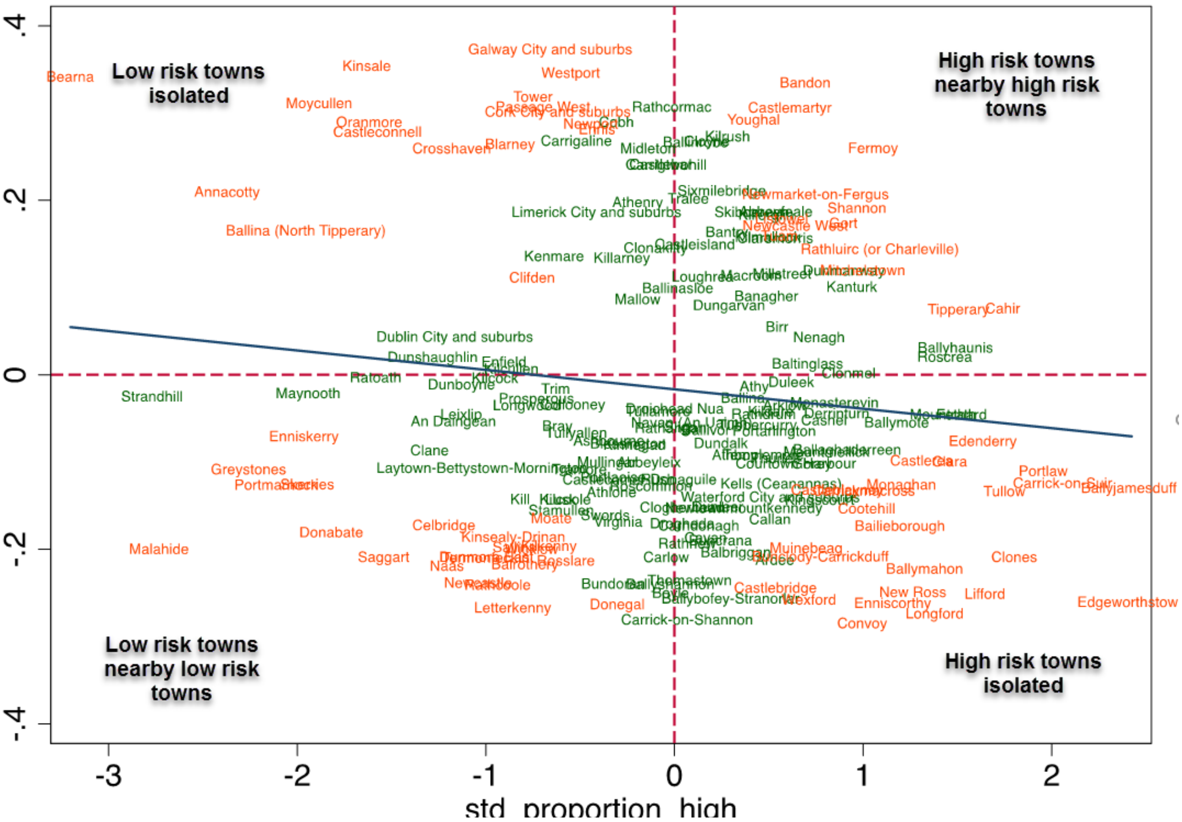


5.2 *Clusters of Exposure*

A natural conclusion from the previous figures is that everywhere is susceptible to automation, with some places that will be more or less impacted than others. But, there also could be a greater spatial concentration of exposure across the country. Figure 7 shows the extent of spatial dependence between low risk and high risk towns across the country. This aspect of the analysis indicates that many *at high risk* towns have *at low risk* neighbours (nearby towns) and many *at low risk* towns have *at high risk* neighbours.

There are also some concentrations of *at lower risk* towns and separately, concentrations of *at higher risk* towns. For instance, in the Dublin city region, Malahide, Skerries and Donabate are all at lower risk of automation. Similarly, some towns are adversely affected by being surrounded by towns *at higher risk* of automation such as Fermoy, Castlemartyr and Bandon (Co Cork) and Shannon and Abbeyfeale (Co Limerick).

Figure 7: Morans I: Measure of Local Spatial Autocorrelation



We can also identify two other patterns from the local spatial autocorrelation estimation where low risk towns and separately high risks towns are located in significant isolation. Some examples of *at lower risk* towns are Kinsale (Co. Cork), Westport (Co. Mayo) and Bearna (Co. Galway). Some examples of *at higher risk* towns include Edgeworthstown (Co. Longford), Carrick-on-Suir (Co. Tipperary) and Clones (Co. Monaghan). This analysis indicates that the spatial exposure has some patterns of clustering but also a spikey zig-zag pattern with many low risk and high towns facing isolated exposure.

5.3 *Modelling the factors which impact exposure of Irish towns to risk of automation*

In order to provide some insight into the factors which might determine the regional risk of automation we estimate equation (1) for the 200 Irish towns for which we have imputed job risk data.

$$Automation\ Risk_i = \beta_0 + \beta_1 Creative_i + \beta_2 Unemp_i + \beta_3 Size_i + \beta_4 Age_i + \beta_5 Industry_i + \beta_6 Nationality_i + \varepsilon_i \quad (1)$$

Where $Automation\ Risk_i$ is the proportion of jobs in town *i* at high risk of automation. As a robustness check this dependent variable is also replaced with a ranked variable which indicates the ranking of *i* from 1 to 200, with 1 being the highest risk and 200 being the lowest risk. $Creative_i$ is the proportion of the workforce which is employed in a creative occupation in town i. $Unemp_i$ is the unemployment rate of town i. $Size_i$ is a series of dummy variables which take a value of zero or one depending upon the size of town i (the size categories used are displayed in Table 1). Age_i age is a series of variables which indicates the proportion of the workforce in each of the age categories used (displayed in Table 1) in town i. $Industry_i$ is a series of variables which indicates the proportion of the workforce employed in each industry (the industries used are displayed in Table 1) in town i. $Nationality_i$ is the proportion of Irish individuals living in town i. The β values are the coefficients of the model and ε_i is the error term.

When estimating the model a series of alternative estimation techniques are applied, to ensure the robustness of the results obtained to alternative estimators. We begin by estimating equation (1) using an OLS regression model with robust standard errors to control for heteroscedasticity. Secondly, in order to account for potential spatial correlation we also run an estimation (1) using a spatial autoregressive estimator. As a further robustness check, to ensure that the results are not biased by our use of the imputed proportion of jobs at risk. We also estimate the model using an ordered probit estimator where the dependent variable is the rank of the risk of automation. Finally, as endogeneity is a potential problem we also estimate the model using an instrumental variable general method of moments estimator. In doing so we need to identify suitable instruments to include. As the number of instruments available is limited we generate artificial instruments through the application of Bartlett's three group method. This approach orders the variables from lowest to highest and generates an instrument which takes a value of -1 for the bottom third of the data, 0 for the middle third of the data, and 1 for the top third of the data. It is important to note that while this method of generating synthetic instruments has been used extensively in the economic geography literature it does not remove the problem of endogeneity, it merely reduces it. Therefore, we are still cautious in interpreting our results, focusing on the identification of associations between the variables as opposed to true causal relationships.

5.4 *The factors determining the exposure of Irish towns to risk of automation*

In this section, we discuss the factors which impact the exposure of Irish towns to automation. Of course, there is an endogeneity (chicken and egg) concern with models like this and there is subsequent uncertainty around causal determination. Nevertheless, associated relations can be identified and provide a rich description of the key areas of concern for future policymaking. The results of the regression analysis are presented in Table 2[4]. In Column (1) the OLS estimation with robust standard errors is presented. Column (2) presents the spatial autoregressive estimation. Column (3) presents the ordered probit estimation. Finally, Column

[4] Our model indicates that there is spatial autocorrelation between the automation exposure of towns and our model is significant and has a very high R-squared at 93 per cent. VIF tests and correlation matrices indicate that there are no multicollinearity concerns in the underlying data.

(4) presents the instrumental variables estimation. We note in relation to the instrumental variable estimation that a test of the exogeneity of the independent variables confirms that the variables are exogenous. Therefore, we do not comment on these results as in this case the OLS estimates are deemed to be more efficient and the sacrifice in efficiency by using an instrumental-variables estimator can be significant.

We find some interesting results in relation to critical mass. Towns with a population less than 5,000 people and greater than 10,000 people are less exposed to automation. This suggests that mid-sized towns may not benefit from the critical mass required to be less exposed and perhaps are not niche enough to have the benefit from being small and distinct. We will elaborate further on this finding in the next section. Not surprisingly we find a significantly large marginal value associated with the proportion of third level graduates in a town. Towns endowed with a more educated workforce are less susceptible to automation. It would be expected that places endowed with a greater proportion of educated workers are more likely to create and attract more highly skilled businesses and jobs that will be less exposed to automation. This is complimented by a greater proportion of creative occupations also significantly reducing automation exposure. It is not surprising that creative occupations are particularly resilient to automation. They have been identified as a crucial pillar for the resilience of economies in the face of impending technological disruption (NESTA, 2015).

Places with younger populations are also less exposed to automation[5]. The most dramatic pattern often described in more peripheral areas is the hallowing out and flight of young talent from more remote areas. The OECD previously highlighted that poor graduate retention and consequent brain drain is a particularly problem in the Border Midlands and Western region (OECD, 2017). It can be identified from the results that industrial structure is a key determinant of automation risk. The results correspond to the patterns illustrated in Figure 3 and they also correspond to other findings in the literature (OECD, 2018; Frey and Osborne, 2017).

There is an exposure hierarchy associated with places that have certain industries and more vulnerable sectors. Places with a greater proportion of employment in mining and quarrying (relative to manufacturing) are the least exposed to automation. This is followed by the arts, entertainment and recreation sector (relative to manufacturing), which aligns closely with the creative occupation effect, previously, reported here. Areas with significant employment in transport and storage, health and support services, public administration and defence, accommodation and food related services, construction and wholesale and retail trade related jobs are also less exposed to automation, relative to areas more exposed to a manufacturing industrial base. Towns with a greater proportion of employment in agriculture are more susceptible to automation, relative to areas more exposed to manufacturing. Surprisingly, places with higher unemployment are less exposed. This may be a signal that some places are already struggling with previous automation disruptions and are in a transition phase and are in effect less exposed to future automation as they are already dealing with past automation disruption. Finally, we find that our diversity measure is not a significant driver of automation risk.

[5] When the reference category is expanded to include the proportion of 19-24 year olds, the results remain robust, where the coefficients on the higher age categories remain positive and significant.

Table 2: Determinant of automation exposure of towns at high risk

VARIABLES	(1) OLS Model	(2) SAR Model	(3) O. Probit	(4) IV Model
Unemployment Rate	-0.115**	-0.114**	-7.506**	-0.128
	(0.0521)	(0.0467)	(3.196)	(0.143)
Creative Occupations	-21.30***	-20.71***	-1,397***	-47.58**
	(6.769)	(6.312)	(472.2)	(21.74)
Population 5,000 to 9,999	0.00754**	0.00748**	0.544***	0.0185**
	(0.00296)	(0.00308)	(0.201)	(0.00841)
Population 10,000 to 49,999	0.00394	0.00315	0.319	0.00860
	(0.00373)	(0.00374)	(0.257)	(0.0102)
Population >=50,000	0.00512	0.00403	0.306	-0.0135
	(0.00887)	(0.00866)	(0.568)	(0.0430)
Third Level Education	-0.538***	-0.547***	-36.23***	-0.537**
	(0.0903)	(0.0715)	(5.725)	(0.241)
Proportion aged 19 to 24	0.237**	0.294***	16.57***	0.187
	(0.0964)	(0.103)	(6.106)	(0.282)
Proportion aged 25 to 44	0.352***	0.364***	24.25***	0.363
	(0.103)	(0.0857)	(6.547)	(0.236)
Proportion aged 45 to 64	0.281***	0.290***	18.46***	0.222
	(0.102)	(0.0890)	(6.593)	(0.226)
Proportion aged 65 plus	0.129**	0.131**	9.705***	0.0650
	(0.0587)	(0.0538)	(3.762)	(0.112)
Agriculture, forestry and fishing (A)	0.232***	0.215**	15.14***	0.363
	(0.0847)	(0.0925)	(5.516)	(0.304)
Mining and quarrying (B)	-1.262***	-1.183***	-82.63***	-0.706
	(0.412)	(0.388)	(27.29)	(0.913)
Electricity, gas, steam and air conditioning supply (D)	-0.820	-0.756*	-52.97	-1.620**
	(0.512)	(0.398)	(34.08)	(0.732)
Water supply; sewerage, waste management and remediation activities (E)	-0.467	-0.474	-29.87	-0.571
	(0.507)	(0.439)	(32.45)	(0.728)

Construction (F)	-0.268***	-0.214**	-17.59***	-0.504**
	(0.101)	(0.101)	(6.447)	(0.231)
Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	-0.137**	-0.113*	-8.620*	-0.295**
	(0.0674)	(0.0659)	(4.492)	(0.139)
Transportation and storage (H)	-0.455***	-0.390***	-28.51***	-0.626**
	(0.0995)	(0.0979)	(6.699)	(0.311)
Accommodation and food service activities (I)	-0.293***	-0.297***	-19.14***	-0.257**
	(0.0581)	(0.0482)	(4.016)	(0.126)
Information and communication (J)	-0.185	-0.123	-13.26	0.626
	(0.171)	(0.162)	(10.98)	(0.582)
Financial and insurance activities (K)	-0.0109	0.0525	-1.036	-0.0611
	(0.113)	(0.0979)	(7.274)	(0.183)
Real estate activities (L)	0.831	0.926	51.18	1.091
	(0.768)	(0.712)	(51.09)	(1.320)
Professional, scientific and technical activities (M)	-0.318	-0.299*	-21.89*	-0.0501
	(0.200)	(0.178)	(13.13)	(0.394)
Administrative and support service activities (N)	0.388*	0.427**	24.52*	0.279
	(0.199)	(0.168)	(12.60)	(0.315)
Public administration and defence; compulsory social security (O)	-0.366***	-0.353***	-26.86***	-0.524***
	(0.0961)	(0.0924)	(6.357)	(0.192)
Education (P)	-0.177	-0.183*	-10.83	-0.240
	(0.111)	(0.0973)	(7.205)	(0.286)
Human health and social work activities (Q)	-0.145**	-0.121*	-9.941**	-0.0504
	(0.0698)	(0.0638)	(4.530)	(0.130)
Arts, entertainment and recreation (R)	-0.629**	-0.535**	-48.19***	0.216
	(0.281)	(0.255)	(17.54)	(0.569)
Other service activities (S)	-0.253	-0.242	-12.45	0.136
	(0.289)	(0.253)	(18.78)	(0.439)
Proportion Irish	0.0100	-0.00398	0.941	0.0129
	(0.0309)	(0.0306)	(1.867)	(0.0943)
			(4.270)	
WY		0.354*		
		(0.197)		

Constant	0.559***	0.390***		0.619***
	(0.0669)	(0.111)		(0.183)
Observations	200	200	200	200
R-squared	0.931			0.905

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusions and Policy Implications

Persistent poverty, economic decline, and limited opportunities are the fundamental drivers of considerable discontent in declining and lagging-behind areas around the world which have become expressed in recent voting decisions in the Brexit referendum, and in the American and European elections (Rodríguez-Pose 2018). The motivation for this paper was driven by those recent developments and the need to identify the significant local effects of automation disruptions that will happen in places across Ireland. How can we shape their future and avoid future geographies of discontent across Ireland?

Our findings conclude a hierarchy of spatial disparities which in summary include: (1) high risk towns near high risk towns; (2) isolated high risk towns; (3) isolated low risk towns and (4) low risk towns near low risk towns. These spatial concerns complicate policy options, because it would not be suitable to have a 'one size fits all' approach. Clearly, not only do many towns have different levels of automation exposure; their favourable or unfavourable spatial exposure in surrounding and nearby towns could also hinder their long run development. Consequently, there is a need to consider regional and local coordination strategies across towns. However, a distinction should be made for towns very exposed to automation that are beyond the city-regions in Ireland i.e. rural areas/urban towns in city regions have different concerns to more remote and peripherally located urban towns and rural areas. The latter face the biggest automation risk and future growth challenges. We would argue these areas need a different policy approach.

In addition to coordinated regional and local strategies, there is also a need for coordinated sector strategies built upon local strengths. It is clear from the results that industry exposure is critical in determining automation exposure. In particular, towns exposed to agriculture and manufacturing should be key concerns as they are likely to be the towns most disrupted by future automation. Smart specialisation strategies and place-based policies (da Rosa Pires et al. 2014) should prove to be a useful policy framework to use in this context. For example, many towns in rural areas in Ireland are highly dependent on agriculture. It is an embedded rural industry with significant local specialised knowledge competencies. Even though many jobs will be automated in agriculture, the ability of towns to leverage from this local knowledge base to create higher added value jobs in related areas will be critical to unlocking untapped potential. Agriculture is closely tied to food innovation, tourism innovation and synergies with the creative industries. The areas of agri-food innovation, tourism and the creative industries are also less exposed to automation as indicated in our results. The creative industries and creative occupations have been identified globally as important contributors to the local and regional economies in rural areas (OECD 2013) leading to creative regions (Scott 2010). The creative industries can be an important catalyst of innovation in rural towns, with spill-overs across many different sectors and they sit at the heart of inclusive, equitable, and sustainable growth and development.

Finally, we have discussed the need for coordinated regional strategies and coordinated sector strategies, but it is also evident from the results that local town place specific factors are driving automation risk. For instance, education levels, age demographics and town size are key issues. Hence, key barriers to unlocking local competencies in peripheral towns will be to curb the brain drain by making skills development and education more financially accessible and remotely possible. Local people will need to respond and drive new social entrepreneurial solutions to tackle the locational challenges as the people in these places are best placed to identify the bottlenecks and problems. In fact, such a model has recently happened spontaneously 'from the grassroots' in peripheral locations in Ireland, which have become known as 'digital hubs'. One such example is the Ludgate Hub in Skibbereen which is attempting to bridge the digital divide between urban and rural areas. If such hubs are supported by nearby regional universities it may help rural areas unlock untapped potential. This bottom-up social-entrepreneurial led initiative may be well placed to successfully help unlock potential in the region. However, one of the trends internationally for successful cities is the presence of successful universities. If universities play a critical role in successful urban development, then they will also need to play a critical role in successful rural development. The ability of regional universities to become more accessible to peripheral communities and to expand their reach to directly support place-based policies such as supporting digital hubs in expanding their delivery of training and education will be critical to the future of remote towns and regions.

It should be noted that the analysis is based on regionally imputed values for towns and covers approximately 86% of jobs in Ireland with the remaining 14% of jobs being in occupations in which there was no data available for automation risk. More precise data on occupations would enable a more detailed analysis of automation risk across Irish regions. These results show how imputation of data for regional analysis of automation risk is possible.

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