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Regional variations in automation job risk and labour market thickness to agricultural employment

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ABSTRACT

Automation has the potential to transform entire agricultural value chains and the nature of agricultural business. Recent studies have emphasised barriers to adoption, as well as issues related to labour market and cultural outcomes of automation. However, thus far, very little attention has been afforded to the regional variations in the potential for automation adoption or threats to agricultural employment. Specifically, research to date does not take into account the local availability of similar occupations including those in different sectors to which displaced workers may transition. Threats to employment and lower numbers of similar jobs locally are particularly salient in rural contexts, given the thin and specialized local labour markets. The aims of this paper are to show the regional distribution of risk to automation for the agricultural sector specifically, and to link these patterns to indicators for occupation specific labour market thickness in Ireland. Using detailed occupational skills data, we construct indices for local labour market thickness conditioned on occupational skills and knowledge requirements. We show that there is substantial regional heterogeneity in the potential threat of automation to the employment prospects of workers currently active in the agricultural sector. This regional heterogeneity highlights the importance of the regional context for designing effective labour market policy in the face of job automation.

1. Introduction

Automation (computer controlled equipment and processes) is expected to become a major disruptive force for business operations, labour allocation, and regional economic development, and for rural areas in particular (OECD 2020). While the impact of automation is expected to permeate throughout each industry's value chain, the outcomes in terms of job creation and destruction are expected to vary substantially from one region to the next (Crowley et al. 2021). Both the OECD (2020) and Frey and Osborne (2017) outline how automation affects the demand for skilled labour, revealing a decrease in the demand for low skilled labour and increased demand for higher skilled labour.

These insights regarding automation and the labour market are the result of a fundamental shift in thinking about the capabilities of automation. Frey and Osborne (2017) showed that recent developments in the fields of machine learning and artificial intelligence greatly expanded the set of tasks that were susceptible to automation. Previously, Autor et al. (2003) split tasks along two axes, routine to non-routine and cognitive to manual. Routine tasks, such as welding (manual) or bookkeeping (cognitive) are considered at least partially susceptible to automation. Non-routine tasks, such as navigating traffic and terrain, or constructing a sales pitch, would be less susceptible to automation in this older model of automation. Frey and Osborne (2017), however, argue that some of these non-routine tasks have already been automated or will be automated shortly, using a combination of big data, machine learning, and improved sensors. Recent studies have highlighted applications using new developments in these broad areas already being rolled out: computer vision to spot plant diseases and identify pests (Carolan 2020), automated steering and milking robots (Rotz et al., 2019), and along the value chains in administration, scheduling, and marketing (Norris 2020). The nature and implications of adoption of these technologies in a rural context is receiving increased attention, ranging from the availability of necessary fundamentals such as broadband infrastructure (Salemink et al. 2017), to implications for labour and equity (Rotz et al., 2019), ownership and data (Carolan 2020), and implications for rural businesses more generally (Norris

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2020; Legun and Burch 2021).

While the literature on the implications of automation for various industries is burgeoning, there is a distinct lack of research dealing with the regional implications of automation for rural areas or agricultural work. Cowie, Townsend, and Salemink (2020), for instance, argue that the expected effects of automation and the fourth industrial revolution (4IR) for rural areas in general remain under-researched in the scientific literature, stating that "[t]he rural should no longer be the tailpiece of urban-centred research on smart developments and 4IR" (p. 175). For the agricultural sector in particular, based on a detailed bibliometric review, Malanski et al. (2020) find that automation and the 4IR do not feature as primary research domains. Crowley and Doran (2019), as a rare exception, take regional variations in the concentrations of skills and agglomeration economies as their starting point and reveal a detailed geography of the expected labour market effects of automation. However, while they consider smaller towns, they do not explicitly consider rural regions.

Generally, agricultural, rural, and less densely populated regions contain more jobs at risk of automation than larger, more dense agglomerations (Frank et al., 2017; Crowley et al. 2021). The case for an increased focus on agricultural automation is particularly pressing for two reasons. First, labour markets are thin in rural regions where most agricultural activity takes place, meaning fewer alternative employment opportunities for displaced workers. These compound the problem of involuntary labour market transitions and their associated negative effects on individual and household distress (OECD 2020; Nikolova and Cnossen 2020). Second, the agricultural sector is highly diverse with substantial geographical specialization (Abson 2019). Within the agricultural sector, regional shocks from automation are compounded by geographical clustering as displaced workers with relatively similar skill-sets may compete for the few similar jobs that are available.

This paper makes three contributions towards addressing the existing gaps in the literature. Firstly, we explicitly analyse local exposure to automation for occupations in agriculture. This addresses the current gap in the literature regarding agriculture specific developments in the 4IR (Cowie et al. 2020; Malanski et al. 2020) and emphasises the unique geographical and labour market positions of agricultural employment. Secondly, we develop a novel approach to measuring local labour market thickness incorporating a measure of skills- and knowledge-based similarity. We address the issue of strict sector or occupational bounds in the job automation risk literature by combining the explicitly regional analyses in automation by Crowley et al. (2021) with the knowledge base framework used by Qian (2017). Finally, we develop a framework for analysing regional patterns in exposure to automation and the ability for local labour markets to absorb displaced labour using Ireland as a case study. The measure we introduce incorporates local externalities in labour market pooling, both in demand and supply of labour, by including employee transitions between similar occupations (Qian 2017).

To assess the local exposure to automation, we adapt the automation exposure model developed by Frey and Osborne (2017) to Irish Census regional occupation data (CSO 2020) for 31 administrative counties and cities to provide a detailed overview of which occupations are at risk of automation. Using the O*NET data (National Center for O*NET Development, 2021a) on occupational skills and knowledge, we construct a similarity index to approximate relative labour market thickness/thinness. Both Arntz et al. (2016), using the OECD (2020) measures, and Bessen (2015), based on an early version of Frey and Osborne (2017), argue that jobs displaced by automation is not the same as jobs lost. Displaced workers can shift to occupations that are at lower risk of automation, provided that this type of employment is available locally. The approach we develop is conceptually similar to the knowledge base approach developed by Qian (2017) and Asheim et al. (2007), but applied at the level of the occupation rather than the region. This approach is used to identify occupations that are similar in content to the occupations at risk. We use these measures to reveal the geography of expected risk associated with automation relative to occupation specific labour market thickness/thinness. Conditioning our results on the skills- and knowledge-composition of occupations means the outcomes incorporate both the rural and the urban risk to jobs of automation. These results provide a first insight into regional differences in the expected stress placed on the labour market due to automation in both urban areas and rural areas.

This paper proceeds as follows: Section two provides a background of the literature on automation more broadly, and for rural areas and agriculture more specifically. Section three outlines the data used for the analysis and the methods applied. All analyses, code, and project-specific data are provided as an appendix, with links provided to the public data sources used. The results from these analyses are presented in section four, followed by a discussion of limitations in section five, and the conclusions and implications for policy in section six.

2. Automation, rurality, and agriculture

2.1. Broad expectations of job automation and disruptions to labour markets

The developments around automation follow in a broader line of adopting machinery and technology to improve productivity, each with its own shifts in demand for skilled and unskilled labour. In a very brief summary,[1] the introduction of the production line in the area of manufacturing led to the vertical disintegration of labour, with individuals specializing into tasks rather than whole products. This led to a decreased demand in high-skilled labour as individuals increasingly focused on small sets of more routinge tasks. Subsequently, mechanization resulted in low skilled routine labour being replaced by machines. This reduced the demand for low-skilled labour and increased the demand for skilled machine operatives. This is broadly speaking where the Autor Levy Murmane (ALM) model of automation fits (Autor et al. 2003), in which tasks are either cognitive or manual, and split up into routine and non-routine. Routine tasks, performed in controlled conditions and with a comprehensive set of rules guiding the process, are subject to automation. Non-routine tasks, even if they are very similar to routine tasks but without controlled and rule guided conditions, are beyond the reach of automation.

One of the key aspects of automation, in line with previous developments in mechanization, is the expected displacement of labour (Frey and Osborne 2017; OECD 2020). Given the prospective nature of the impacts of automation, there is much disagreement on the expected directions regarding labour and skills demand. Precise estimates of occupations' exposure to automation vary greatly depending on the method of assessment. In the more moderate estimates (OECD 2020) 14 per cent of jobs across OECD countries are at risk of being automated altogether, while an additional 32 per cent could see significant changes, while the estimations by Frey and Osborne (2017) are higher, suggesting that 47 per cent of jobs (in the US labour market) are at high risk of being automated. The main difference between both methods is that the OECD (2020) method relies on individual level task descriptions, while Frey and Osborne (2017) use occupational level task descriptions. Occupations (e.g. "Farm workers") can contain substantial heterogeneity in terms of the specific tasks an individual may perform. Frey and Osborne (2017) initially use expert judgment to identify occupations that are completely automatable for a subset of occupations, and subsequently use a probabilistic model to identify the tasks that contribute to automation risk for all occupations. Nedelkoska and Quintini (2018), which forms the basis for OECD (2020), are informed by these task probabilities of automation. They start from the tasks that are unlikely to be susceptible to automation, the so called automation bottlenecks identified in the methodology of Frey and Osborne (2017) and apply these to a

[1] Frey and Osborne (2017) provide a much more comprehensive overview.

different dataset that contains individual's self-reported assessments of the tasks they perform. Taking this lower level of aggregation as a basis leads to fewer jobs classified as having either a high or a low risk of automation, and more jobs at the medium level of risk. Although Frey and Osborne (2017) and OECD (2020) return different values for the absolute risk of automation, both results are similar in their ranking of jobs at risk of automation (Nedelkoska and Quintini 2018; Frank et al., 2017, 2019). Similarly, both methods result in relatively large shares of the labour market exposed either to full automation, or significant changes to occupational tasks because of automation. So while there is some uncertainty and discussion around the absolute values of automation risk Frank et al. (2019) suggest that the values of the OECD (2020) and Frey and Osborne (2017) be taken as relative, as opposed to absolute, indicators of risk.

What happens to individuals whose tasks are automated is the next point of contention (Frank et al., 2019). On one side of the spectrum of possible outcomes, the work by Bessen (2015) shows that the introduction of robots historically has had little to no effect on employment numbers while simultaneously raising wages, as a result of increased productivity. The same conclusion is reached by Lane and Saint-Martin (2021), based on a literature review, stating that most of the empirical results thus far reveal a small or ambiguous impact of automation on jobs. On the other extreme, automation can be expected to eradicate the need for the majority of human labour (for an overview and critical review, see Wajcman 2017). Between these, Arntz et al. (2016) and Lane and Saint-Martin (2021) review a number of studies suggesting labour displacement and shifting demands in terms of skill composition, rather than substitution. Labour saving technologies require development and implementation, subsequent lower production costs will increase demand for products, and in many cases, some human labour will still be required to complement the automated processes (Lane and Saint-Martin 2021). One example of this in the agricultural context, given in Rotz et al. (2019), is where automated steering on tractors is used to complement lower skilled labour. Both in the skilled and the unskilled scenarios, one person drives the tractor. The effect of de-skilling in terms of machine-operation is offset by an increased and possibly unmet demand for skilled labour required for the implementation of automation (Rotz et al., 2019; Wajcman 2017). This leads to the idea of a bifurcated labour market, with plenty of low-skilled and high-skilled jobs, but fewer middle skilled jobs. Frey and Osborne (2017) find that this may not be the case in general, with the demand for occupations requiring[2] a bachelor's degree remaining mostly intact, while occupations with lower educational requirements bearing the brunt of the expected automation related displacement.

2.2. The ALM model and agricultural employment

Since the onset of the 4IR, the conceptualized split between routine and non-routine tasks meant until recently that most processes performed in agriculture were less exposed to automation. While driving machinery in strictly regulated environments were implemented in for instance container-ports (Liu et al., 2004), the variability of cropland layouts, weather and soil conditions, yields, and tasks that were needed while navigating, placed these beyond similar levels of automation (Bac et al., 2014). The complications involved in the harvesting of crops, for instance, include: issues in detecting the crop; detecting whether the crop is ready for picking; and the manual dexterity to perform the picking without damaging either crop or remaining green-stock. Manual farm labourers can quickly and efficiently perform the cognitive tasks of identifying what needs to be picked, and the manually dexterous task of picking the crop, and for such reasons automation beyond machination made only little headway in most areas of farming (Bac et al., 2014).

[2] Technically, the results are based on the degree attained, rather than the degree required to fulfill the job.

Recent developments in the design and capabilities as well as cost of robotics have changed the likelihood of automation disruptions in agriculture dramatically. Graetz and Micheals (2018), for instance, calculate that the quality-adjusted cost of robotics decreased 80 per cent between 1990 and 2015. With increasingly cheap and available processing power, more and better sensors, and the introduction of machine learning, machines are expected to take over more non-routine tasks (Frey and Osborne 2017). Over the past decade it has become clear that tasks such as navigating difficult terrain, identifying crops, crop-maturity, and operating in non-routine environments can be automated either now or in the near future (Legun and Burch 2021). As a result of these advances in technologies, automation and its consequences are now of increased relevance to rural economic policy.

2.3. Rural specialization, migration, and mobility barriers

The impact of future automation will most likely be shaped by distinct industrial structures, skills and knowledge bases (OECD 2020). Crowley, Doran, and McCann (2021) provide a first assessment of the geography of these impacts. They consider two alternative processes based on a detailed analysis of regional industrial composition and specialization: First, highly specialized regions are no more or less exposed to job automation, relative to less specialized regions. However, more diverse regions (or more specifically, regions with high levels of unrelated variety) are more likely to be resilient to shocks which they argue can be attributed to the portfolio effect of Jacobs externalities. The results in Crowley et al. (2021) point to the importance of diversity (unrelated variety) over specialization as instrumental in providing regional resilience to the shock of automation. Furthermore, they identify that regions benefiting from higher population densities and higher shares of knowledge and creative workers are less exposed. Together, in general, these agglomeration factors are more likely to be found in regions benefiting from labour market thickness.

Rural areas present a number of specific challenges to displaced workers as almost by definition they possess thin labour markets (Findlay et al. 2000; Stockdale 2006). Thin labour markets mean fewer alternative employment opportunities are available locally, and larger distances between rural labour market centres mean longer travel times for those willing (or having) to go further afield for employment. Rural areas provide fewer opportunities for entrepreneurship (Delfmann et al., 2017), innovation (Salemink et al. 2017; Norris 2020), and have lower productivity (Bosworth and Venhorst 2018). Explanations for this lower level of entrepreneurship are that rural areas are less well connected (Cowie et al. 2020) and have smaller local markets in terms of both labour supply and consumer demand (Delfmann and Koster 2016; Delfmann et al., 2017). Finally, low densities of labour and firms are of themselves associated with lower levels of innovation (Koster et al., 2020). Both lower levels of alternative employment and a lower capacity for new firm formation mean displaced workers in rural areas face a steeper slope towards labour market re-entry than those in urban areas. The argument here aligns with predictions of the disequilibrium model of migration where migration is the outcome of a disequilibrium between regional labour demand and labour supply functions. Regions experiencing a decrease in labour market opportunities should experience negative net migration or increased commuting (Rijnks et al. 2018; McCann 2013), where commuting over longer distances is an unstable temporary resolution (Hoogstra et al. 2011; Hoogstra et al. 2017). Both the individuals migrating (Tiebout 1956) and the regions losing inhabitants (Bosworth and Venhorst 2018) incur a cost in this transition.

From a demographic point of view rural areas differ form urban areas. Both population decline and population ageing mean the share of older individuals in the labour force is higher (Franklin and van Leeuwen, 2018). Older workers are at a higher risk of labour market displacement and struggle to find new work (OECD 2020). Koster and Brunori (2021) show that older age groups are less likely to have recently attended non-formal education (e.g. on the job training) and re-skilling. As age is inversely related to the time to recuperate investment in new skills, it makes intuitive sense that older individuals are less likely to attend non-formal education. However, this lower probability of re-skilling means workers that are more exposed to automation and with more outdated skill-sets (OECD 2020) will have a lower probability of obtaining the skills required to re-enter the labour market. Indeed, Koster and Brunori (2021) find that both age and risk of automation are negatively associated with the probability of attending non-formal education, and the OECD (2020) find that older aged individuals need more time to find new employment. In terms of relocating, older individuals face higher barriers to mobility (Morrison and Clark 2011). These barriers to mobility are not exclusive to older aged individuals, with work by Storper (2018) and Iammarino et al. (2019) highlight barriers involving place-based skills deficits (i.e. the interconnectedness of human capital means it can only be acquired *in situ*), varying mortgages costs, or costs of living in rural to urban migration. The combination of labour displacement as a result of automation and the unique geographical challenges faced by displaced rural workers highlight the current urgency for insight into exposure to automation, digitalization, and robotization.

2.4. Knowledge bases

The match between an individual's current skills-sets and the skills-content of locally available jobs is an important moderating factor to the transition to new employment. Conventionally, regional specialization and concentration of related and unrelated variety are used in economic geography to explain regional economic performance (Brown et al. 2013; Crowley et al. 2021). Among the externalities used to explain the association between concentration of firms and regional economic growth is the idea of a shared pool of labour: regions with a high density of firms that require a certain skills-set attract individuals with those skills. The local availability of this pool of suitable labour subsequently reduces firms' labour search costs. Similarly, in the case of labour market displacement, individuals should fare better in regions where similar skills are in demand. Previous empirical findings confirm that skills relatedness is an important factor in people's movement between jobs (Boschma et al. 2014). This makes intuitive sense, as most people will build on their experience and skills when looking for a new job. Nedelkoska and Quintini (2018) show that individuals at high risk of losing their job through automation in Germany are more likely to obtain a second qualification that is similar in skills-content to their first qualification, enabling a transition to occupations at a lower risk of automation. Combining the insights regarding the importance of skills content and lower skills development for individuals at high risk of automation (Boschma et al. 2014; Koster and Brunori 2021), and the importance of local over inter-regional labour market opportunities (Boschma et al. 2014; OECD 2020), we argue that to accurately model the local exposure to automation requires a novel measure of skills and knowledge specific labour market thickness.

In this paper we adapt a common framework to study regional concentrations of industry types, the knowledge base apparatus, to measure concentrations of skills and knowledge for individual workers. Knowledge bases have previously been used to explain clusters of innovation and firm performance (Qian 2017). Asheim, Coenen, and Vang (2007) initially used the concept of a knowledge base to explain the differences in industry performance by region. The idea is that the co-location of similar sets of knowledge, combined with their associated methods of communication ('face-to-face' or 'buzz') contribute to and enhance locational externalities. Asheim, Coenen, and Vang (2007) argue for three knowledge bases, the analytical (scientific), synthetic (engineering), or symbolic (creative) knowledge bases, each relying in different measures on 'buzz' (informal, group based knowledge) or 'face-to-face' (complex tacit knowledge) for transmission, while Qian (2017) identified six knowledge bases from empirical data (management, biomedical, engineering, arts and humanities, transportation, and agricultural). We use a similar empirical application as the one in Qian (2017), applied to occupations rather than regions, to identify patterns of similarity between occupations. By taking the skills and knowledge content of occupations across industries we are able to determine potential and probable transitions for individuals at high risk of automation.

2.5. Geographical context

This section provides background context on the Irish agricultural sector.[3] In total 265,400 people were employed in the agricultural sector in Ireland in 2016 and this figure has remained relatively stable over the past 10 years (CSO 2018). The EU Labour Force Survey (LFS) in 2016 identifies that Ireland has the lowest proportion of female farmers of any EU country and the highest proportion of people aged over 65 employed in the agricultural labour force (Eurostat 2019). Family labour (defined as persons who help another member of the family to run an agricultural holding, provided they are not an employee of the holding) in Irish farms accounts for over 90% of agricultural work.

Based on the Irish Farm Structure Survey (CSO 2016) in 2016 the total number of farms in Ireland is approximately 137,500 with the average farm size being 32.4 ha, which is above the EU farm size average of 16.6 ha (Eurostat 2019). This was a fall on 1.5% in the total number of farms in Ireland since 2013. Of these approximately 137,100 are family farms with 88% of these being a male holder and 12% being a female holder. Only 5% of these farms are run by someone under the age of 35 while 30% are run by individuals over the age of 65 (CSO 2016). Of the almost 4.9 million hectares of Agricultural Area Used (AAU) land in Ireland in 2016, 4.1 million was dedicated to Grassland and the remainder comprised of 208,400 dedicated to cereals and 71,100 dedicated to other crops, fruits and horticulture.

In terms of farm types, specialized beef production dominates accounting for approximately 57% of farms across Ireland and in that context follows farm patterns in North West Europe where specialist livestock farming is the dominant activity. However, in terms of Ireland's regions, specialized beef production is concentrated in the border, midlands and west (BMW[4]) region of Ireland accounting for 58.7% of farms (Eurostat 2019). Specialist dairy production accounts for approximately 11.7% of farms in Ireland but 78.3% of these farms are in the southern and eastern (SE) region of Ireland, showing a clear regional divide. This has implications for regional farm productivity. The average standard output per farm in the SE was just under €65,000, while it was just under €29,000 in the BMW.

3. Data and methods

3.1. Data

3.1.1. Occupations and risk of automation

To establish regional variations in the automation job risk, this paper applies the estimates derived by Frey and Osborne (2017) to Irish Census data for2016.[5] Briefly summarised, Frey and Osborne (2017) use

[3] Note we focus mainly on describing the state of Irish agriculture in 2016 as this is the date of the last Irish Census (which is the main source of data used for our analysis).

[4] While the region under consideration in this paper remains entirely in the European Union, it stands to reason that the current and expected changes to the border arrangements with the United Kingdom will affect various aspects of the agricultural sector, both in the neighbouring BMW regions and for the Irish agricultural sector. Given the uncertainties of the exact arrangements, and the absence of reliable data regarding the impact of these changes on automation in the agricultural sector, we dare not speculate on what transitions may be expected, but emphasise that this is an issue of critical importance and uncertainty for the region.

[5] The 2016 Census is the most recent Census for Ireland.

machine-learning experts to assess whether a subset of 70 occupations could be "sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment" (p.263, Frey and Osborne 2017). Using O*NET data (National Center for O*NET Development, 2021a) on task levels performed within those occupations, Frey and Osborne (2017) then expand the probabilities of automation to the entire set of 702 occupations in the database. In their final step, occupations are categorised as either high, medium, or low risk of automation. Occupations at a high risk of automation are those that score a probability of more than 70 per cent, medium risk have a probability of between 50 and 70 per cent, and low risk occupations are below 50 per cent (Frey and Osborne 2017; Crowley and Doran 2019).

The occupational risk codes provided by Frey and Osborne (2017) are for the 2010 United States Standard Occupational Codes (SOC, Office of Management and Budget 2009). To apply these codes to the Irish data, the codes are initially transferred to ISCO codes (International Labour Office 2012), for which crosswalks are available (Bureau of Labor Statistics 2012). The ISCO codes were subsequently adapted to the Irish data, following Crowley and Doran (2019), yielding a total match of approximately 86 per cent of all Irish occupations.

A number of alternative estimations of automation job risk have been provided by other authors. Nedelkoska and Quintini (2018) use data at the level of jobs, nested in the occupations used by Frey and Osborne (2017). A single occupation category, e.g. farmers, encompasses a variety of different types of jobs, and each job may have a different exposure to automation. A key finding from this study is that the overall risk may be lower, and that the Frey and Osborne (2017) paper overestimates both high risk and low risk occupations. Nedelkoska and Quintini (2018), however, conclude that the increased resolution alters the shape of the distribution of risk of automation, leading to fewer jobs classified as at a high risk of automation, but leave the general ordering (low to high) intact (Nedelkoska and Quintini 2018). For our data focusing on agriculture in Ireland, the data used by the OECD (2020) or Nedelkoska and Quintini (2018) provide insufficient numbers of cases to reliably analyse automation risk at the sub-occupation level, with only eight respondents in the survey. Lane and Saint-Martin (2021) provide an overview of several other studies focusing on Artificial Intelligence (AI) as the disrupting change and highlight some different methods of classifying the exposure to AI. Our ability to use these as inputs for our analysis is limited to the availability of detailed risk classifications at the occupational or job level, which are not provided by the other studies. We therefore proceed using the Frey and Osborne (2017) assessment, acknowledging that the ascribed risks are ordered correctly but may overestimate the absolute risk for higher risk occupations, and underestimate the absolute risk for lower risk occupations.

A benefit of using occupational risk classifications tied to the O*NET datasets is that these datasets are rich in information on occupational compositions. The datasets provided allow for the combination of the risk of automation with the requirements placed on the skills and knowledge by the employees. For our study, we use the O*NET data tables on the level and importance of skills and knowledge by occupation. The O*NET data tables are constructed using a combination of job-incumbents and expert analysts (Fleisher and Tsacoumis 2012). These data are used as inputs to assess occupational similarities, which are then transformed into indices for occupation specific local labor market thickness.

3.1.2. *Regional data from the Irish Census*

For the regional analyses we use the Irish 2016 Census data for Local Authorities in Ireland (N = 31). This is the lowest level of aggregation for which detailed occupational data are available. The Irish Census is conducted every five years, most recently in 2016. The mean number of jobs in 2016 per county was 54,055, up slightly from 53,579 in 2011, with a median of 43,489 in 2016 (up from 42,938 in 2011). The largest areas in the data in terms of employment are Dublin City and Cork County at 206,395 and 151,121 jobs, and the smallest are Leitrim and Longford at 10,992 and 13,328 jobs.

3.2. *Methods*

The aims of this paper are to show the regional distribution of risk to automation for the agricultural sector specifically, and to link these patterns to indicators for occupation specific labour market thickness. The former is relatively straightforward and follows the established literature (Frey and Osborne 2017; Frank et al., 2019; Crowley et al. 2021). In the following section we therefore focus on the methods and data used for deriving the occupation specific labour market thickness indices.

The O*NET tables used in this study contain detailed data on the content of occupations. The content assessed in the O*NET data is organized in the O*NET content model (National Center for O*NET Development, 2021c). The data are organized in six categories, including Occupation-Specific Information, which is the foundation for the assessment of job risk of automation, and Worker Requirements, which forms the basis for this analysis. The Worker Requirements datasets include detailed information on the Skills and the Knowledge required to perform a certain occupation, distinguishing 29 types of skills and 33 types of knowledge. Supplemental Tables S1 and S2 list all Skills and Knowledge assessed.The data on Skills and Knowledge are each collected in a slightly different way. Information on occupational Knowledge requirements is collected through standardized employee surveys, while information on occupational Skills are collected from a group of occupational analysts.[6] For both Skills and Knowledge, data are available on the *level* required, and the *importance* of this aspect within the occupation (see National Center for O*NET Development, 2021b for more detail on the interpretation of the level and importance). In this paper we focus on the level required to perform an occupation, as the skill-topology determines whether an individual may be able to transition without substantial re-training (Alabdulkareem et al., 2018; World Economic Forum 2018).

To give an impression of the content of the O*NET tables used in this study, Fig. 1 shows a subset of the indicators used for three occupations: *farmers*, *psychologists*, and *conservation and environmental associate professionals*, all plotted relative to the skills and knowledge employed by farmers. Psychologists require more in terms of therapy and counseling, sociology and anthropology, speaking and service orientation. Conversely, farmers require higher levels of skill in terms of production and processing, operations monitoring, management of material resources, quality control, and so on. On the other hand, conservation and environmental associate professionals are much more closely aligned in terms of skills and knowledge to the occupational requirements of farmers. There are differences in terms of the level of history and archeology, or communications and media, but in general the occupational requirements are closely aligned. While farmers are considered at high risk of automation, conservation and environmental associate professionals are considered at low risk.

In this paper we use k-means clustering to systematically group together occupations that are similar over a broad range of skills and knowledge. The approach we use is similar to the knowledge base approach by Qian (2017), who used principal components to identify the main types of knowledge that are associated with innovation. Knowledge base definitions range from the very broad (tacit-codified spectrum, Lever 2002), to more specific dimensions such as analytic, synthetic and symbolic (Asheim et al. 2007), or management, biomedical, engineering, transport, agricultural, and arts and humanities (Qian 2017). The knowledge bases are identified based on the occupational use of types of knowledge provided by the O*NET data sets, and

[6] For a more comprehensive overview of the data collection skills assessment processes see Fleisher and Tsacoumis (2012).

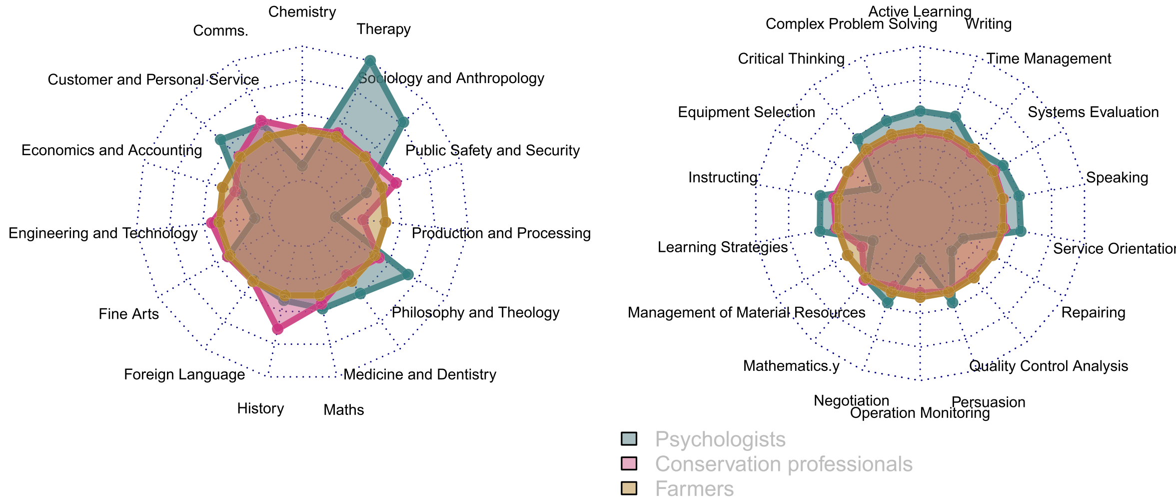

Fig. 1. Similar and dissimilar jobs based on skills and knowledge requirements.

subsequently aggregated using numerical classification algorithms. In the case of Asheim et al. (2007) and Qian (2017), principal component analysis means a reduced number of dimensions of knowledge are identified.

For this study we deviate from the conventional calculation of knowledge bases in three ways. First, we calculate knowledge bases at the level of occupations, rather than regions. The occupational approach allows us to estimate local labour market thickness where the regional approach does not. Second, whereas Qian (2017) take the product of both knowledge level and importance to calculate regional knowledge intensity, we limit the data used in our paper to the level variables. The reason for this is that the levels of skills and knowledge required dictate whether an employee can transition between occupations, rather than the importance of those skills within those occupations. Finally, we extend the data used to include both the level of knowledge and the level of skill required in each occupation. While the focus on knowledge makes sense in the context of new economic geography models of regional growth, as a key driver of innovation and entrepreneurship (Koster et al., 2020), both skills and knowledge deficits determine the degree of re-training involved to transition from one occupation to another.

To calculate occupational similarity we use a k-means clustering analysis across the skills and knowledge components of all occupations. The k-means clustering analysis is an unsupervised machine learning technique that groups similar observations together. The central idea is that observations are plotted on an n-dimensional space based on n characteristics (variables). In our case, the skills and knowledge levels form the characteristics, and the observations are the occupations. The algorithm then places the occupations within groups in such a way that the within-group distance is minimized, i.e. the occupations in each group are most similar, and the difference between occupations in different groups is maximized. We use the base kmeans package (R Core Team 2021), taking Euclidean distances as our distance measure, and the Hartigan and Wong (1979) algorithm to optimize clusters. We use the gap-statistic to find the optimal number of clusters, and use 50 random starts of the algorithm to ensure the results are not based on a single estimation. The gap statistic (Tibshirani et al. 2001) maximizes the difference of the between-cluster variation for k clusters with the difference under the null-hypothesis of no clustering. A large gap statistic means that the distribution of occupations grouped in k clusters differs most from a uniform distribution of points. We use the implementation from the *clusGap* function (Maechler et al., 2021), which selects k such that it is no more than one standard error lower than the first local maximum. To assess the robustness of the identified groupings we perform a bootstrap analysis ($N = 1000$) and calculate the Jaccard similarity coefficient (Henning 2020) weighted by the number of jobs in each occupation. The Jaccard similarity coefficient compares bootstrapped clusters with the original cluster to assess how similar they are. The coefficient is a proportion where the enumerator is the number of jobs that are both in the original cluster containing, for example, "Farmers," and in the bootstrapped cluster containing the same occupation. The denominator is the number of jobs that are in either of those clusters.[7] If the sets are perfectly concordant, the Jaccard statistic equals 1, while the theoretical minimum approaches 0. If the same jobs are in the relevant cluster less than half the time ($JacM < 0.5$) this indicates the cluster could not be established with any real certainty. If the Jaccard coefficient exceeds 0.7 the clusters are recovered relatively well, while Jaccard coefficients over 0.9 indicate high cluster reliability.

4. Results

4.1. Agricultural occupations

The first step in the analyses is to identify which occupations are agricultural. Occupations are not exclusively nested within industries. Industries are determined at the level of the establishment, whereas occupations are determined at the level of the individual worker. Accountants, for instance, may find employment across a range of industries. To identify which occupations are agricultural we take the share of jobs in an occupation that are classified as being part of the broad industry group agriculture, forestry and fishing. Table 1 shows the results of this exercise. For instance, 98 per cent of *farmers* are employed in the broader agricultural industries,[8] and similarly high shares are found for occupations that can be easily classified as agricultural. Lower shares are found in the *horticultural trades* and *managers and proprietors in forestry, fishing and related services*. For this study, we classify occupations as agriculture if more than half of all jobs in that occupation are within the broader industry group of agriculture, forestry and fishing. Consequently, the next occupation in terms of agricultural share in Table 1, *sports players*, and all occupations with a lower share of jobs in agriculture are not included as Agricultural occupations. Based on this definition we define eight occupations as being agriculture based. The next column shows the total number of jobs in 2016 in each occupation in the agricultural sector in 2016. By far the largest group are *farmers*,

[7] $J(A,B) = \frac{|A \cap B|}{|A \cup B|}$

[8] 1.5 per cent of farmers are not classified in a specific industry, 0.2 per cent are in (E) Water Supply, Sewerage, Waste Management and Remediation Activities.

Table 1
Agricultural occupations.

Detailed.Occupational.Group	PerCentOfOccupation	Jobs	Auto_Cat	Cluster	JacM	JacSD
Farmers	98.0	67,960	High Risk	7	0.717	0.250
Managers and proprietors in agriculture and horticulture	87.6	918	Low Risk	9	0.750	0.224
Forestry workers	84.7	1006	High Risk	7	0.731	0.235
Agricultural and fishing trades n.e.c.	82.2	1847	Medium Risk	7	0.731	0.235
Agricultural machinery drivers	69.9	425	High Risk	11	0.755	0.191
Fishing and other elementary agriculture occupations n.e.c.	59.5	1746	High Risk	14	0.744	0.230
Managers and proprietors in forestry, fishing and related services	52.6	205	Low Risk	9	0.750	0.224
Horticultural trades	50.7	564	Medium Risk	7	0.697	0.281
Sports players	35.1	370	Low Risk	13	0.202	0.262

[a] Auto_Cat: Job automation risk category.
[b] Cluster: K-means cluster identifier.
[c] JacM: Jaccard similarity coefficient.
[d] JacSE: Jaccard similarity standard error.

with 67,960 jobs in that group. *Farmers* are also at a high risk of automation, which applies to *forestry workers*, *agricultural machinery drivers*, and *fishing and other elementary agriculture occupations not else classified*. Occupations in management in the agricultural sector are at a lower risk of automation, while those employed in the trades-related occupations are classified as a medium risk.

4.2. Occupations and clustering

Fig. 2 shows the evaluation metrics for the k-means clustering analysis. Based on the gap statistic optimalization routine, the optimal number of clusters is 23. An overview of these clusters is provided in Fig. 3. The overview is not very instructive due to the large number of clusters. While the optimal number of clusters is 23, agricultural occupations are confined to four of these clusters. In the following analyses we focus our interpretations on these four clusters.

Fig. 4 gives a more detailed look at the first of the four agricultural clusters. As is usual in displaying k-means clusters, the x- and y-axes represent the first two components of a principal component analysis performed on the occupational skill and knowledge data (Kassambara and Mundt 2020). These two components account for just over 60 per cent of the total variation in the data (see Fig. 3). Points that are closely placed together represent similar jobs (on these two principal components). All the points shown in Fig. 4 are part of this one cluster. Finally, there are three types of data shown in the drawing of the points. The shape of the points corresponds to whether the occupation is agricultural or not. The size of the point corresponds to the log of the total number of jobs in that occupation in 2016, and the colour reflects the risk categories of automation as defined by Frey and Osborne (2017).

Cluster 7 in Fig. 4 includes most of the agricultural occupations including *farmers* and *forestry workers*. Both *farmers* and *forestry workers* are considered to be at high risk of automation. The cluster contains a number of jobs at low risk of automation, such as *ship and hovercraft officers* and *health and safety officers*, although these occupational groups are considerably smaller in numbers of jobs than *farmers* or *forestry* *workers*. Other occupations, such as *van*, *taxi*, and *bus and coach drivers* are more numerous but are more likely located in urban rather than rural regions.

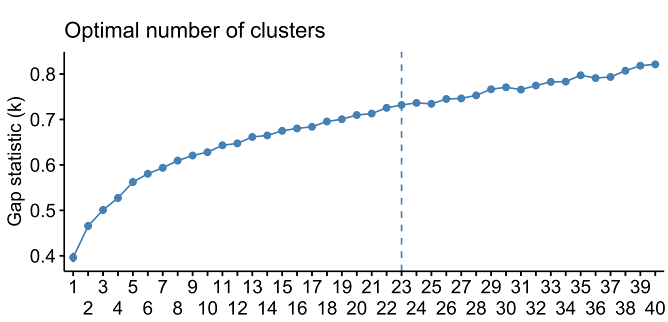

Fig. 2. Gap-Stat for k-means model.

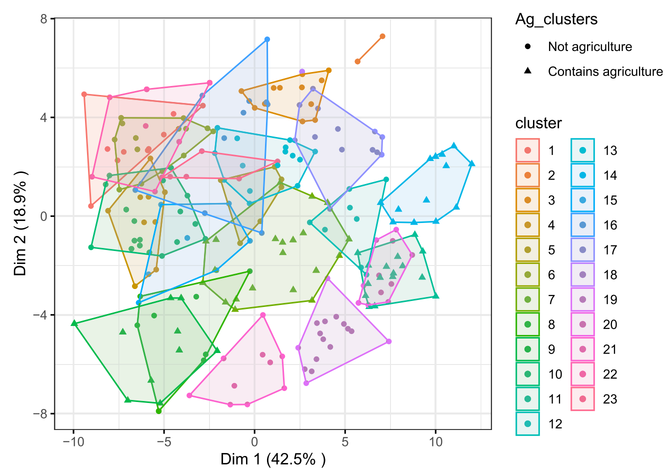

Fig. 3. Overview of k-means clusters (dimensions 1 and 2).

Fig. 5 shows the occupations in the second cluster. Fig. 5 contains only one occupation in agriculture, *managers and proprietors in forestry, fishing, and related services*, and no occupations in this group are at high risk of automation.

Fig. 6 presents cluster 11 which includes the *agricultural machinery drivers*. This cluster consists almost entirely of occupations at high risk of automation. Most occupations in this cluster represent machine operatives and factory work, with only *upholsterers* classified as low risk. The occupations in this cluster are relatively isolated in terms of their skills and knowledge, which, combined with their high risk of automation, means that these occupations are most precarious.

Finally, cluster 14 in Fig. 7 contains *fishing and other elementary agriculture occupations n.e.c.*, which is at a high risk of automation. This cluster contains mostly occupations that are at a medium or high risk of automation. *Cleaners and domestics* are the largest low risk occupation by numbers. It should be noted that this particular cluster is characterised by four occupations with the suffix n.e.c., which stands for not else classified. The results in this Figure should therefore be taken with some caution, as the occupational definitions underpinning these results are less clearly defined.

Table 2 shows the risk of automation by cluster and subsequently lists the agricultural occupations in that cluster by risk category and number of jobs (in 2016). The largest cluster, cluster 7, contained the high risk occupations *farmers* and *forestry workers*, and a number of medium risk occupations from the agricultural sector. The *farmers* are by far the largest group of workers at a high risk of automation. In this

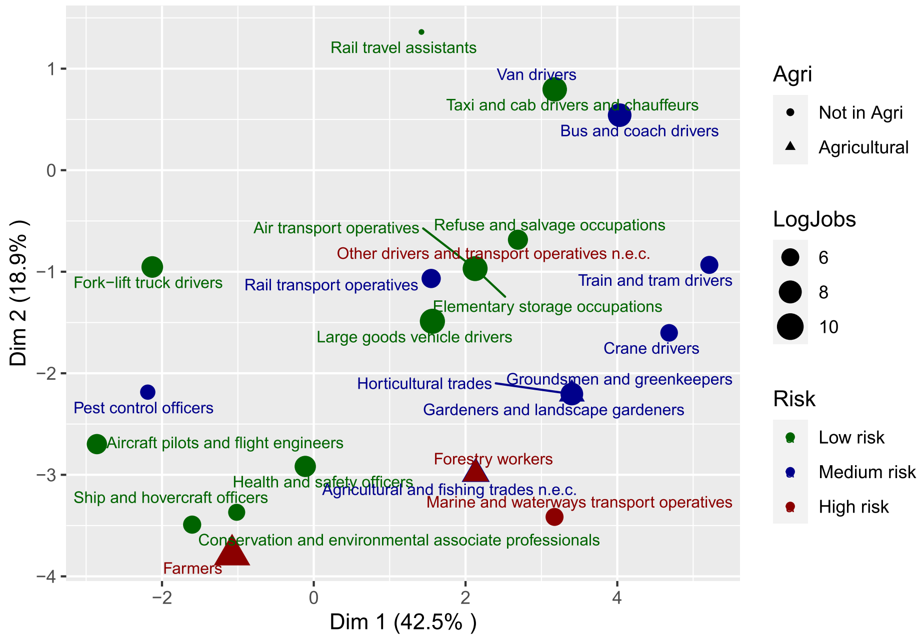

Fig. 4. Cluster 7: Detail.

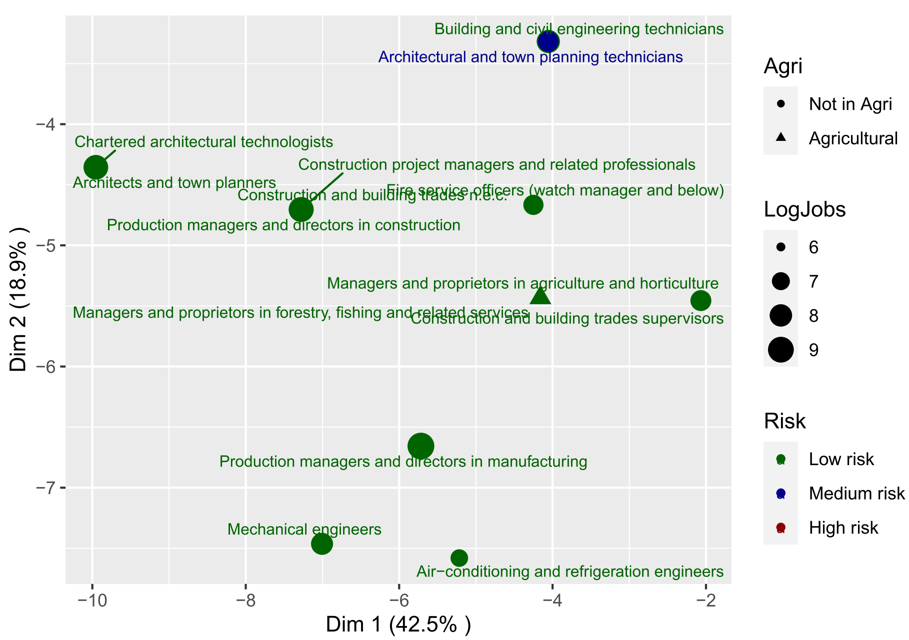

Fig. 5. Cluster 9: Detail.

cluster, the overall ratio of high risk to low risk occupations is 1.04, meaning there are slightly more jobs at a high risk of automation than there are low risk alternatives. The second largest cluster containing agricultural occupations, cluster 14, is similar in this respect, with a 1.29 ratio of high risk to low risk jobs. The agricultural occupations in this cluster are *fishing and other elementary agriculture occupations n.e.c.* and *fishmongers and poultry dressers*. Their 3697 jobs make up a small fraction of total employment in this cluster (98,740), but because the ratio of high risk to low risk jobs is higher they may face increased competition when looking for similarly skilled alternative employment.

The final two clusters bookend the distribution of the high risk to low risk occupations. On the safe end, cluster 9 (containing *managers and proprietors* in both *agriculture and horticulture* and *forestry, fishing and related services*) has no jobs at a high risk of automation, 56,519 out of 59,469 jobs are classed as a low risk of being automated. The lower risks found for management professionals are in line with previous findings using the same data (Frey and Osborne 2017; Crowley and Doran 2020). On the other end of the spectrum, cluster 11 has 56,217 jobs at high risk of automation throughout all sectors, and only 881 low automation risk jobs (a ratio of 63.8). The high risk agricultural jobs make up a fraction

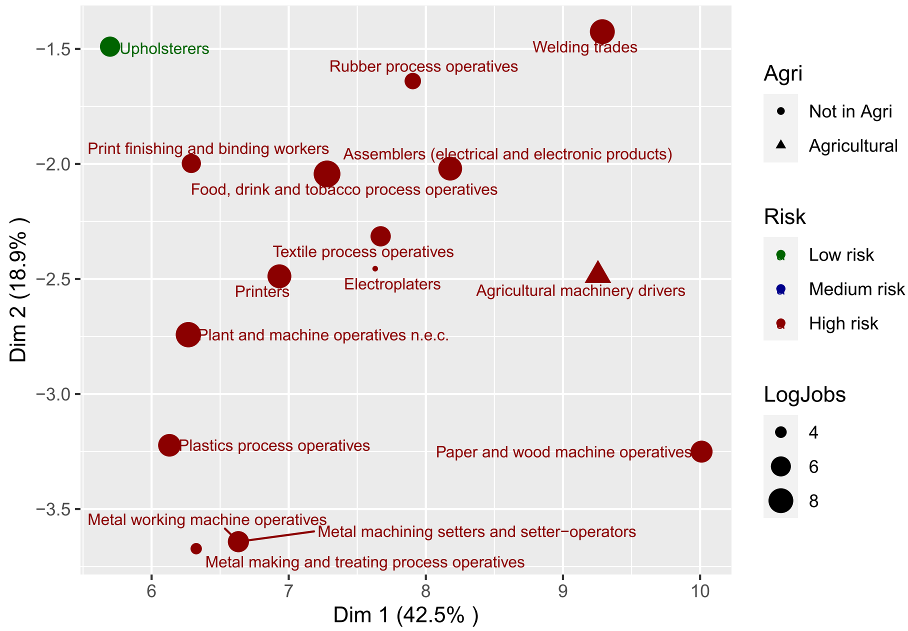

Fig. 6. Cluster 11: Detail.

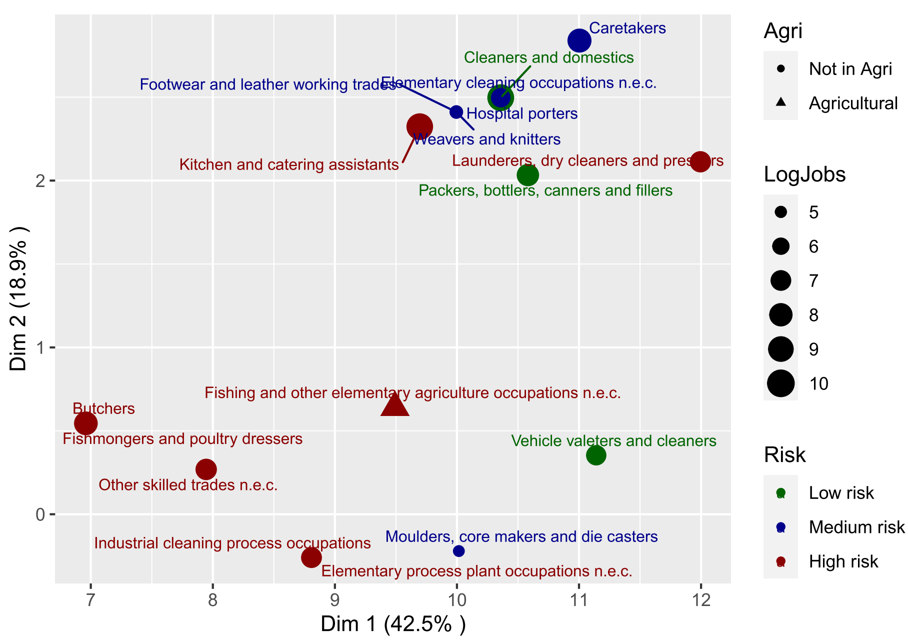

Fig. 7. Cluster 14: Detail.

of this total and are *food, drink and tobacco operatives* (20,097),[9] *paper and wood machine operatives* (1,838), and *agricultural machinery drivers* (718). In this cluster, individuals having to find new employment in the face of automation have very few jobs with similar skills and knowledge requirements available to them, and face increased competition for these jobs. Crucially, for all the clusters, these relative sizes of jobs at a high or low risk of being automated are likely to be spatially uneven.

Of the agricultural occupations at high risk of automation in cluster 7 female employment accounts for 7.63% of employment as farmers and 5.81% as *forestry workers*. Slightly lower gender splits are observed in the matched non-agricultural occupations which vary between 1.45% and 8.05%, with the exception of *horticultural trades* in which 33.51% of employees are female. Within cluster 9 there is a relatively higher proportion of females employed in the *Managers and proprietors in forestry, fishing and related services* occupation. For cluster 11 there is a very low proportion of female employment in the *Agricultural machinery drivers* occupation, where females account for only approximately 0.33% of employment. However, they represent a much larger share of employment in the two matched non-agricultural sectors. Finally, in cluster 14 we observe that females account for approximately 40.17% of the

[9] We acknowledge that the tobacco industry differs from the food and drinks industries as there is increased pressure to divest away from tobacco production. Our data do not allow us to separate these occupations at the regional level, but we note that the Irish economy as a whole contains only 251 individuals employed in the tobacco production sector. We believe this represents a small enough proportion of the overall occupations that this does not substantially alter our results.

Table 2
Jobs by cluster and occupation.

Cluster	Low Risk	Medium Risk	High Risk	Agricultural Occupations	Risk	Occ. Jobs	PctFemale
7	71,321	35,969	74,275	Agricultural and fishing trades n.e.c.	Medium Risk	2590	2.32
				Gardeners and landscape gardeners	Medium Risk	6143	8.05
				Groundsmen and greenkeepers	Medium Risk	2822	1.45
				Horticultural trades	Medium Risk	1222	33.51
				Farmers	High Risk	71,178	7.63
				Forestry workers	High Risk	1340	5.81
9	56,519	2950	0	Managers and proprietors in agriculture and horticulture	Low Risk	1083	9.92
				Managers and proprietors in forestry, fishing and related services	Low Risk	402	27.95
11	881	0	56,217	Agricultural machinery drivers	High Risk	718	0.33
				Food, drink and tobacco process operatives	High Risk	20,097	29.37
				Paper and wood machine operatives	High Risk	1838	7.10
14	38,756	10,062	49,922	Fishing and other elementary agriculture occupations n.e.c.	High Risk	3303	40.17
				Fishmongers and poultry dressers	High Risk	394	15.00

employment in the *Fishing and other elementary agriculture occupations n.e.c.* but only 15% in the non-agricultural matched occupation of *Fishmongers and poultry dressers*. The patterns observed suggest that for females employed in occupations in the agricultural sector there is a slightly lower proportion of matched occupations which may be suitable for them to transfer to (assuming current gender splits across occupations persist).

The Jaccard coefficients shown in Table 1, indicate that the identified clusters are relatively stable. The lowest Jaccard coefficient is 0.697 for the cluster containing *horticultural trades*, while the clusters containing *agricultural machinery drivers*, *managers and proprietors in agriculture and horticulture*, and *managers and proprietors in forestry, fishing, and related services* are more reliably defined at 0.755 and 0.750 for the latter two. The cluster that contains *sports players* is the most unstable, with a Jaccard coefficient of 0.202[10].

4.3. Regional exposure to automation

Moving on to the regional distribution in risk of automation, Fig. 8 shows a ratio of high risk jobs (left) and medium risk jobs (right), using the definitions by Frey and Osborne (2017), divided by the number of low risk jobs. A higher ratio means a larger number of jobs are at risk relative to the number of safer jobs. Similar to Crowley and Doran (2020), we find substantial variation across regions. The regions surrounding the cities of Dublin, Cork, and Galway appear to be relatively well insulated from automation. Higher exposure to automation is found along the border region, and midland regions of Ireland.

The relative risk to automation in Fig. 8 does not take into account the capability of the local labour market to create alternative jobs and to absorb any loss of jobs. The three maps (Fig. 9) show the ratio of jobs in high risk occupations over those in low risk occupations for clusters 7, 11, and 14 (cluster 9 does not have jobs in the high risk category). In these maps, regions towards the red end of the spectrum represent a larger number of high risk jobs for each low risk job in the same occupational cluster. Yellow regions represent a one to one match of jobs at high risk to jobs at low risk of automation. Cluster 7, containing *farmers*, *forestry workers* and *farm workers* shows a distinct north - south pattern, with the regions around the border having around 1.5 jobs at risk of automation per 1 job that is relatively safe. A similar spatial pattern exists for Cluster 14, with larger shares of jobs exposed in the midland and borders regions, while the areas near cities are less exposed. This spatial concentration of thin occupation-specific local labour markets is of critical interest in terms of their ability to absorb a loss of jobs due to automation, and employment related induced migration from those regions. Individual willingness to commute is limited (Hoogstra et al. 2017). Larger regions with thin labour markets mean displaced workers may find themselves facing either long commuting times or, when the burden of the commute is sufficiently large (Stutzer and Frey 2008), moving away.

It is important to highlight the differences in legend colors, with Cluster 11 revealing a much larger range of the ratio of high risk to low risk jobs (see Table 3). Whereas clusters 7 and 14 have at most an exposure of just over 3 or just under 2 high risk jobs per low risk job (respectively), in Cluster 11 this ratio is at a minimum of 18 and expands to 280. There are two main factors contributing to this large risk ratio: First, on the enumerator side, there are many jobs in the high risk group in cluster 11 including plant, machine, and process operatives (see Table 2 and Fig. 6). The second factor is the denominator, containing very few jobs (mainly *Upholsterers*). These observations contextualize the size of the relative risk, but leave intact the interpretation that a large number of individuals in these occupations will have to transition to occupations with different skills and knowledge sets.

5. Conclusions and discussion

5.1. Spatial proximity of similar occupations

It is becoming increasingly apparent that the anticipated fourth industrial revolution will not affect all places in the same manner (OECD 2020; Crowley and Doran 2020). Regions vary in terms of industry composition and agglomeration externalities (Crowley et al. 2021), access to the relevant infrastructures (Salemink et al. 2017), and age and skills composition of the workforce (Nedelkoska and Quintini 2018). While the literature on jobs' risks of automation is burgeoning (Frey and Osborne 2017; Frank et al., 2019) less attention is paid to the position of occupations in rural regions in general, and the agricultural sector more specifically (Cowie et al. 2020). Based on the current literature there are a number of reasons for paying more attention to rural regions. First, rural regions have by definition thinner labour markets and distances between current and alternative jobs are larger (Findlay et al. 2000; Stockdale 2006). Individuals whose jobs are at risk of automation face potentially long commutes or they will have to migrate to work (Hoogstra et al. 2017). Not all people will be able to move and those that remain potentially face a 'spatial trap' (Iammarino et al. 2019) of low growth and low opportunities. Second, the agricultural sector contains a large share of individuals in occupations at a high risk of automation (Frey and Osborne 2017; Nedelkoska and Quintini 2018) and it is unknown to what extent these occupations are part of the same knowledge bases (Qian 2017). As a result, displaced workers may face increased competition of similarly skilled workers for relatively few alternative jobs available in the region. Finally, rural regions have faced larger challenges in the uptake of infrastructure and technology that allows for job automation (e.g. infrastructure Salemink et al. 2017), but recent developments in terms of technology (Legun and Burch 2021) and cost (Graetz and Micheals 2018) mean automation is making headway in agriculture.

[10] This occupation was not included in the list of agricultural occupations in this paper.

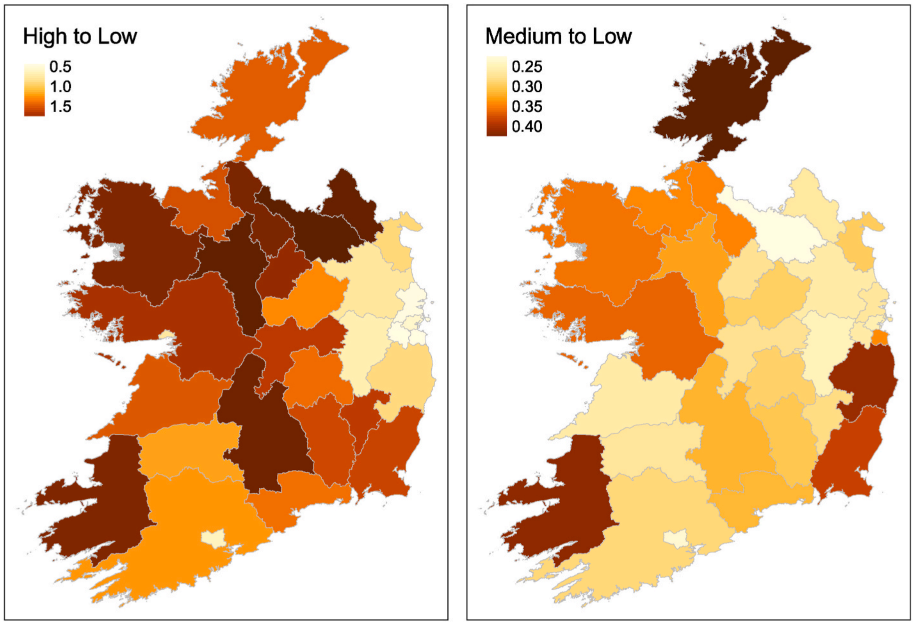

Fig. 8. Number of high risk jobs (left) and medium risk jobs (right) per low risk job: regional.

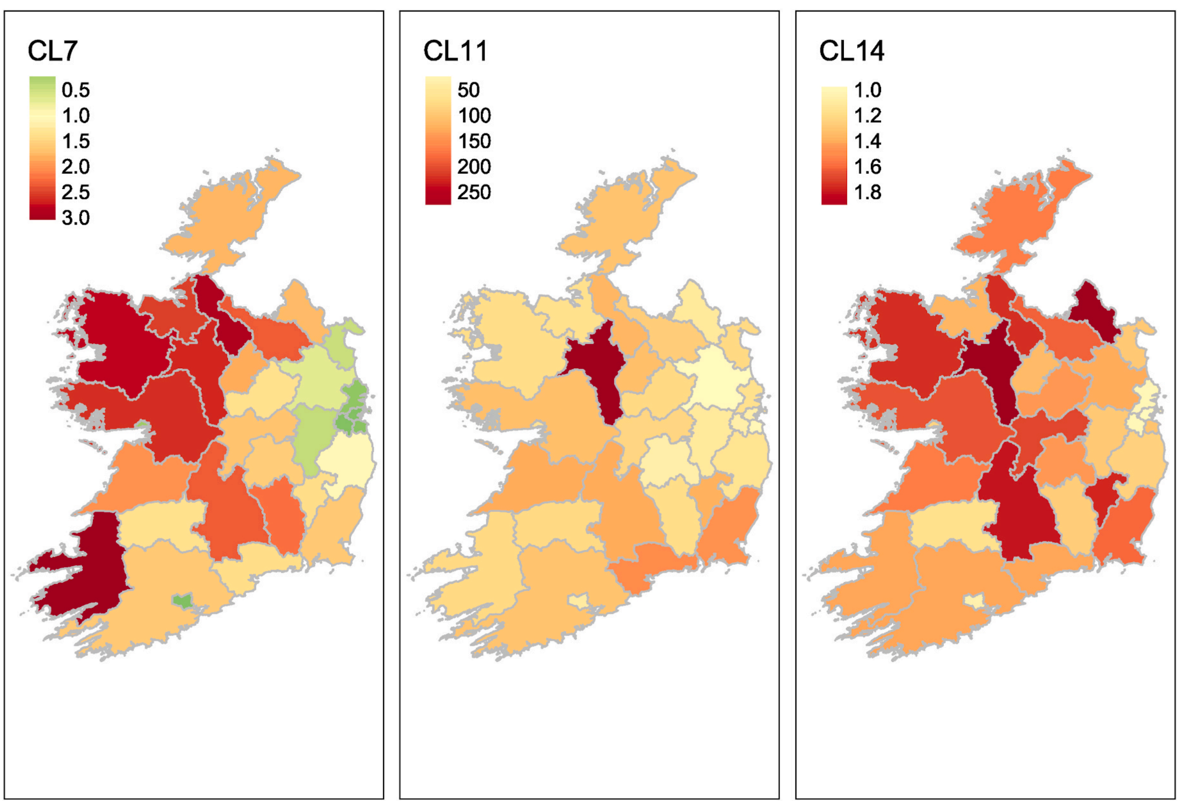

Fig. 9. Risk ratio: High over low risk jobs.

Table 3
Ratio high risk to low risk jobs by cluster.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Cluster 7	0.033	0.579	1.61	1.474	2.276	3.055
Cluster 11	18.172	54.851	76.80	86.224	106.270	280.333
Cluster 14	0.971	1.278	1.42	1.442	1.635	1.964

In this paper we identify and address three gaps in the literature on job risk of automation in agriculture. Firstly, we address the lack of research into agricultural employment risk of automation by explicitly analysing the local exposure to automation for occupations in agriculture in Ireland. This addresses the current gap in the literature regarding agriculture specific developments in the 4IR (Cowie et al. 2020; Malanski et al. 2020). Secondly, we identify which occupations are in close proximity to the jobs being automated on the dimensions of skills and knowledge (based on National Center for O*NET Development, 2021a), rather than through strict sector or occupational bounds. By emphasising the content of occupations we are able to include inter-sectoral employment transitions as an adaptive strategy to job automation. Thirdly, we develop a framework for analysing regional patterns in exposure to automation combined with the measure of available relevant occupations in the region. The measure we introduce incorporates local externalities in labour market pooling, both in demand and supply of labour, by including employee transitions between similar occupations (Qian 2017). This paper represents the first effort to both take into account the interaction between the skills and knowledge of employees at risk of automation, and condition the anticipated regional effects on the similarity of the occupations in those regions.

We show that there are four clusters, along dimensions of skills and knowledge, that contain agricultural occupations. Broadly speaking, the lowest risk of being automated applies to managers and proprietors in the agricultural sector, which is in line with previous results found by Crowley and Doran (2019) and Frey and Osborne (2017) for the economy as a whole. Farmers, who make up the largest group of jobs at a high risk of automation, find themselves in a cluster with roughly a one to one ratio of high risk and low risk occupations. However, these ratios are spatially heterogeneous, with a cluster of high ratios in the West and Border Regions of Ireland. Even though for the country as a whole a relatively large group of similar occupations exists, those in the West and Border Regions of Ireland will most likely have to move in order to access them. Food, drink and tobacco process operatives, the second largest group of agricultural jobs, are in a cluster which is almost exclusively at a high risk of being automated, meaning migration will not improve their labour market opportunities. The ratio is highest in Roscommon, but for individuals in this sector alternative employment will most likely mean re-skilling. Finally, the cluster that contains fishing and fishmongers, is relatively evenly spread in terms of high to low risk ratios, with a slight concentration of higher risks in the midlands region of Ireland.

The results presented in this paper provide a starting point to constructing place-based policy interventions. In this paper we focus mainly on the responses available to the individual (e.g. moving or re-skilling), but the transition to increased automation is going to affect regional economies as a whole. Especially in regions where large numbers of jobs are at high risk of automation we can expect increased unemployment and a fall in labour force participation (Nedelkoska and Quintini 2018), long run effects on income per capita growth (Tselios 2009), and other economic sectors reliant on agricultural workers through Jacobs externalities (Crowley et al. 2021). These process can undermine the potential for economic and social creativity in the Border and Midland regions, resulting in a downward spiral to regional economic shrinkage or stagnation. Out-migration as a result of automation, while a solution to the individual migrant, can compound problems occurring in shrinking regions (Hospers 2013) and contribute to the spatial traps for people unable or unwilling to move (Morrison and Clark 2011; Iammarino et al. 2019).

These outcomes highlight the importance of the scale of measurement when discussing the responses to exogenous shocks. For individuals, the possible adjustments to an employment shock due to automation include migration and re-skilling, with the cost of the adjustment proportional to its size. At the level of the regional economy, several properties emerge: In this paper we discuss related variety, where the measure of relatedness is a function of the occupation's skills and knowledge requirements. Increased concentrations of local related variety mean displaced individuals face lower adjustment costs and decrease the probability of individuals becoming spatially trapped. However, as Crowley et al. (2021) note, regional resilience to exogenous economic shocks increases with the diversity of the regional economy: the more heterogeneous the economic composition in a region, the less likely it is that a large share of the economy will be affected by a downward turn. While diversity appears to benefit a region, differences in occupational skills- and knowledge-composition will inhibit individual transitions. As Martin and Sunley (2015) discuss, the appropriate measurement of regional resilience and a synthesis of its underpinning factors are still undecided. This is true also for the individual's response to economic shocks. While our data does not permit us to come to conclusive statements regarding the role of specialization, related variety, and diversity in labour market scarring of individuals affected by economic shocks, our results do indicate that the coping strategies required by individual workers are regionally heterogeneous. To aid individual and regional resilience to the shock of automation, we therefore emphasise the importance of place sensitive strategies. At the level of the individual, Koster and Brunori (2021), for example, find that individuals in jobs at a high risk of automation are less likely to attend non-formal (on the job) training. They also show that active labour market policies can stimulate non-formal training, but do not disaggregate this second finding to automation risk or regional outcomes. Combining these findings with our results, there appears to be a need for significant investment in local technical and vocational training and retraining programmes targeting agricultural workers to minimize gaps in job skills matching, improve industry-university links, and to foster risk-taking and start-ups for agricultural workers looking to diversify into new areas.

5.2. Measuring risk of automation

Measuring the occupational risk of automation is not straightforward, and some caveats are relevant to the results in this paper. The main discussion in measuring the risk of automation is between those using the method by Frey and Osborne (2017), occupations at risk defined by the tasks they contain, and those that take a lower level of aggregation and calculate risks based on the jobs (nested within occupations, Nedelkoska and Quintini 2018). While the resolution provided by measuring tasks at the level of the job rather than the occupation would be preferable, in the case of agriculture in Ireland the number of relevant cases in the job-specific dataset is simply too low (standing at eight cases). The Nedelkoska and Quintini (2018) method returns a higher percentage of jobs at a medium risk, and fewer on either extreme, than the Frey and Osborne (2017) data, but the ordering stays mostly intact (Frank et al., 2019). In terms of the results found in this paper, it is possible that the numbers of high risk occupations that are eventually automated, or face significant disruption due to automation (Frank et al., 2019), end up lower than the estimates in this paper. If the ordering in risk of automation remains the same, however, the spatial concentration of risk and labour displacement remains in tact, albeit with lower numbers displaced. The results target processes that will take place in the (near) future, and as such which of these measures is more correct is currently not available for empirical verification.

The second issue with measuring the risk of automation is that the estimates concern merely the risk to current jobs of disruption due to automation. We currently have no measure available to us that might inform the creation of new jobs through, or in parallel to, automation, but new job creation will undoubtedly take place (Lane and Saint-Martin 2021). In this paper we take the risks as representing jobs entirely or partially lost due to automation, or substantial restructuring of the job and tasks associated with that job. While the estimates do can not be taken as a certain number of jobs lost, they do reflect a relative rank in the expected degree of disruption in each sector (Frank et al., 2019). For the regional analysis, we have at present no reason to suspect that the relative risk ratios would be affected.

Finally, the development and implementation of automation in a rural context does not take place in isolation. Critical infrastructures need to be in place for many automation processes (e.g. high data throughput requires broadband, Salemink et al. 2017), innovation often takes place at the level of major technological corporations, rather than individual farmers (Rotz et al., 2019), and there are substantial issues around ownership of data and processes that need careful attention

(Carolan 2020). As a result, the process of automation will most likely display temporal variations for different occupations.

5.3. Towards a research agenda

The results presented in this paper emphasise the regional heterogeneity in both the job risk of automation and the likelihood that this will result in a spatial trap across regions in Ireland. However, there are several issues that we were not able to address in this study that warrant more detailed attention. Data-limitations mean that for the present study a more detailed breakdown of occupations in the agricultural sector was not possible. We were not able to distinguish between the risk of automation to, for instance, cattle and crop farming. While a number of sources (e.g. Carolan 2020) detail the role of automation in different sections of the agricultural sector, a more broadly validated set of disaggregated job risks of automation is currently not available. Similarly, while the proportion of female labour in agriculture is relatively low, it is likely that different genders sort into different occupations in agriculture as well as in occupations outside of agriculture that make up the relevant skills- and knowledge clusters. It stands to reason that males and females will experience different risks to automation and can require different strategies to individual resilience (Asadullah and Kambhampati 2021). Although not specific to the agricultural sector, Brussevich et al. (2019) find that there are concerns about the degree to which female and male risks of automation diverge, potentially widening the gender-employment gap. They note, in addition, that there exist substantial regional heterogeneities to these processes. One key related aspect of this dynamic for rural regions is the role that agricultural firm locations and their associated non-agricultural activities can play in the rural regional context (Barbieri and Mahoney 2009; Markantoni et al., 2013). While the majority of farmers are male, their business (and household) locations house additional activities run by female members of the household. The motivations to start a side-activity in a rural or declining area are more likely to include considerations regarding local quality of life (Delfmann et al., 2017). Relocation of the main activity may, therefore, impact both the other members of the household's entrepreneurial activity and carry negative multiplier effects for rural quality of life.

Although the gender dimension is important regarding rural socioeconomic composition it is by no means the only aspect of the automation debate that would benefit from closer attention. Leonard et al. (2017) highlight the age composition of farmers as a critical factor to the sustainability of agriculture. As the farmers' population ages naturally and through a lower rate of entry of younger farmers, farm succession has become a problematic issue in many modern economies (Leonard et al., 2017). Parallel to the issue of farm succession, farm investment in businesses with older proprietors will likely decrease, as the returns on investment will not materialize until after farm succession or retirement. There is a distinct regional component to this issue, as Cavicchioli et al. (2018), for instance, find that in the Italian context farm succession near wealthy urban areas appears less problematic than in peripheral rural areas. The implication of this regional split and if similar patterns are replicated in other countries is that current regional discrepancies will be reinforced, compounding the problem of the spatial trap in remote regions.

5.4. Final thoughts

In this paper we introduce a measure of local labour market thickness conditional on skills and knowledge similarity that should be easily applicable in studies dealing with regional labour markets. Taking skills and knowledge, rather than classical sectoral boundaries, as our main differentiator allows us to incorporate inter-sectoral job transitions as well as use a more precise measure of similar jobs within sectors. The outcomes highlight the importance of the regional context, e.g. the cluster of at risk farmers in the north-west of Ireland, as well as the more general labour market context, e.g. the high automation risk of plant operatives, for the occupations under consideration. This paper represents a first foray into the regional heterogeneity of the job risk of automation, as well as the potential regional impact (high to low risk ratio) to individuals facing automation related job losses. We uncover a novel aspect to the risk of automation.

Credit author statement

Richard H. Rijnks: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing Original Draft, Writing Review and Editing, Visualization. Frank Crowley: Conceptualization, Data curation, Writing Original Draft, Writing Review and Editing. Justin Doran: Conceptualization, Data curation, Writing Original Draft, Writing Review and Editing, Project administration, Funding acquisition.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrurstud.2021.12.012.

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