

Current and Future Waves of Technological Transformation: Potential Economic Impacts and the Challenges for Public Policy in Ireland

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Abstract: Change is a constant and economic history has been shaped by not only multiple waves of technological change but the transformative impact of these changes for both industry and society. As new technologies come to pervade more sectors and occupations over time, it is likely that this technology will give rise to challenges and risks but also opportunities and benefits. If we are honest, we cannot know for certain the trajectory of emerging technologies but for this paper, we aim to make a contribution by looking at the possible impact of current – and future – waves of technological change in Ireland. Building upon earlier work, we suggest that Ireland is relatively more exposed to AI than is the case for other advanced economies and that factors such as gender, age and educational attainment have an important role to play here. We contend that the extent to which AI augments – or replaces – human labour in the medium to long-run will depend on a variety of economic, social and policy factors (including levels of AI regulation and the future interaction between AI and advanced robotics). We consider the limitations of this type of work and suggest some possible avenues for future analysis. We show that that multiple aspects of public policy will have an important role to play; that the process of technological change has the potential to impact Ireland’s Exchequer in many ways (including the risks posed by any potential global speculative investment bubble); and that issues such as lifelong learning, public trust and social inclusion cannot be overlooked..

Keywords: artificial intelligence, technological change, labour markets, public policy, Ireland

JELs: J21, J24, O31

1. INTRODUCTION

The process of technological transformation is not new but rather, it is continuous albeit that the speed of change does tend to vary over time. In some cases, change has occurred rapidly but in other cases it has been incremental over successive years (or even decades). This notwithstanding, the prospect of change can give rise to uncertainty and anxiety as to the implications for the macroeconomy, employment and earnings. For instance, the various waves of automation witnessed over many decades led to concerns around substantial job losses. Undoubtedly, there has been displacement between sectors – or reduced demand for certain occupations – but the aggregate level of employment has continued to expand (Przegalinska and Wright, 2021; Terborgh, 1966). This, however, is not a basis for complacency as the global economy adjusts to a broad range of new technologies including, but not limited to, the deployment of artificial intelligence (AI) alongside advanced robotics, quantum computing, cell and gene therapies, nanotechnology, biotechnology, distributed ledger technologies, augmented reality and 3D printing.

Public expectations around emerging technologies such as AI – and the associated commercial investments – may well be running ahead of the actual capabilities of this particular technology. At the current juncture, some cynicism is emerging regarding the potential of AI technology to deliver the kind of transformative change that the market is anticipating. While a significant sum have been invested to date, it is unclear when the technology will deliver a return on this investment.³ Acemoglu has suggested that AI can carry out just 5% of jobs, downplaying the prospect of an impending *economic revolution*.⁴ The ECB has also raised concerns about the possibility of an AI-related

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Disclaimer: The views expressed herein are those of the authors only. All errors and omissions are our own.

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³ “AI will take time to show a return on investment”, *Financial Times*, July 2024.

⁴ “AI Can Only do 5% of Jobs, Says MIT Economist Who Fears Crash”, *Bloomberg*, October 2024.

asset price bubble, given the concentration of market capitalisation and earnings among few US firms.⁵ In addition, AI adoption by enterprise continues to lag.⁶ It should be noted, however, that a lull in the pace of adoption following the initial investment in an emerging technology is to be expected (and is in line with the dynamics of the productivity J-curve (discussed below)). Another important consideration is the speed of change and whether this is accelerating, as evidenced by Google's recent unveiling of the new Willow quantum microprocessor.

The Irish economy has for many years had exposure to – and has developed a broad-based expertise in – a range of emerging and frontier technologies, including microprocessors and bio-pharma as well as cybersecurity, communication platforms and e-commerce. Ireland also has a long track record of attracting, and retaining, FDI and has become an important hub for many MNCs (or multi-national corporations). Consequently, close to 10% of Ireland's workforce are engaged in ICT and other high value-added categories of employment. To put this differently, close to 263,000 persons were employed in the 'foreign-owned' MNC sector⁷ of the economy by 2023 (up by 75% since 2012). Given the foregoing, policy-makers in Ireland are keenly aware of the potential implications of technological change for Ireland's future economic performance. In the most recent National Risk Assessment (Government of Ireland, 2024), AI and other advanced technologies were identified for additional prominence. The latter assessment recognised the likely opportunities that AI will provide and the need to adapt to new technologies in order to maintain Ireland's competitiveness but it also noted that *'disruptive potential could negatively affect existing jobs or sectors, undermine critical infrastructure, or bring about ethical or legal risks'*.

The growing importance of certain types of work in Ireland's economy over time is also a function of the global distribution of 'compute' resources. The term compute here refers to applications requiring resources for purposes such as computation and processing (i.e. cloud computing or big data). This is a core input to the development and deployment of AI. For instance, Central Processing Units (CPUs), Accelerated Processing Units (APUs) and Graphics Processing Units (GPUs) are considered compute resources. Lehdonvirta et al. (2024) consider the global deployment of those chips necessary to underpin compute for AI development and deployment (i.e., to train AI models). They also consider the geographic dispersal of public cloud compute⁸ (or 'public cloud regions'), including market leaders such as AWS, Microsoft Azure and Google Cloud. The aforementioned work found that a small number of countries constitute 'Compute North' (or those countries which host the technology necessary for AI development). The rest of the globe is categorised as 'Compute South' (i.e. technology for AI deployment rather than development) and 'Compute Desert' (i.e., those countries which host no public cloud AI compute at all).

The vast majority of countries across the globe have no public cloud regions. Despite its small size, Ireland is one of only 39 countries to host at least one public cloud region and is one of only 17 countries – Compute North – where the type(s) of high-end chips required to provide compute for AI are located. Indeed, close to 20% of the EU27's GPU-enabled regions are based in Ireland (rising to 25% for more advanced chip technology).⁹ These technological investments are certainly promising when one considers the prospects for Ireland in a changing global economy but it should not go unnoticed that – in Ireland at least – these developments are being driven by private sector actors. Recent data indicates that the Rest of the World (i.e., foreign funding) accounts for close to 10% of the total R&D spend in the EU. For Ireland, however, the equivalent figure is closer to 26% whilst the Government share of total R&D spend in Ireland is almost half of the EU average.¹⁰ The role of the private sector in Ireland is not necessarily a bad thing but it does underscore the importance of giving due consideration to the role of the State in preparing the economy to respond to these changes (and the readiness, and/or capacity, of the State to do so). There is also a need to reflect on our shared cognitive dissonance. In other words, we can often hold two (potentially) contradictory views: (i) previous waves of technological change may have impacted certain occupations negatively but never led to a net decrease in employment; and (ii) past events are no indicator of future outcomes.

This paper builds upon our earlier work – Williamson et al. (2025) – and extends that analysis in order to consider broader technological and public policy challenges for Ireland arising from technological change. In particular, the paper considers the potential for impacts that extend beyond 'narrow' AI applications alone, including the possible impact of advanced robotics on occupations currently assessed as having limited exposure to narrow AI. It also considers a range of public policy challenges arising from technological change, including those relating to the public finances, lifelong learning, public trust and social inclusion.

⁵ "Financial Stability Review", ECB, November 2024.

⁶ "AI is showing 'very positive' signs of eventually boosting GDP and productivity", Goldman Sachs, May 2024.

⁷ Specifically, this refers to foreign-owned State Enterprise Agency client firms. Most of these firms are IDA Ireland client firms.

⁸ These large providers are sometimes referred to as 'hyperscalers' and the reference to 'public' does not imply any Government affiliation (but rather that these services are available on demand and shared by many customers).

⁹ Ireland being home to two of the EU27's 11 GPU-enabled regions as well as two of the EU27's eight AI10-enabled regions (the latter being the Nvidia A100 GPU developed in 2020).

¹⁰ [R&D expenditure - Statistics Explained](#)

The paper then assesses Ireland’s overall labour market exposure (and complementarity) to AI and places these results in a comparative international context. We also examine the characteristics of persons in highly exposed occupations. In undertaking this work, the authors seek to contribute to the emergent discourse around AI and the labour market, while recognising that this can only represent an initial contribution. We are clear that the process of AI adoption remains at a relatively early stage, that this limits the availability of real-world empirical data and that further analyses will be necessary over time. Indeed, we recognise the uncertainty inherent in the future trajectory of these disruptive technologies.

The remainder of this paper is structured as follows. Section 2 summarises the relevant literature, while Section 3 outlines the methodological and theoretical approaches adopted in this paper. Section 4 presents the main results, followed by a discussion in Section 5 of the potential public policy challenges arising. Section 6 concludes.

2. LITERATURE

The emergence of advanced digital systems, including advanced robotics and AI technology, is often characterised as the advent of a fourth industrial revolution. Schwab (2016) has outlined three previous industrial revolutions, roughly each one a hundred years apart. Each of these had a transformative impact on the production process, income levels and standards of living. The first industrial revolution (c. 1784) came with the use of steam power to mechanise production. This preceded a second industrial revolution (c. 1870) that saw electricity powering mass production, while a third industrial revolution (c. 1969) was marked by the use of electronics and information technology to drive automation. Building on the groundwork laid during the latter period, the fourth industrial revolution is developing at an unprecedented pace. Within these distinct periods of innovation, development and change, new industries, occupations and tasks have emerged while others have diminished or disappeared entirely. For example, advancements made in the extraction of petroleum during the late-1800s enabled the production of kerosene – leading to the decline of the whale oil industry – whilst kerosene would come to be supplanted by the use of electricity.

2.1 Capital distribution

The adoption of AI technology by industry could significantly disrupt our current understanding of “typical” economic activity. AI systems have the potential to bring about extraordinary benefits for society but also to sow disruption across many sectors of the economy, including labour markets globally. Each previous industrial revolution had a transformative impact but also created winners and losers in the labour market: eliminating some jobs but generating and augmenting others. As AI comes to pervade more sectors and occupations over time, it is likely that this technology will give rise to challenges and risks but also opportunities and benefits. Whilst prior technological developments are generally considered to have been a global net ‘good’, we must always remind ourselves that past performance is no guarantee of future results. Indeed, the key difference here is the nature of tasks that will be transformed. AI has the potential to perform complex cognitive tasks, setting it apart from previous general-purpose technologies which primarily affected physical tasks at the time of their invention. Certain tasks within occupations will become susceptible to automation, while others will benefit from AI assistance, enhancing productivity and augmenting human capabilities. The extent to which jobs are enhanced, rather than replaced, will depend on how well the strengths of AI and humans can complement each other within each job. There will also be a role for public policy and regulation in shaping the balance between technology, capital and labour.

2.2 Labour and productivity

The impact of technological change upon the labour market is perhaps best represented by the contention that 60% of all jobs in the US today did not exist less than a century before (Autor et al., 2022). Research by the IMF (Cazzaniga et al., 2024) has found that 40% of employment globally is exposed to AI. This rises to 60% of employment in advanced economies with approximately half of these considered to be negatively affected. This paper finds that, as a result of capital deepening and a productivity surge, AI adoption can boost total income, and, if AI is complementary to labour in certain occupations and productivity gains are sufficiently large, higher growth and demand for labour could more than compensate for the partial replacement of labour tasks, increasing incomes along most of the income distribution. From a labour market perspective, the current international literature typically only provides an indication of impacts based on recent understandings of AI applications and does not attempt to predict how AI technologies will evolve in future, nor the rate of adoption across the enterprise base. There are those with a pessimistic viewpoint that suggest that AI will have a detrimental effect on employment through the substitution of capital for labour. There are also those optimists that expect that there will be significant efficiency gains associated with the use of AI that will result in the creation of new job and task opportunities. For instance, Frank et al. (2019) have found that AI will likely impact on specific skills rather than on whole occupations. In other words, whilst many jobs may be exposed to AI, relatively few are at risk of disappearing completely.

There are also those – for example, Felten et al. (2021, 2023) – that have suggested that the most exposed industries will likely be those “white-collar” industries requiring high levels of education whilst a survey of AI experts concluded that certain skills required in high-skilled roles are susceptible to automation due to recent advances in AI. There is also potential for a high level of complementarity between AI and human capabilities for many ‘highly exposed’ roles. The OECD has found that being highly exposed to AI may be beneficial for workers, provided they have the skills to use AI technologies effectively (Lane, Williams and Broecke, 2023). Other studies – such as the World Economic Forum’s Future of Jobs Survey 2023 – have found that the number of companies expecting AI to be a net creator of jobs is far greater than those expecting AI to be a net displacer.

Acemoglu (2024) estimates modest effects on total factor productivity (TFP) from AI within the next decade, with an upper bound of 0.07% in terms of annual TFP growth. The impact on GDP is also estimated to be modest, and within the range of 0.9% to 1.1% over the next decade (although this could be as high as 1.8% in the event that there is a large AI investment boom). In terms of labour productivity, however, the latter work suggests that any gains will be quite low (at 0.1% p.a.), albeit that other research has estimated that the growth will be far higher (at between 1.5% and almost 3.5% p.a. over the next decade). Recent work by the OECD has found that annual labour productivity growth could be increased by close to 1% in the US but that the comparable increase for other advanced economies would likely be lower¹¹ (Filippucci, Gal and Schief, 2024). Furthermore, recent research from the US has found that even where AI yields increased labour productivity, this may not impact evenly across the workforce or result in broad-based wage growth (National Academies of Sciences, Engineering, and Medicine, 2024).

There is, however, a significant degree of uncertainty with regard to how future waves of technological change will impact the economy. Whilst the labour market (including labour productivity) will be a key channel for the transmission of the impact of new technologies across the broader economy, the extent to which AI augments – or replaces – human labour then into the future will depend on a variety of economic, social and policy factors (including levels of AI regulation). A key factor in this regard will be the speed of adoption, across both sectors and countries (Figure 1). A summary of some of the key literature in this space is provided in Tables 1 and 2 (see: Annex).

Table 1 outlines the main findings of Trammel and Korinek (2023) on the effects of AI on output growth, the labour share, and wages across different model types. These models differ in how far AI can substitute for labour, contribute to idea generation, and augment capital. The authors find that AI could significantly alter long-run growth dynamics, challenging Kaldor’s (1961) “stylised facts” about stable output and labour shares. If human labour remains essential to production, the labour share stays positive and humans retain economic importance. In any scenario where AI capital can self-improve and innovate without human input, however, the implications for labour are far more disruptive. Finally, the authors note that while current models do not show a clear mechanism for existential risk from AI, this reflects a limitation of existing growth frameworks rather than reassurance. Table 2 provides an overview of estimates of the exposure of global labour markets to the adoption of AI technology, as derived from a review of the relevant literature. This table further details the type of technology examined (e.g. generative AI, robotics) and includes additional notes where relevant. As shown, estimates of the exposure of the global labour market range from 15% to as high as 40%, however, there is considerable variability across the range of studies.

2.3 Considering the unknowable

A number of commentators have voiced a concern that expectations are running far ahead of the reality (at least in the medium-term). For instance, Daron Acemoglu of MIT has estimated that only five per cent of all jobs will be impacted by AI – whether these are replaced or assisted – over the coming decade and that much of the productivity gains and efficiencies that are currently envisaged will not be realised for many years (Fox, 2024). Indeed, there is some cynicism emerging regarding the potential of AI technology to deliver the significant change that investors are expecting. While a significant sum has been invested to date, it is unclear when the technology will deliver a return on this investment.¹² The ECB has also raised concerns about the possibility of an AI-related asset price bubble, given the concentration of market capitalisation and earnings among few US firms.¹³ In addition, AI adoption by enterprise continues to lag.¹⁴

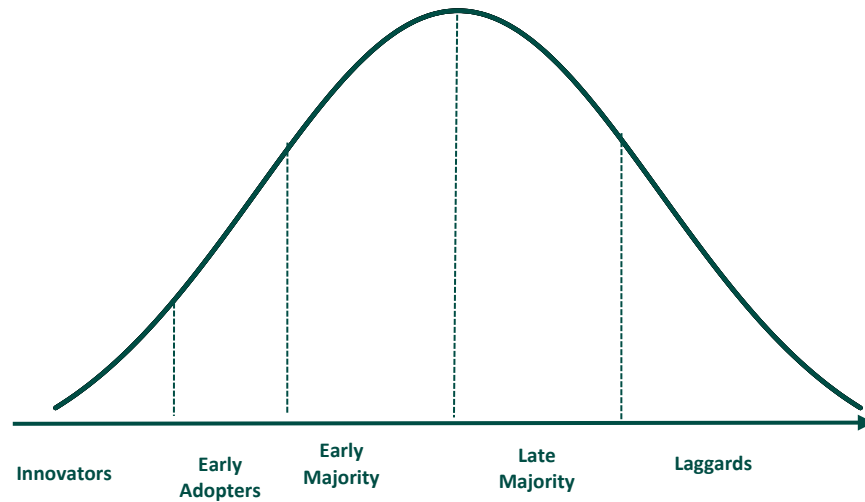
¹¹ Due to slower rates of adoption.

¹² “AI will take time to show a return on investment”, *Financial Times*, July 2024.

¹³ “Financial Stability Review”, ECB, November 2024.

¹⁴ “AI is showing “very positive” signs of eventually boosting GDP and productivity”, *Goldman Sachs*, May 2024.

Figure 1: Example of the Adoption Curve



Source: Authors' based on Rogers (2003). Note: the adoption curve describes the time from initial take up of a new technology by early innovators to widespread adoption and use.

Korinek and Suh (2024)¹⁵ have presented three alternate scenarios regarding the trajectory of AI development and assigns each scenario with at least a 10% probability of occurring. These scenarios range from “business as usual”, where AI has a relatively muted impact on employment, to the advent of AGI in as little as five years, with explosive economic growth implications. For each scenario, this paper warns of the need to reform social security nets, tax systems, the conduct of monetary policy, and financial regulations. In practice, regulations, constraints on capital investment and accumulation, and societal preferences on the role of AI, could all act to limit AI progression and adoption. Brynjolfsson and Unger (2023)¹⁶ also present alternate pathways to describe the macroeconomic impact that AI adoption could have, in terms of productivity, income inequality and industrial concentration, emphasising the role played by public policy in determining which path will ultimately be followed. This paper outlines that no scenario represents a foregone conclusion, and the realisation of the “better future” will require creative policy experiments, including a set of goals for what society wants from AI (as opposed to negative outcomes that need to be avoided), and the flexibility to evolve, alongside the rapidly evolving technological possibilities of AI technology.

These authors find that public policy will ultimately determine the extent to which AI complements – rather than substitutes for – labour, as well as the ability of firms to access AI technology irrespective of their size class. The paper flags an imbalance between the research efforts advancing the frontier of AI technology and the more limited research aimed at understanding the economic and social consequences of adoption. As examined by Acemoglu (2024), the macroeconomic implications of the recent advances in AI technology remain an open question. Acemoglu outlines the potential types of macroeconomic effects that AI can have in the medium run, from revolutionising the economy and bringing about massive improvements in productivity, to more modest impacts on productivity and costs, with ambiguous possible effects on wages. However, the paper notes that there is no evidence of revolutionary effects to date.

3. DATA AND METHODOLOGY

3.1 Constructing a measure of exposure and complementarity

The AIOE (exposure index) measure is derived by breaking down occupations into their constituent tasks and analysing the degree of overlap between these tasks and various AI technologies. Using crowd-sourced dataset¹⁷ on the relatedness between given AI applications and a set of occupational abilities, Felten et al. had previously

¹⁵ *Scenarios for the Transition to AGI*, Korinek and Suh (2024), NBER Working Paper, Available at: <https://www.nber.org/papers/w32255>

¹⁶ *The Macroeconomics of Artificial Intelligence*, Brynjolfsson and Unger (2023), IMF, Available at: <https://www.imf.org/en/Publications/fandd/issues/2023/12/Macroeconomics-of-artificial-intelligence-Brynjolfsson-Unger>

¹⁷ This data set was created using survey responses of “gig workers” from Amazon’s Mechanical Turk web service. Respondents were asked to assess the relatedness between ten AI applications (such as image recognition and translation) and fifty-two occupational abilities (such as oral comprehension and peripheral vision).

constructed a “relatedness” score (bound between 0 and 1) between each occupational ability and each AI application.¹⁸ An occupational ability’s AI exposure (A_{ij}) measures the extent to which each ability is exposed to AI. This is weighted by the prevalence (L_{jk}) and importance (I_{jk}) of that ability within each occupation and scaled by the weighted sum of all abilities used within an occupation (the denominator) to create an AIOE score. Abilities that are essential to an occupation have high prevalence and importance scores, while the opposite is true for abilities that are used less often. This ensures that AIOE provides a relative measure of AI exposure.

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}}$$

An AIOE score, however, only assesses occupational exposure and is agnostic as to whether an occupation is likely to be substituted or complemented by AI. To resolve this issue, Pizzinelli et al. constructed a complementarity measure, θ , to augment the AIOE score. This measure adjusted specifically for two dynamics: job contexts and job zones. The former refers to those factors that shape the nature of work and the latter refers to factors such as occupations characterised by similar levels of education, on-the-job training, and professional experience required to perform the work.¹⁹ A given occupation is assigned a measure of potential complementarity of AI with that occupation and the baseline AIOE exposure level is then adjusted. For the purposes of this paper, we utilise this complementarity adjusted AI occupational exposure (C-AIOE) index to identify the occupations in Ireland that are most exposed to AI and to measure the extent to which AI is a substitute (or complement) for labour in those occupations.

This index provides a quantitative measure of the exposure of different occupations to AI technologies. The main advantage of this methodology compared to others is that it controls for complementarity to better measure occupational exposure to AI. Other studies focus on occupations that could be automated, without adjusting for complementarity (e.g., OECD, 2023; Briggs and Kodnani, 2023; Webb, 2020), or focus on specific AI applications. The World Economic Forum (2023), for example, assessed potential occupational AI exposure and complementarity to large language models only. The AIOE (exposure index) measure, originally constructed by Felten et al. (2021), is derived by breaking down occupations into their constituent tasks and analysing the degree of overlap between these tasks and various AI technologies.

$$C-AIOE_i = AIOE_i * (1 - (\theta_i - \theta_{MIN}))$$

Analysing these two criteria in tandem (exposure and complementarity) is critical to understanding the potential labour market shifts each occupation might encounter over time. Occupations heavily exposed to AI, where tasks can be performed autonomously, may witness a decline in demand for human labour, with implications for labour income and income inequality. Conversely, heavily-exposed occupations with a high degree of complementarity to AI could see productivity enhancements, leading to an increased demand for labour. Complementarity can only be leveraged, however, if workers develop the skills required to take advantage of AI as a supporting technology. The median values for AIOE and θ ²⁰ used here are taken from Felten et al. and Pizzinelli et al., respectively, to allow for cross-country comparisons.²¹ When interpreting the findings presented below, it is important to bear in mind that the measures of exposure and complementarity used in this study are both relative measures. They describe which occupations are more or less exposed/complementary than others. A high C-AIOE score does not mean that an occupation, or tasks within that occupation, will be replaced, but rather signifies its comparatively higher exposure to AI than other occupations.

This analysis was undertaken as an early contribution to the public discourse in this field but there are, however, some important caveats attaching to this work. Firstly, the measure of AI exposure used in this study – drawing on the work of Felten et al. – focuses on ten specific AI applications, all of which can be considered to be “narrow” AI. Given that Felten’s work was published in 2021, it does not capture the latest advancements in AI

¹⁸ The AI applications were based on categories defined by the Electronic Frontier Foundation’s (EFF) AI Progress Measurement project, while occupational abilities were extracted from the Occupational Information Network (O*NET) database developed by the United States Department of Labour.

¹⁹ As with the AIOE measure, this complementarity measure was created by using aspects of the O*NET repository, specifically work contexts and job zones. O*NET defines work contexts as the “physical and social factors that influence the nature of work”. These include contexts such as “public speaking” and “frequency of decision making”.

²⁰ These are used here: the median values for AIOE and θ across all US SOC-2010 occupations are 6.002 and 0.576, respectively.

²¹ Pizzinelli et al. later converted the US-based SOC occupations into broader ISCO-08 occupations for their analysis. ISCO is the International Standard Classification of Occupations. For the purposes of this paper, it was possible to map ISCO-08 occupations to UK SOC codes, which is the occupational classification system used in Ireland, using a crosswalk from ISCO-08 to UK SOC-2010.

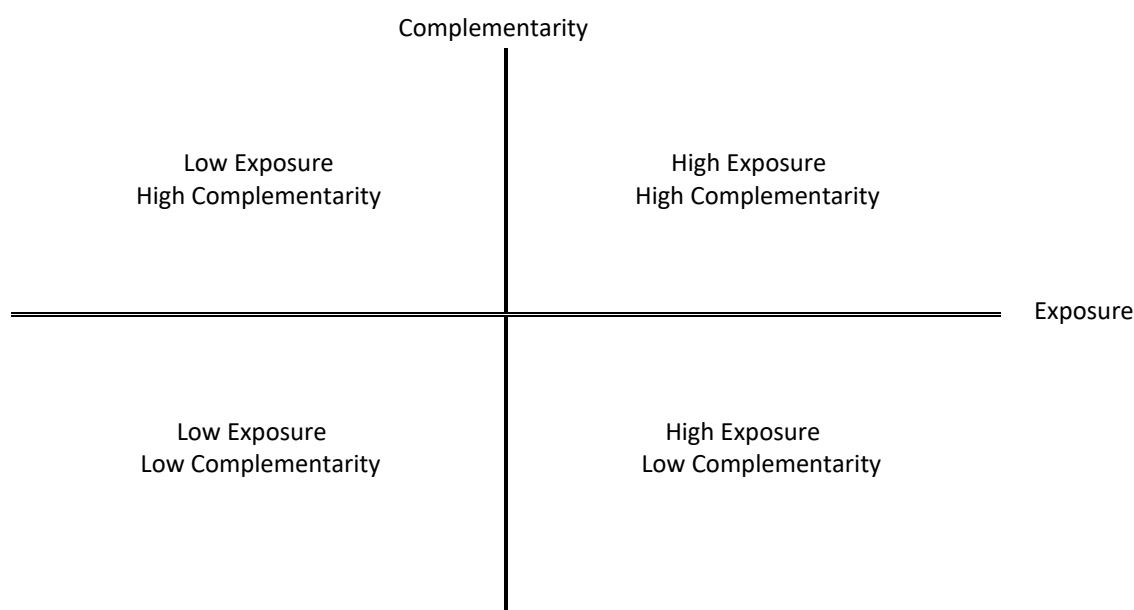
technology, such as document summarisation or LLM-based searching – AI applications that are already widely used through software such as ChatGPT, Gemini, Copilot and others. As with any new technology or innovation, research on the impact of AI will always lag behind the rapid pace of development in the field.

Secondly, this analysis provides a static view of AI exposure and complementarity. The analysis does not consider workers' ability to re-locate across sectors or to develop new skills to realise the benefits of AI, even when their occupation has relatively low complementarity with AI applications. The analysis only provides an indication of relative exposure based on recent understandings of AI applications²² and does not attempt to predict how AI technologies will evolve in the future, nor the rate of adoption across the enterprise base. The extent to which AI augments or replaces human labour will depend on a variety of economic, social and policy factors, including levels of AI regulation.

3.2 Conceptual framework

We outline a framework whereby each occupation is presented as belonging to one of four categories: (i) High Exposure, High Complementarity; (ii) High Exposure, Low Complementarity; (iii) Low Exposure, High Complementarity; and (iv) Low Exposure, Low Complementarity (Figure 2). Quadrants are segmented using the median values of both AIOE and θ . In other words, an occupation is considered to be 'highly exposed' if its AIOE value is greater than the median AIOE across all occupations. Similarly, if an occupation's complementarity value θ is greater than the median θ across all occupations, then it is considered to be 'highly complementary'. If an occupation has high exposure and low complementarity then it is considered to be 'at risk'. Importantly, as the quadrants are split using the median values of both exposure and complementarity of US-SOC occupations, the total number of occupations is not split equally between the four quadrants in Ireland. For example, 72 occupations are considered to be in a relatively 'at risk' (high exposure, low complementarity) category, while 105 occupations are located in the 'high gain' (high exposure, high complementarity) quadrant in Ireland. The US-SOC figures are used to allow for consistent cross-country comparisons.

Figure 2: Conceptual Framework for AI Exposure and Complementarity



Source: IMF

²² These exposure/complementarity levels are relative across occupations. In a scenario where an equal number of people were employed in each occupation, 25% of employment would fall into each of the respective exposure/complementarity categories.

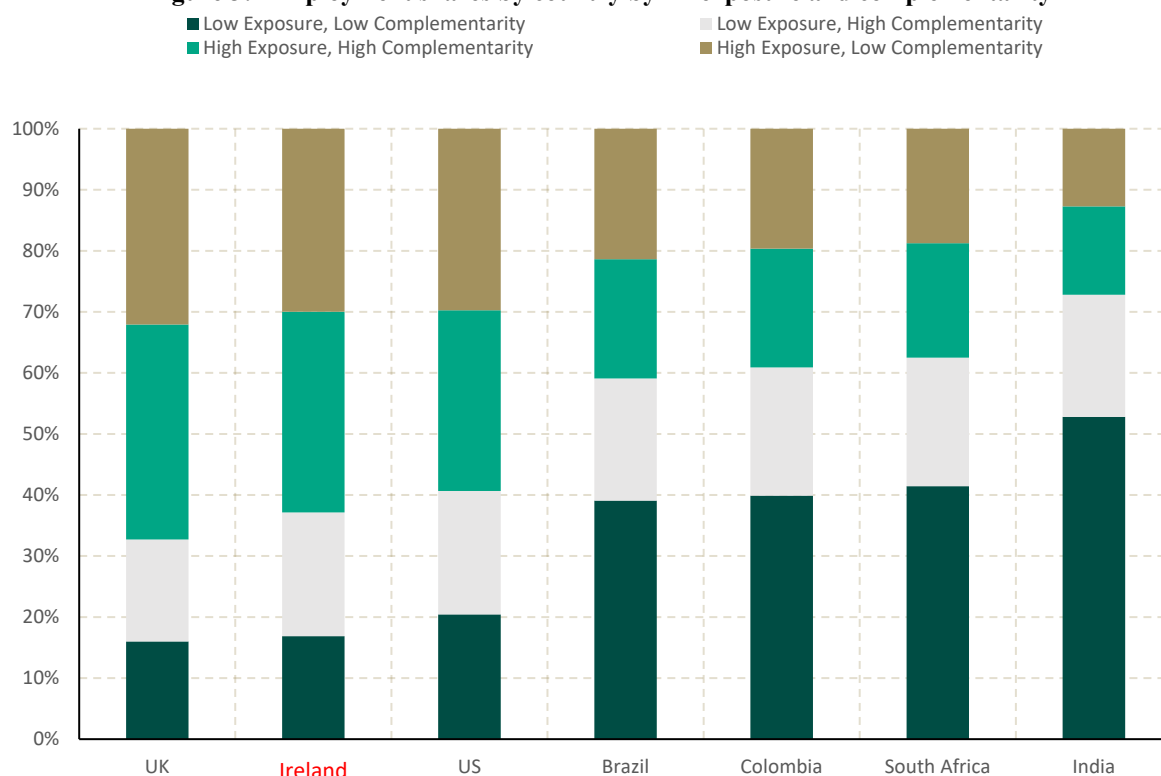
4. RESULTS AND DISCUSSION

4.1 Overall results and international comparators

The IMF has estimated that 60% of employment in advanced economies is highly exposed to AI. Our own work, however, has indicated that 63% of employment in Ireland is relatively highly exposed to AI, with 30% of employment falling into the ‘at-risk’ category (or high-exposure, low-complementarity)²³ and approximately 37% of persons work in occupations that are considered to have low exposure to AI. These results would suggest that Ireland’s labour market is marginally more exposed to AI than the advanced economy average, with 63% of persons in employment working in highly exposed occupations. In their analysis, Cazzaniga et al, focused on six countries at various levels of economic development: the UK, US, Brazil, Colombia, South Africa and India. Figure 3 presents a visual representation of the employment shares in each exposure-complementarity category within each country. For comparison, Ireland’s shares of employment have also been included below.

Of this cohort, only the UK has greater labour market exposure to AI than Ireland, with 67% of persons in employment working in highly-exposed roles. In the US, just under 60% of persons are employed in highly exposed roles, in line with the average across all advanced economies (Cazzaniga et al, 2024). While Ireland may have a higher-than-average share of persons in highly-exposed roles, Ireland also has a high share of persons working in high-complementarity roles. Approximately 53% of persons in Ireland work in roles which are highly complementary to AI, compared to 52% in the UK, and 50% in the US. In emerging market economies, such as India, the share of persons working in highly exposed roles is much lower, although a far lower proportion of persons work in roles that are highly complementary to AI. There appears to be a high degree of polarisation in exposure to AI in the Irish labour market. On the one hand, a considerable share of workers are employed in high-exposure, low-complementarity roles, and are therefore at higher risk of labour displacement. On the other hand, there is a substantial share of workers employed in high-exposure, high-complementary occupations. According to the IMF, these are the workers that are most likely to gain from increased AI adoption, potentially experiencing productivity gains.

Figure 3: Employment shares by country by AI exposure and complementarity



Source: IMF and author’s calculations

²³ There are a number of caveats in relation to this work to be borne in mind. Firstly, the AIOE measure of AI exposure developed by Felten et al focuses on ten specific AI applications, all of which can be considered to be ‘narrow’ AI and does not capture more recent technological advancements. Secondly, as with any new technology or innovation, research on the impact of AI will always lag behind rapid pace of development of the field. The analysis provides an indication of exposure based on recent (2021) understandings of AI applications and does not attempt to predict how AI technologies will evolve in future.

4.2 Results by economic sector and occupation

To give some indication as to the type of roles that fall into each category, four occupations per quadrant are labelled in Figure 4. The roles of ‘Nurses and Midwives’ and ‘Barristers and Judges’, for example, are highly exposed to AI but also display a high level of complementarity. In comparison, ‘Telephone Salespersons’ and ‘IT Operations Technicians’ are also highly exposed to AI but have relatively low levels of complementarity with the technology. For ‘Telephone Salespersons’, the extent to which AI replaces human labour will depend on a number of factors, including societal preferences and the value consumers place on human-to-human interaction. For instance, AI may be adept at handling routine telephone queries but non-standard conversations are likely to require human intervention. In other words, AI may struggle to build meaningful long-term relationships with clients and these can be critical for creating customer loyalty. This example underlines the fact that there remains a great deal of uncertainty of AI’s potential impact on various occupations, and results should be interpreted with this in mind.

The bottom right quadrant can be viewed as reflecting an ‘at risk’ area, where occupations are relatively more exposed and substitutable to AI applications. The closer an occupation is to the bottom right-hand corner, the greater its relative risk to AI. It is again important to highlight that occupations falling into this category will not necessarily be substituted (or transformed) by AI. Rather, our current understanding of AI applications indicates that these are the occupations which would be most at risk, relative to other occupations. There are 72 occupations in Ireland which fall into this category. These occupations account for 30% of total employment in Ireland. When we consider the position of different occupations, Figure 6 illustrates the share of employment in Ireland within each exposure/complementarity category across broad occupational groups.

For instance, highly skilled occupations such as Managers, Directors and Senior Officials, alongside Professional Occupations, are highly exposed to AI. These, however, are also likely to benefit from high levels of complementarity. For those working in Professional Occupations, two-thirds of same work in high-exposure, high-complementarity roles. Persons in these occupations potentially have the most to gain from AI, provided they are equipped with the skills to use AI as a supporting technology. On the other hand, Administrative and Secretarial Occupations and Sales and Customer Service Occupations are considered to be most ‘at risk’ from AI, relative to other occupations. Almost all occupations falling into these two broader occupational groups are in the ‘at risk’ category. These workers may need to be targeted for re-skilling and up-skilling interventions to ensure smooth transitions to more viable occupations. Other occupational groups, such as Elementary Occupations, Process Plant and Machine Operatives, and Skilled Trades Occupations, are considered to be relatively low risk in terms of their exposure to AI. These groups may have greater exposure to other digital technologies such as robotics, however, which isn’t captured in this measure of AI exposure.

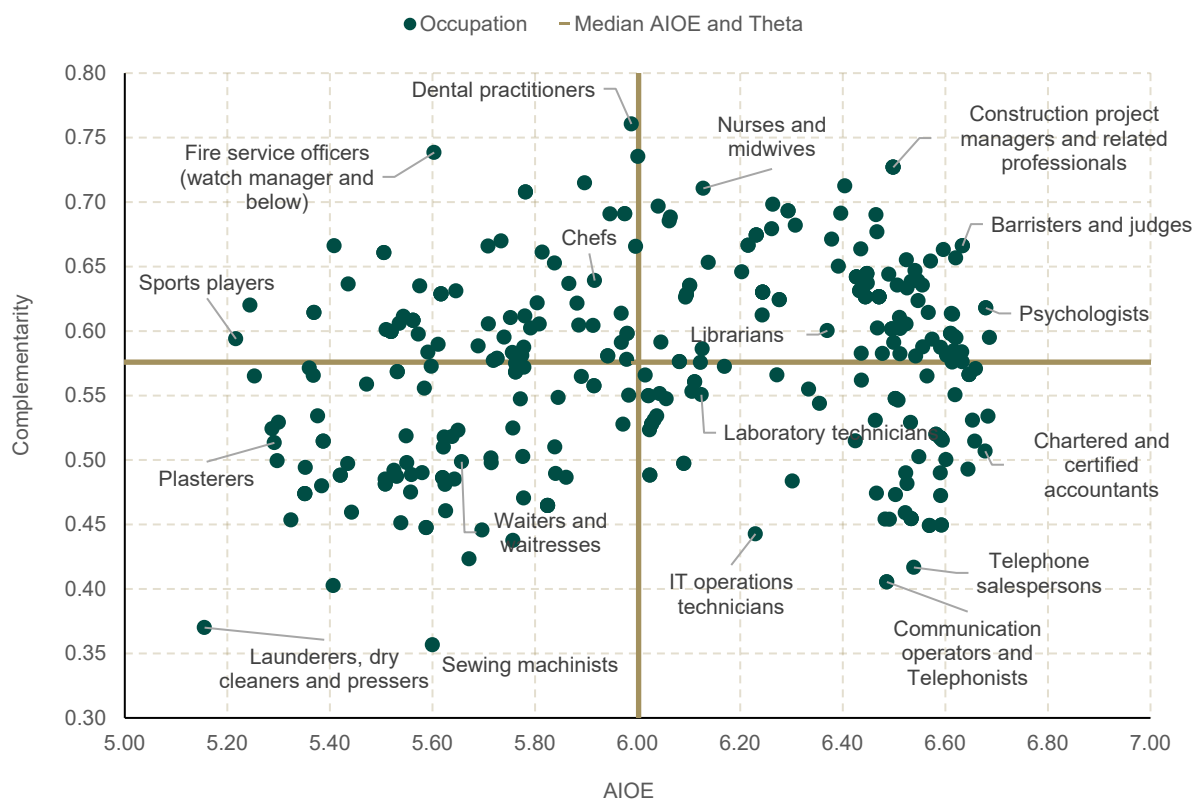
Alternatively, we can examine these analyses through the prism of those NACE sectors in which persons are employed. The ‘Financial and Insurance’ and ‘Information and Communication’ sectors are most exposed to AI, with 97% and 94% of persons in these sectors working in highly exposed occupations, respectively. The majority of these workers are in relatively ‘low complementarity’ roles, potentially posing a risk to employment as occupations within these sectors are relatively substitutable to AI. However, increased AI adoption within these sectors will give rise to new firms and new jobs, especially those involved in the designing and building of AI systems. There will therefore not necessarily be job losses in these sectors, but rather a redeployment of labour from low complementarity to high complementarity roles. Ireland’s skills architecture will need to be adaptable enough to ensure that education and training provision is aligned with rapidly changing skills needs.

At the other end of the spectrum, the Agricultural, Forestry and Fishing sector is least ‘at risk’ from increased AI adoption, with the majority of persons working in this sector being employed in low exposure roles. Worth noting is the extremely high share of persons in high exposure, high complementarity roles within the Education sector. AI has the potential to enhance various teaching and administrative processes within the education sector. In particular, AI has the potential to automate marking for certain types of tests (e.g. multiple choice) and provide real-time feedback on students’ work. In addition, AI may also be able to assist with curriculum design and creating new teaching materials, freeing up teachers to focus on tasks that require human interaction and creativity. This sector therefore potentially has the most to gain in terms of productivity improvements, provided workers are equipped with the skills to use AI as a supporting technology.

From a Gross Value Added (GVA) perspective, sectors with the highest GVA – with the exception of manufacturing (although this will be highly exposed to robotics) – appear to be the most exposed to AI applications. In simple terms, GVA is the value that producers have added to the goods and services they have bought. It is a measure of the individual contributions of different sectors to the economy. Sectors highly exposed to AI could potentially benefit most from increased productivity, investment and competitiveness. This would serve to boost GVA further but these sectors most likely to face the greatest labour market disruptions. In the

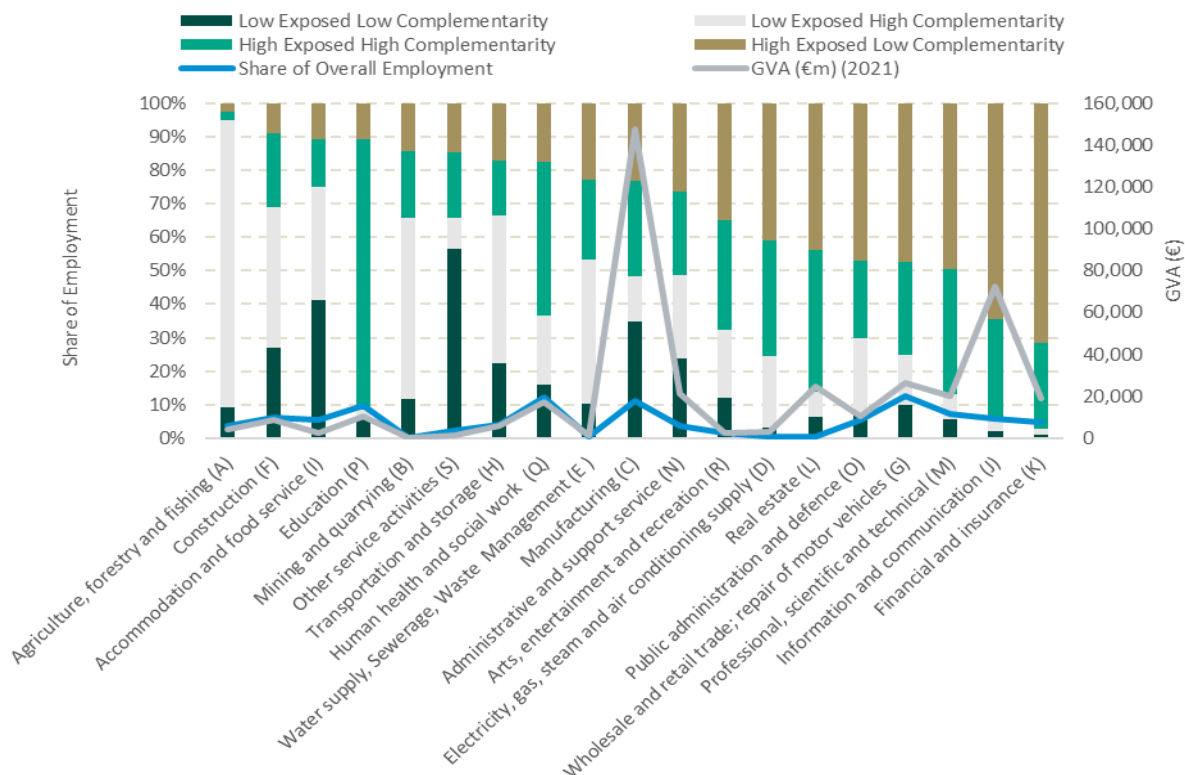
text that follows, we consider how AI exposure and complementarity varies with workers' demographic characteristics. It is possible to build a picture of the type of workers that are most vulnerable to AI, and those that are most likely to benefit from AI adoption.

Figure 4: AI Exposure (AIOE) and Potential Complementarity (θ) in an Irish Context



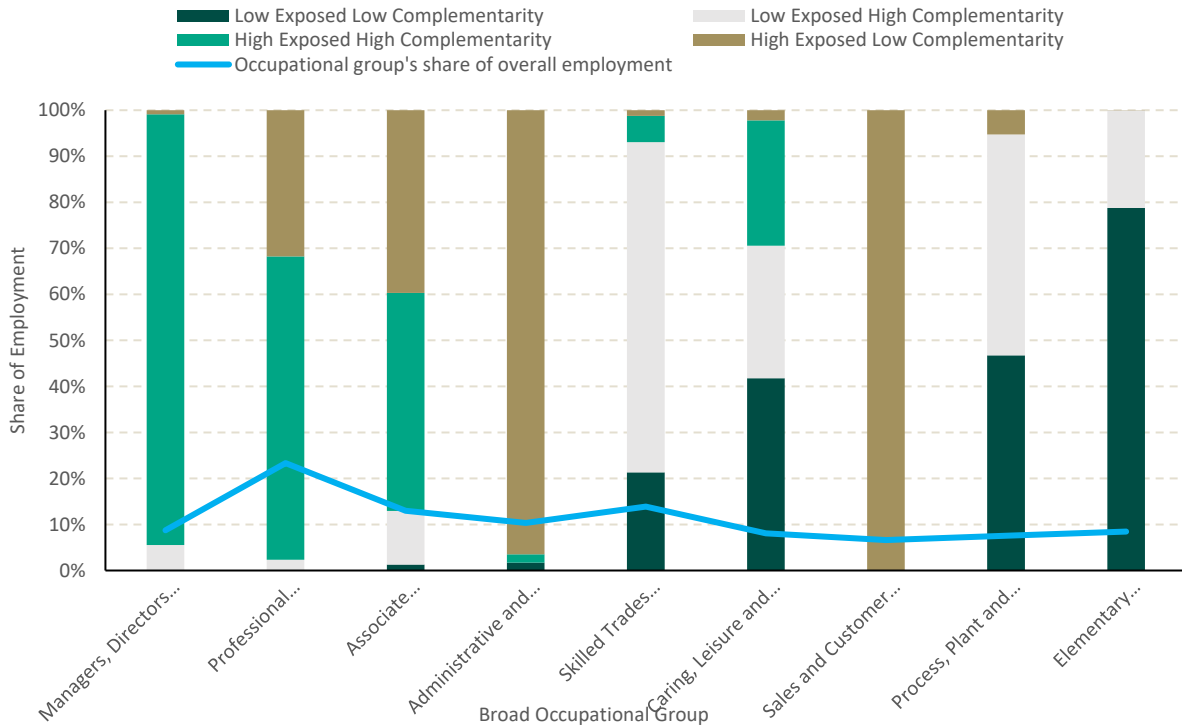
Source: Authors' calculations

Figure 5: AI exposure and complementarity across economic sectors



Source: Author's calculations

Figure 6: AI exposure and complementarity across broad occupational groups



Source: Author's calculations

4.3 Overview of additional considerations

When looking at exposure and complementarity, the relative employment shares differ significantly for males and females (see: Annex). Females are far more likely to work in highly exposed roles compared to males, with 76% of females working in occupations in these categories. This is compared to 51% of males. Furthermore, approximately 38% of females are employed in roles which are considered to be most 'at risk' of AI disruption, far higher than the share of males in this high-exposure, low-complementarity category (23%). For example, approximately 5.8% of females are employed as 'Sales and Retail Assistants', an occupation which is considered to be highly exposed with low complementarity. In comparison, only 2.5% of males are employed in these roles.

Younger workers (with the exception of those aged <24 years) appear to be slightly more exposed to AI compared to older workers, with greater shares working in both 'at risk' and 'high gain' roles (Figure 8). This is expected given the educational attainment levels of the various cohorts. Older workers are much more likely to have left education with no/few formal qualifications and consequently, to be working in those Elementary or Skilled Trades roles which have relatively low exposure to AI. Despite their lower exposure, older workers are less likely to engage in lifelong learning and are typically less proficient at using digital technologies. It will be important to ensure that AI re-skilling/up-skilling interventions manage to reach groups that have previously had little engagement with the further education system.

An individual's educational attainment is a strong predictor of their likely exposure and complementarity to AI in their job. It is possible to assess the varying levels of educational attainment levels with regard to AI exposure and complementarity. Exposure to AI increases as educational attainment increases. Approximately 95% of persons with a Doctorate work – or did work (for unemployed persons) – in occupations that are highly exposed to AI. This compares to just 26% of persons in the lowest educational attainment category (no formal education/primary education/lower secondary education). It is notable that exposure to AI not only increases with educational attainment, but complementarity does too. Persons with the lowest levels of educational attainment are more likely to work in low complementarity jobs (49% of persons in this category are in/were in high complementarity roles), compared to 80% of persons with a Doctorate.

Finally, this analysis suggests that there is a positive correlation between AI exposure and earnings. Approximately 44% of occupations in the first decile are 'highly-exposed' to AI, compared to 97% in the 9th decile and 90% in the top decile. Potential AI complementarity also increases with earnings, in a similar vein to educational attainment. This suggests that higher earners stand to benefit most from increased AI adoption, with potential implications for income inequality. This is consistent with findings by the IMF (Cazziniga et al, 2024). Occupations in the 'at risk' high exposure, low complementarity category, are more evenly distributed across the earnings distribution, however, with the highest share of occupations in this category falling in the 6th income decile.

4.4 Examples of a Labour Market Beyond AI: Advanced Robotics

As presented in Section 4 above, there are a variety of elementary and skilled trade occupations – from cleaners and drivers to decorators and tilers – that would appear to have a limited risk of exposure to AI but this is not the whole story. The AIOE measure presented earlier does not capture exposure to AI-enabled robotic technologies. At present, some but not all robotics incorporate AI technologies. This is, however, clearly an area characterised by rapid and significant change and the integration of advanced robotics and AI has the potential to further impact the labour market. For instance, we can already see the emergence of AI-powered robots with the ability to collect, analyse, and act on information about their surroundings in near real-time in order to complete tasks. These robots use cameras, accelerometers, and sensors – for vibration, proximity, and other conditions to collect information about their environment – which allows them to undertake real world physical tasks. Examples of these include the use of AI-enabled robots to greet customers in stores and provide personalized information and directions; to harvest vegetables; to serve made-to-order lattes in coffee shops, and to handle physically demanding and/or dangerous tasks. There is then the potential for impacts that go beyond ‘narrow’ AI alone and this will ultimately further re-shape the labour market for what we may now consider to be ‘manual occupations’ (i.e., driverless vehicles and the automation of tasks such as tile-laying, window-cleaning, and landscaping services).

5. CHALLENGES FOR PUBLIC POLICY

Those analyses presented above demonstrates that there are a number of sectors across Ireland’s economy that are exposed to some degree of risk (i.e., high exposure but low complementarity). This includes a broad range of sectors – from manufacturing to professional services and from ICT to finance – that make an important contribution to the economy in terms of employment generation as well as value-added and tax revenues. Indeed, a number of these sectors are characterised by a high concentration of foreign-owned firms and the latter have consistently been an important source of high-end employment. For instance, the MNC sector provides close to 10% of total employment in Ireland at present as well as close to 58% of total GVA²⁴ across the economy. The challenges which rapid, and accelerating, technological change pose for public policy, however, are not simply limited to considerations around employment. These will inevitably also touch on the necessity to re-focus Ireland’s FDI proposition in a way that allows us to not only maintain our current MNC base but also ensures that we remain a destination of choice for future waves of investment. The State will also have a central role to play on issues pertaining to regulation and compliance, in taking steps to remove any barriers to the adoption of new technologies and in supporting the SME sector to make the transition.

5.1 Public Finances

In addition to remaining competitive for future FDI, there are also considerations relating to Ireland’s Exchequer. In the first instance, these relate to the composition of Exchequer revenues given that Corporation Tax now accounts for 27% of total Exchequer revenues (compared to 11% a decade previously (Figure 7)). A question arises then as to the capacity of the public finances to absorb – and adjust to – any unexpected and rapid structural change in the balance between corporation, consumption and income taxes. A further consideration is necessity of meeting the demand for further public expenditure. For instance, there will continue to be increasing demand on the National Grid arising from the necessary accelerated electrification of our economy and society, including energy consumption from data centres located in Ireland, in part due to the digitalisation of enterprise (and in particular, the use of energy-intensive AI technology). This will require elevated future investment in the National Grid. The National Competitiveness and Productivity Council (2024) has noted that data centres equipped to support AI servers are significantly more energy intensive. These could potentially consume ten-fold more energy than standard data centres currently located in Ireland. Based on projected demand from existing and proposed data centre projects that are either already connected to the National Grid or have signed connection agreements, data centres will drive a significant increase in aggregate power consumption over the coming decade.

Further development of this critical digital infrastructure, notably in respect of power-intensive AI data centres, would clearly accelerate this trend. Given that data centre projects are, however, a potentially important anchor²⁵ for the presence of many high value-added enterprises in Ireland, it is difficult to reasonably argue that Ireland can continue to attract and retain such investment without unlocking development in associated enabling infrastructure. To ensure continued economy-wide decarbonisation, and robust energy security, this will require further investment in renewable energy, dispatchable electricity generation, and the National Grid. (Figure 8).

²⁴ Refers to non-financial corporations in 2023.

²⁵ This remains to be seen as it is unclear as to whether Ireland will be – in the long-term – a viable location for next generation data centres.

Figure 7: Composition of Tax Receipts 2013-2023

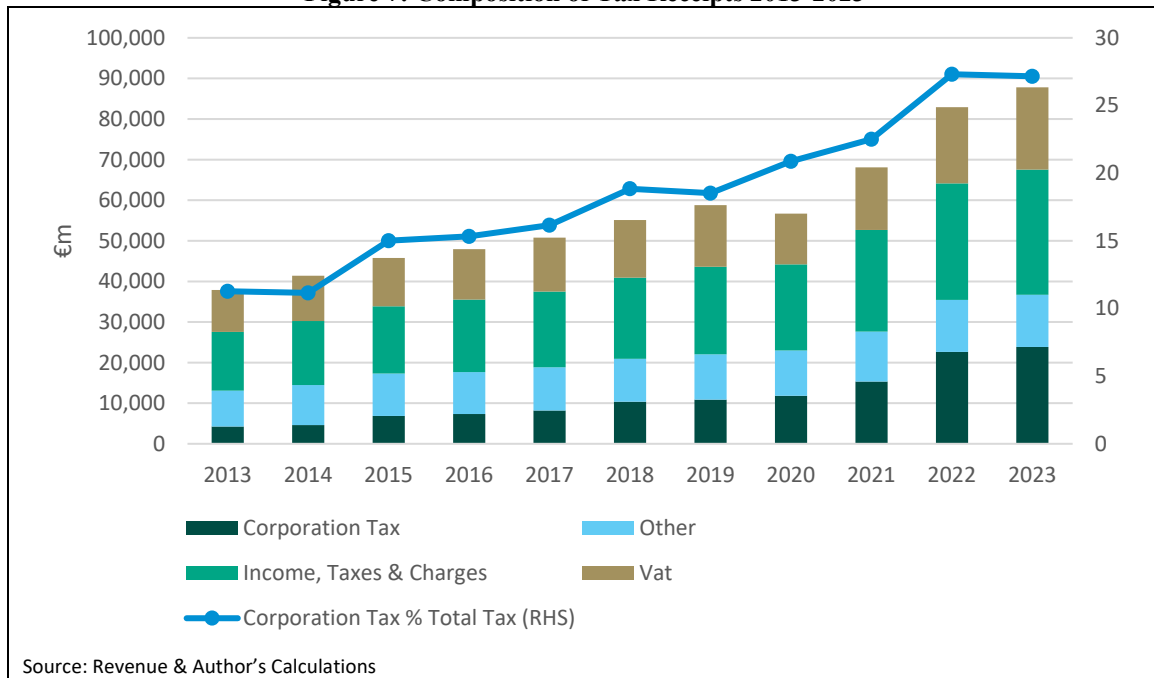
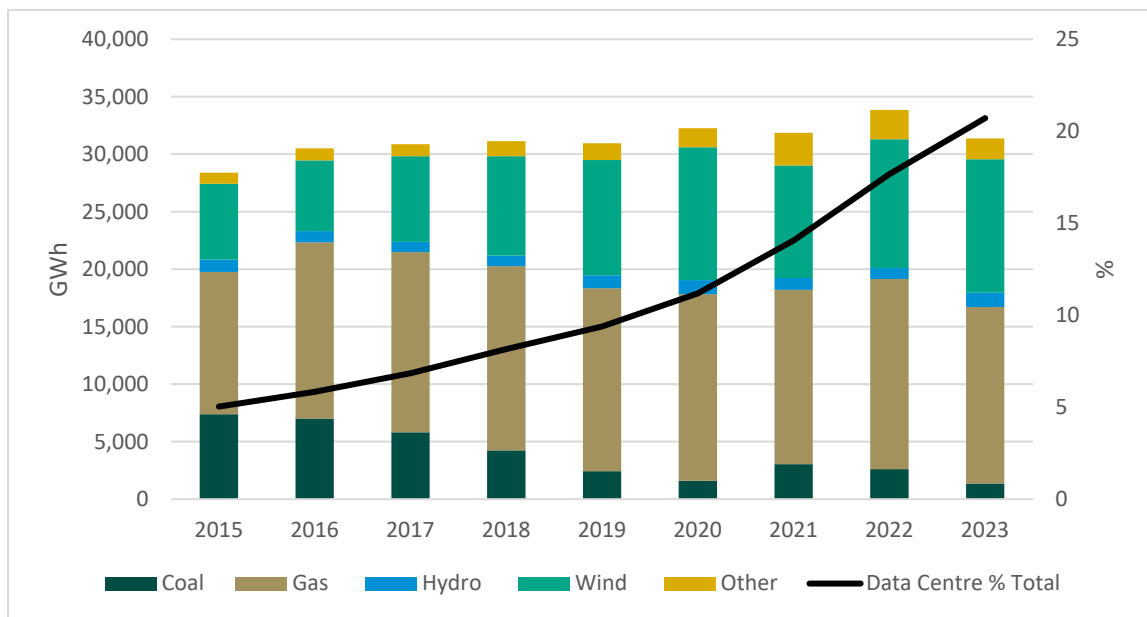


Figure 8: Electricity Generation by Fuel Type²⁶ and Data Centre Energy Consumption as % of Total Metered Consumption



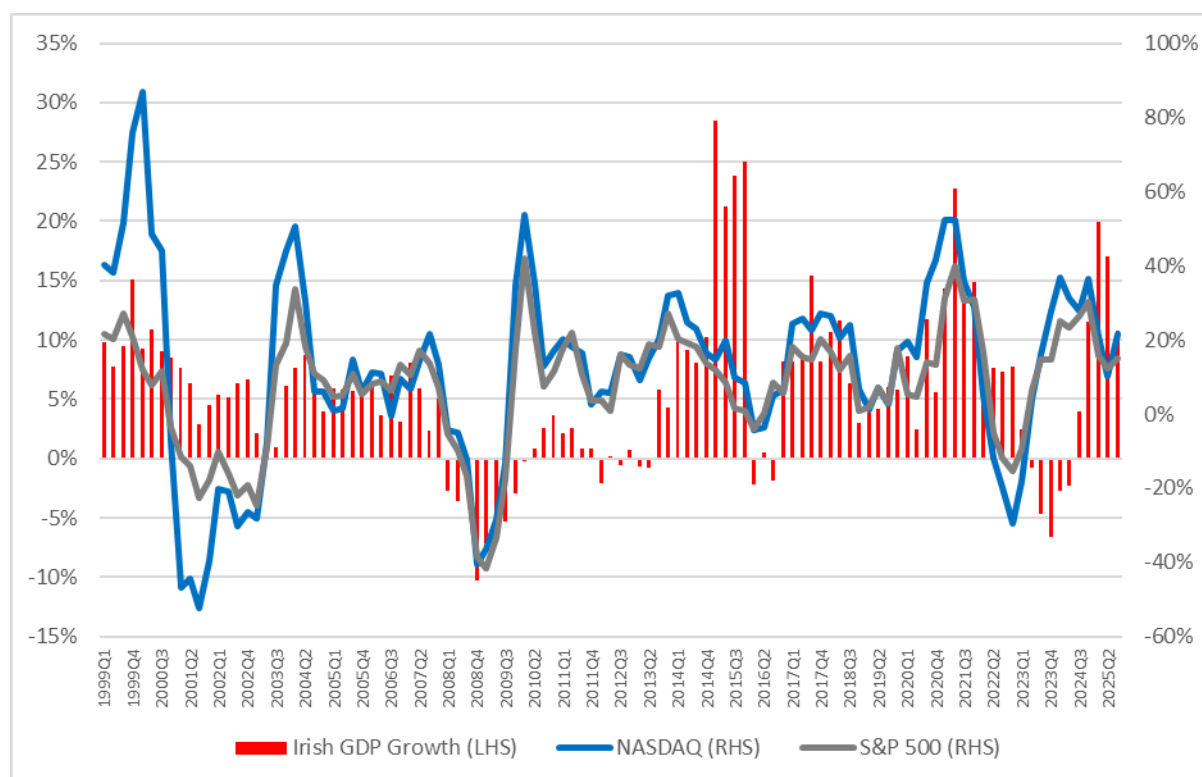
Finally, there is also the risk of damage to Ireland's economic growth (and tax revenues) arising from the bursting of any (possible) speculative bubble around AI investments. It is clear that many large corporations are investing significantly in AI and other new technologies with a small group of core MNCs leading in this regard. Some of these corporations have in turn, now come to account for close to 30% of the entire S&P 500 Index. In the case of Nvidia alone, the share price has increased by 300% in just the past two years and the market capitalisation of this one corporation is now greater than the UK's GDP (see Table 3).

²⁶ 'Other' includes oil, biofuel, waste and solar PV.

Table 3. Market Cap of the five largest US technology firms

Company	2016 Market Cap	2021 Market Cap	2026 Market Cap (February)	2016 vs. 2026
Nvidia	\$57.53B	\$735.27B	\$4.184T	+7,180%
Apple	\$608.96B	\$2.901T	\$4.055T	+566%
Microsoft	\$483.16B	\$2.522T	\$2.925T	+505%
Amazon	\$356.31B	\$1.691T	\$2.380T	+568%
Alphabet	\$546.19B	\$1.918T	\$4.01T	+634%

In previous periods, we have witnessed the impact of the bursting of stock market bubbles in the US – the dotcom bubble in 2000 and the GFC in 2008, for example – rippled outwards and how these impacted the global economy (including Ireland) and weighed on sentiment and investment. In the case of the former, this was one of the factors which contributed to a global slowdown in 2000 and 2001. For Ireland, this was echoed in a notable fall-back in the rate of economic expansion in late-2000 and again in late-2001 (Figure 9) and in sectoral terms, there was a year-on-year fall in ICT employment in late-2000 and early-2001.²⁷ In the case of the latter period, much has already been written on this topic but suffice to say, this greatly exacerbated the consequences of the ending of our own domestic construction boom with significant adverse impacts upon growth, employment and tax revenues. Beyond these specific considerations, the Exchequer will no doubt have a role to play in a variety of other areas, including the funding of education, activation and upskilling measures as well as ensuring that Ireland’s social welfare system continues to protect those most at-risk (perhaps, ultimately, through some form of Universal Basic Income (UBI)).

Figure 9: Ireland’s GDP Growth (q-on-q) versus change NASDAQ and S&P 500 (quarterly average)

Source: Authors' based on NASDAQ; S&P

²⁷ Between 2002-2004, there were annualised declines in ICT sector employment for ten consecutive quarters.

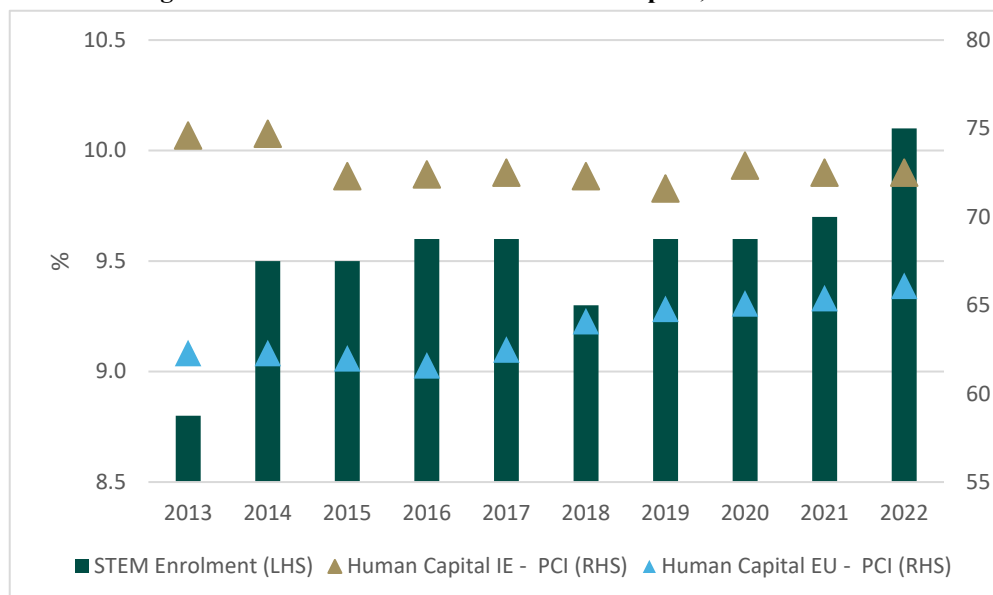
5.2 Education, Skills and Lifelong Learning

Public policy will also need to be sufficiently agile to avoid a two-tier labour market and to ensure that social safety nets are fit-for-purpose. In terms of education and skills policy, the work presented above indicates that AI is highly complementary with higher levels educational attainment. The capacity to leverage the potential benefits afforded by AI requires that workers develop the skills necessary to take advantage of AI as a supporting technology. This, in turn, underscores the importance of public investment in education, including life-long learning and the provision of upskilling and reskilling opportunities. Programmes aimed at continuous skills development for young cohorts (given their high relative exposure), and to promote the greater participation of women in high complementarity roles will be key to facilitating a just transition, and to ensure that Ireland is well positioned to take advantage of future opportunities.

According to the UN's Productive Capacities Index (PCI), Ireland already scores highly in terms of human capital.²⁸ Ireland scored 73 in 2022 (compared to 66 for the EU as a whole) but there is still work to be done. Ireland lags not just the US (82) but also small, advanced economies such as Finland (90) and New Zealand (80). The proportion of students enrolled in STEM subjects (Science, Technology, Engineering and Mathematics) in Ireland has increased significantly over recent years (Figure 10) and by 2022, Ireland had the highest proportion of tertiary education graduates in STEM subjects (40%) across the EU. This compared very favourably with the EU average (23%).²⁹

This notwithstanding, the Irish Universities Association (2023) have criticised public policy relating to STEM as inadequate and called for greater integration between second and third-level education. Ireland also outperforms almost all EU member-states – as well as North America – in terms of expected years of schooling³⁰. An Irish child can now expect to spend approximately 19 years being educated. The comparative figure in 1990 was less than 13 years (with an increase of almost three years occurring between 1997 and 1998 following the phasing out of third-level student fees between 1995 and 1997). Indeed, only Australia, Finland and New Zealand performed better than Ireland under this metric (based on data as at 2022). This metric, however, does not reflect the subjects being taught during this period. Furthermore, whilst the take-up of lifelong learning in Ireland has improved over time, it still remains very low. For instance, only 12% of persons participated in learning in 2023 (Figure 11 a and b). This is below the EU average and significantly lags the performance of countries such as Sweden and Denmark. The OECD has found that the number of days of instruction in a school year in both lower and upper secondary public school are particularly low in Ireland³¹ whilst the instructional time allocated to maths and science at primary level lags the EU average. Indeed, the National Academies of Sciences, Engineering, and Medicine (2024) found that AI will have a significant impact on education at all levels. This relates not solely to the delivery – and take-up – of lifelong learning but also to what subjects are taught at school and how they are thought.

Figure 10: STEM Enrolment and Human Capital, 2013-2022



Source: Eurostat & UNCTAD PCI

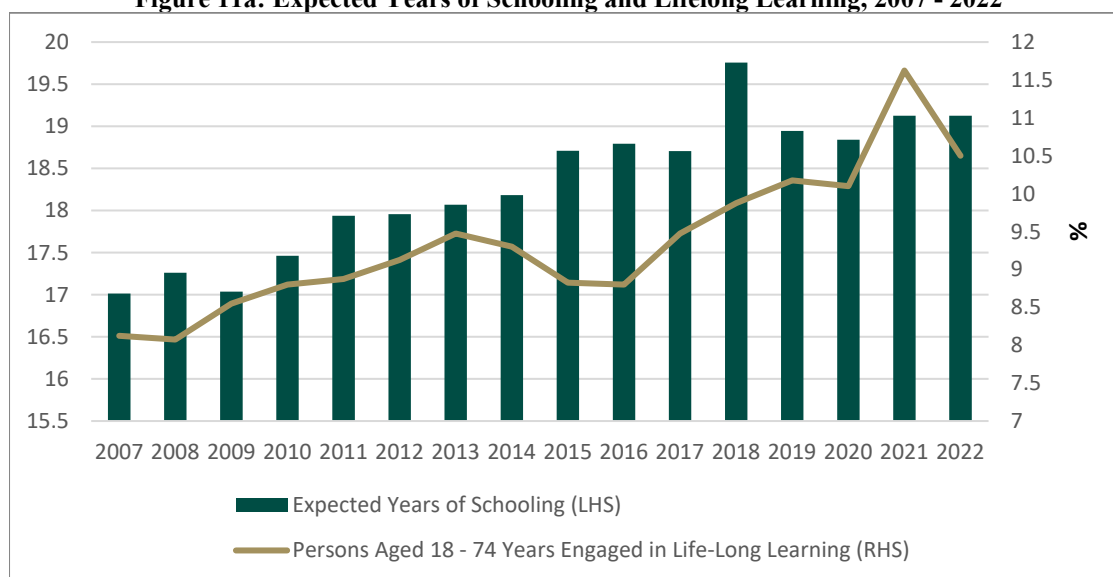
²⁸ This measure captures the education, skills and health conditions possessed by population, and the overall research and development integration in the texture of society through the number of researchers and expenditure on research activities.

²⁹ [Tertiary education statistics - Statistics Explained](#)

³⁰ Number of years a child of school entrance age can expect to receive if the current age-specific enrollment rates persist throughout the child's years of schooling.

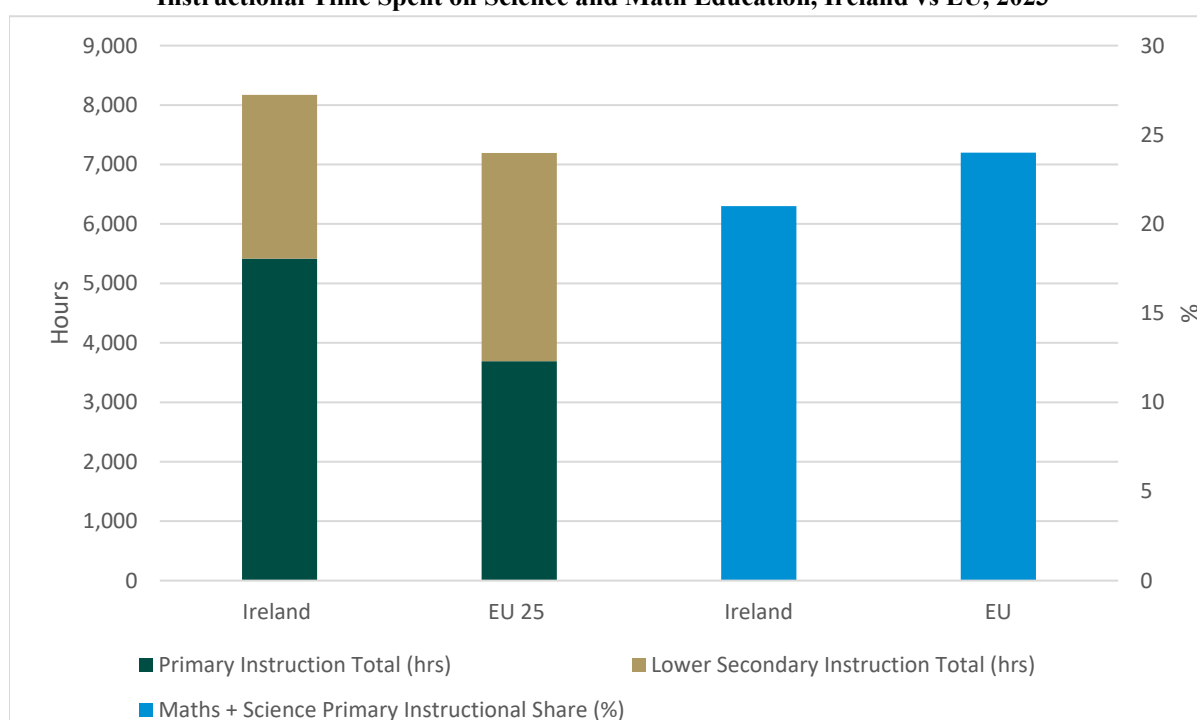
³¹ [Education GPS - Ireland - Overview of the education system \(EAG 2024\)](#)

Figure 11a: Expected Years of Schooling and Lifelong Learning, 2007 - 2022



Source: Our World in Data (UNDP, Human Development Report (2024)) and CSO

Figure 11b: Total Instructional time in Primary/Lower Secondary Education and Proportion of Instructional Time Spent on Science and Math Education, Ireland vs EU, 2023



Source: OECD

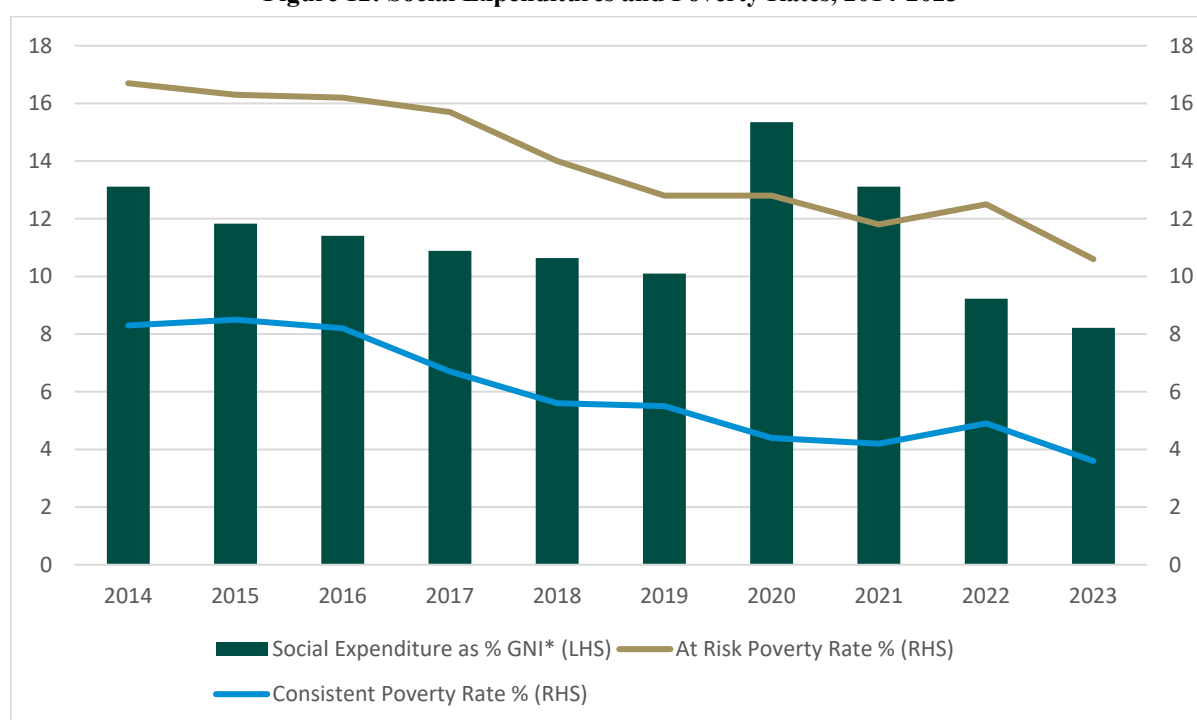
5.3 Public Trust and Social Inclusion

Ireland has made significant progress in terms of tackling poverty and inequality over the past decade. Both the AROPE³² and consistent poverty rates have fallen since 2013 (Figure 12) but technological change will present a new range of challenges to be addressed. Public policy has a role to play in ensuring that technological change does not compound existing inequalities. Specifically, there is a need to ensure that robust frameworks are in place to ensure distributive justice in the allocation of access to beneficial forms of technology lest change happens in a manner that further disenfranchises poorer communities, reduces opportunities and narrows the scope for upward social mobility. To this end, public policy will need to be agile, promoting a fair transition and – should displacement occur – assist workers in adapting to a changing labour market.

³² At risk of poverty of social exclusion

Finally, the National Competitiveness and Productivity Council (NCPC) recently developed a new *Competitiveness and Productivity Framework*, an analytical tool to guide and shape future analysis of these themes in the Irish context (Coates et al., 2024). This framework identified six drivers of competitiveness and productivity, including macroeconomic stability; infrastructure; and education and skills. This framework posited effective and stable public institutions – including the role of reputational capital to the State – as an important determinant of broader macroeconomic stability but this is another sphere where AI could potentially present a challenge to public policymakers. More specifically, the spread of misinformation – including the increasing prevalence of realistic but false images and audio (or deepfakes) and online echo chambers – could have serious and negative consequences for public discourse via the rise in polarisation and separation that will likely follow (European Parliament, 2023). These factors represent a threat to both public trust in these shared institutions and to democracy as well as posing risks with regard to data protection, privacy rights and the cybersecurity of public services.

Figure 12: Social Expenditures and Poverty Rates, 2014-2023



Source: CSO and Author's Calculations

6. CONCLUDING COMMENTS

The paper then assesses Ireland's overall labour market exposure to AI and places these results in a comparative international context. We do so by means of building upon methodologies developed by Felten et al. (2021) and Pizzinelli et al. (2023) in order to create a complementarity-adjusted AI occupational exposure (C-AIOE) index for Ireland. This approach allows us to consider both exposure and complementarity in parallel. This is critical to understanding the potential labour market shifts a given occupation might encounter over time. For instance, those occupations heavily exposed to AI – and where tasks can be performed autonomously – are likely to see a decline in demand for human labour. By contrast, heavily-exposed occupations with a high degree of complementarity to AI could see productivity enhancements, leading to an increased demand for labour. This paper suggests that the impacts of AI on the labour market are unlikely to be uniform. We find that 63% of employment in Ireland is relatively highly exposed to AI, with 30% of employment falling into the 'at-risk' category.

This finding suggests that Ireland is relatively more exposed to AI than is the case for other advanced economies. We also find distinct differences in the likely impact of AI adoption for workers across multiple dimensions. For instance, we find that female workers in Ireland are far more likely to work in highly exposed roles compared to males and that younger Irish workers are more exposed to AI than are older workers. We also find that whilst exposure to AI increases in line with educational attainment, so too does complementarity. The extent to which AI augments, or replaces, human labour in the medium to long-run will depend on a variety of economic, social and policy factors, including levels of AI regulation. Furthermore, the capacity to leverage the potential benefits afforded by AI requires that workers develop the skills necessary to take advantage of AI as a supporting technology.

As with any new technology or innovation, research on the impact of AI will always lag behind the rapid pace of development in the field. The measure of AI exposure used in this study focuses on ten specific AI applications, all of which can be considered to be “narrow” AI. Given that Felten’s work was published in 2021, it does not capture the latest advancements in AI technology, such as document summarisation or LLM-based searching. These are AI applications that are already widely used through a variety of software models. Furthermore, the AIOE measure used here does not capture exposure to advanced robotics. As noted above, advanced robotics – and the integration of same with AI – will further re-shape our understanding of the future of work and have profound impacts on the labour market. The analysis presented here only provides an indication of impacts based on recent understandings of AI applications and does not attempt to predict how AI technologies will evolve in future, nor the rate of adoption across the enterprise base.

These impacts, and the scale and speed of change, present a series of challenges for public policymakers. It is clear that the economic impact is dependent on a variety of factors, from the rate at which AI’s capabilities evolve to the scale and speed of adoption to a series of demographic, social, institutional, and political forces. The recency of these developments means that it is quite challenging to forecast the impact of these changes but it is clear that these will not impact solely on the labour market but will also have consequences for public policy in terms of Budgetary strategy, public trust, education and social inclusion. Indeed, whilst technological change – and in particular, AI – will present challenges for policymakers, there will also be opportunities. For instance, many advanced economies are currently experiencing a tight labour market and it is possible that labour scarcity could become more pronounced over time as the population in these countries ages (alongside low birth rates and a rising ratio of older persons to workers). It may be that AI will form some part of the solution to this scarcity. AI adoption is also likely to impact on graduate recruitment in highly exposed sectors, disrupting early career employment opportunities. Further, the convergence of AI, robotics, and quantum computing could amplify automation capabilities, enabling machines to perform more complex physical, analytical, and optimisation tasks. This raises long-term questions about the distribution of GVA between labour and capital. If productivity gains from these technologies accrue mainly to the owners of capital, the labour share of GVA could decline. These issues merit further discussion in future work. Finally, this is clearly an area that requires ongoing and inter-disciplinary work to enable us to better understand the impact of technological change and how best the State can respond to emergent risks and challenges.

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ANNEX

Table 1. Implications of AI for growth, the labour share and wages – range of models

Model Assumptions	Reference	Impact on Economic Growth	Impact on the Labour Share	Impact on Wages
HS in production and capital-augmenting technology growth	Acemoglu and Restrepo (2018)	No change in long-run output level, or growth rate	Approaches 1	Upward shift in wage path
HS (but not PS) in production and capital-augmenting technology growth	Nordhaus (2021)	Type I growth explosion	Approaches 0	Type I growth explosion
PS in production and capital-augmenting technology growth	Trammell and Korinek (2023)	Type I growth explosion	Approaches 0	Driven to low but constant rate
HS in final good production, HS in robotics production	Mookherjee and Ray (2017); Korinek and Stiglitz (2019)	Increase in long-run growth rate	Approaches 0	Driven to low but constant rate
HS in final good production, LS in robotics production	Mookherjee and Ray (2017); Korinek (2018)	Shifts output path up, without changing growth rate	Pushed to positive constant (not necessarily lower or higher)	Pushed to positive constant (not necessarily lower or higher)
PS in production, with one-off capital-augmenting technology increase, and savings increase	Korinek and Stiglitz (2019)	Type I growth explosion	Approaches 0	No change in level or growth rate
LS in production and task automation and replacement	Acemoglu and Restrepo (2018)	Type I growth explosion	Pushed to positive constant (not necessarily lower or higher)	Type I growth explosion
HS in production and task automation and creation	Hémous and Olsen (2014)	Type I growth explosion	Approaches 0	Type I growth explosion
AI-assisted elasticity-change in idea discovery	Agrawal et al (2019)	Type II growth explosion	n/a	n/a
HS in production and HS in idea production	Aghion et al (2019)	Type II growth explosion	n/a	n/a

Notes. HS, LS and PS refer to High Substitutability, Low Substitutability and Perfect Substitutability, respectively. Type I growth explosion refers to a continuous acceleration in growth, where the growth rate grows without bound. Type II growth explosion refers to an acceleration in the growth rate that is rapid enough to produce infinite output over a finite time period.

Source: Authors' based on Trammel and Korinek (2023).

Map 1: Cloud Services

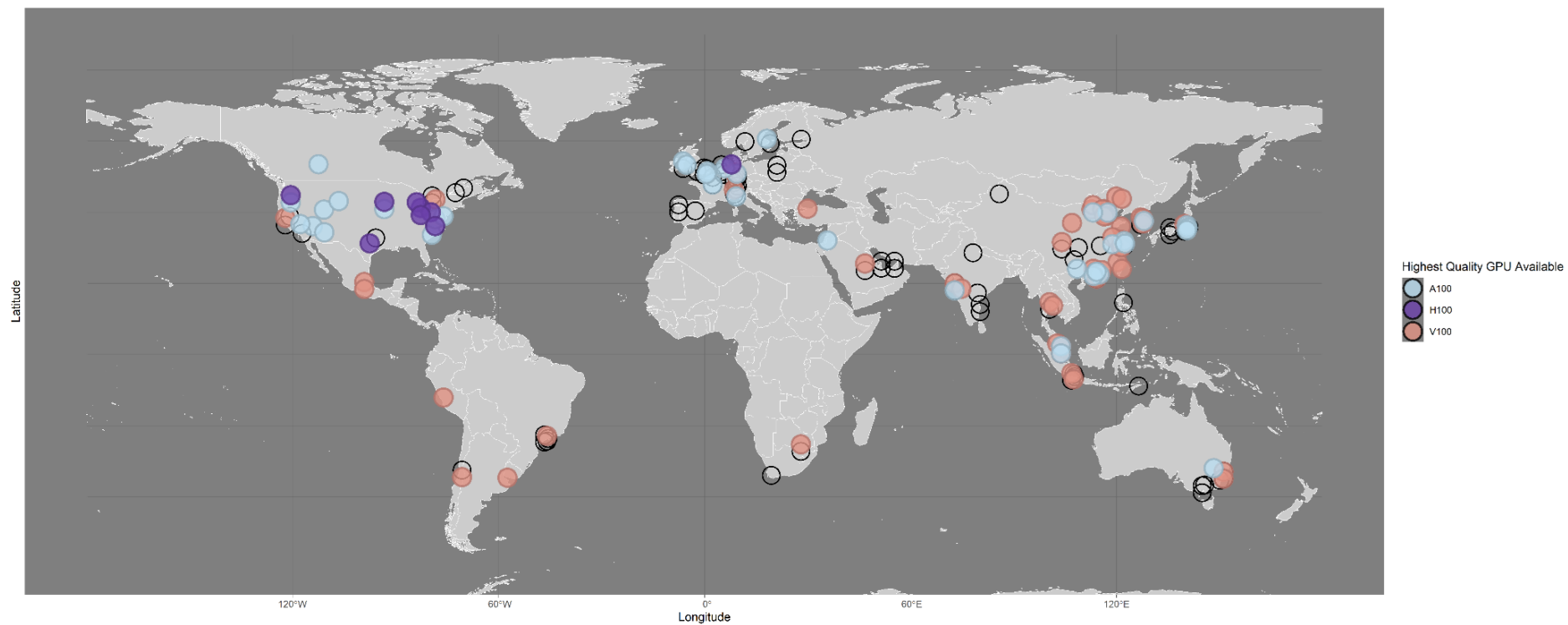
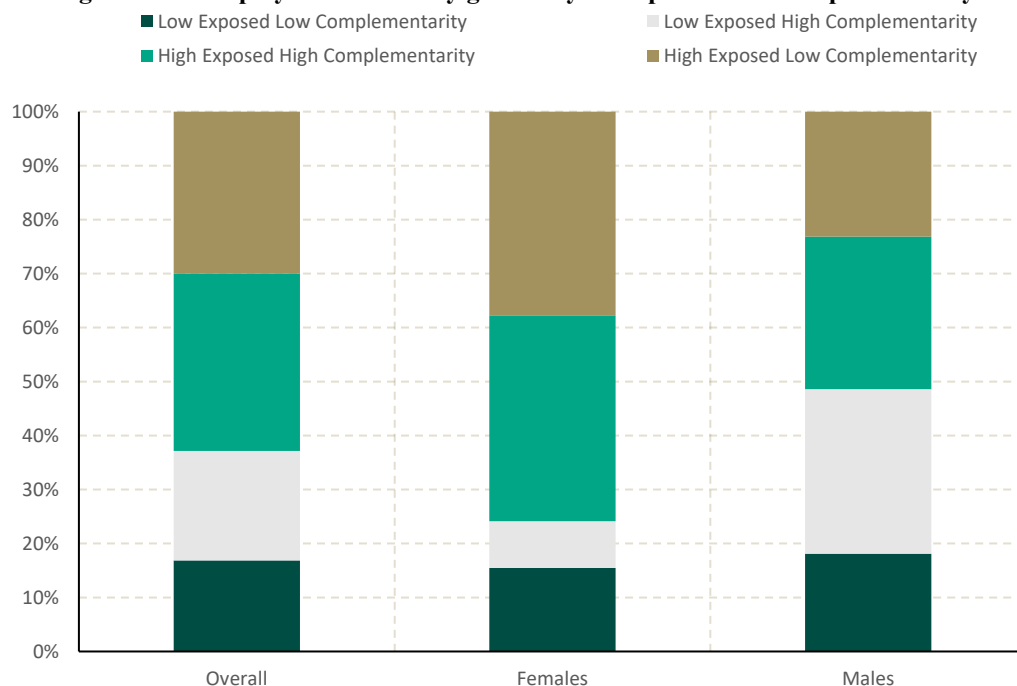


Table 2: Estimates of the exposure of the labour market to AI adoption

Paper	US	Global	Europe	Other	Technology	Notes
Department of Finance/Department of Enterprise, Trade and Employment (2024)	n/a	n/a	63% - Ireland	n/a	Focuses on Generative AI. Does not account for the interaction between AI and robotics.	Figures relate to overall exposure, which is further assessed in terms of substitutability and complementarity.
Jung and Desikan (2024)	n/a	n/a	11%-59% - UK	n/a	Range based on here-and-now technology, to more integrated technology.	Overall exposure is assessed, however, there is no quantification of exposure in terms of substitutability and complementarity.
Manyika et al (2017)	23%	15%	24% - Germany	9% - India 13% - Mexico 16% - China 26% - Japan	Automation driven by robotics and AI technologies.	Refers to percentage of work activity hours expected to be automated by 2030.
Briggs and Kodnani (2023)	25%	18%	24% - Euro Area 25% - UK	26% - Japan 29% - Hong Kong 24% - Argentina 23% - Chile	Automation driven by generative AI technologies. With robotics, the US estimate rises to 35%.	Exposure defined by share of tasks that AI can be expected to perform. This is used to derive estimates for the share of employment exposed to automation. Exposure is assessed in terms of substitutability and complementarity.
Agrawal, Gans, and Goldfarb (2020)	34%	n/a	n/a	n/a	Improvements in predictive modelling and decision-making through machine-learning.	Includes discussion of potential for machine-learning technology to both replace and substitute for labour.
Hawksworth and Berriman (2018)	38%	n/a w	31% - Ireland 30% - UK 44% - Slovakia 34% - Austria 31% - Netherlands 30% - Belgium 30% - Denmark 25% - Norway 22% - Finland	24% - New Zealand 24% - Japan 22% - South Korea	AI and robotics driving automation of routine and physical tasks.	Derived from a task-based assessment of individual roles. Describes three waves of automation over the period to the 2030s (algorithm, augmentation, and autonomy).
Muro, Maxim, and Whiton (2019)	46%	n/a	n/a	n/a	AI and robotics.	Based on the current-task automation potential of occupations.
Frey and Osborne (2013)	47%	n/a	n/a	n/a	AI and robotics.	This figure relates to the percent of employment in the high-risk category for automation.
Cazzaniga et al (2024); Pizzinelli et al (2023)	60%	40%	70% - UK	41% - Brazil 39% - Colombia 37% - South Africa 26% - India	Focuses on Generative AI. Does not account for the interaction between AI and robotics.	Figures relate to overall exposure, which is further assessed in terms of substitutability and complementarity.

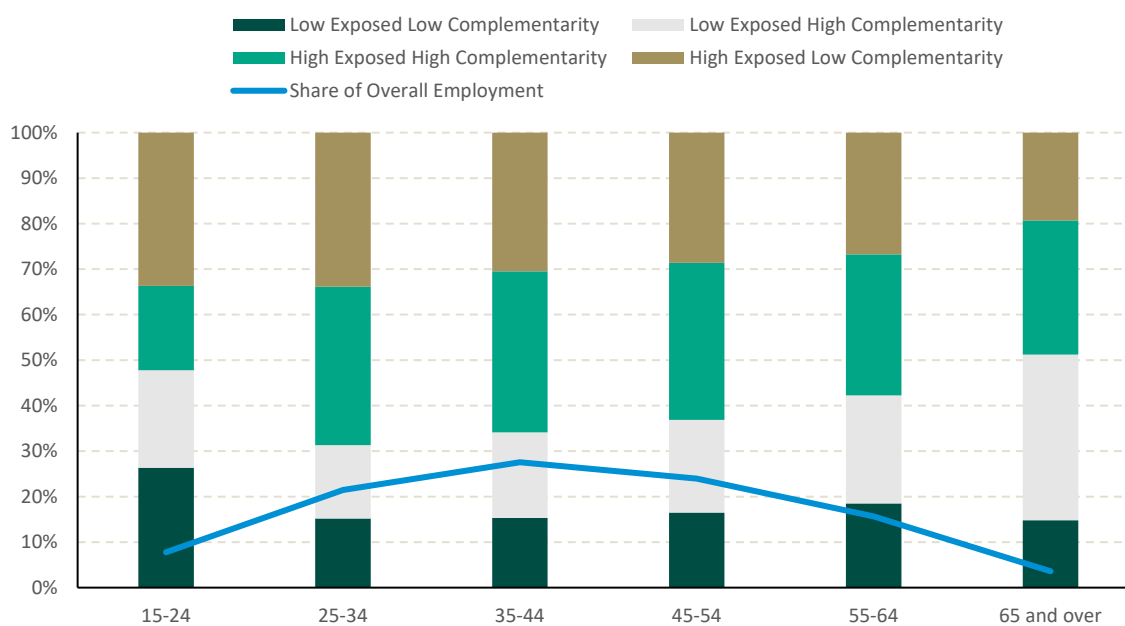
Bowles (2014)	n/a	n/a	54% - EU-28 49% - Ireland 47% - UK 51% - Germany 51% - Finland 54% - Estonia 50% - Netherlands 50% - Belgium 50% - Denmark 54% - Austria 55% - Slovakia	n/a	AI and robotics.	This figure relates to the percent of employment in the high-risk category for automation.
Eloundou et al (2023)	19%	n/a	n/a	n/a	Focuses on generative AI, specifically large language models (LLMs). Does not account for the interaction between AI and robotics.	Exposure defined based on whether the use of LLMs reduces the time taken to complete a task, without an adverse impact on quality.
Albanesi et al (2023)	n/a	n/a	23%-29%	n/a	Focuses on generative AI, specifically large language models (LLMs). Does not account for the interaction between AI and robotics.	Exposure based on tasks and occupations being in the upper tercile of the exposure measures used.
Arntz, Gregory and Zierahn (2016)	9%	n/a	12% - Austria 6% - Estonia 8% - Ireland 10% - UK 7% - Sweden 11% - Slovakia 10% - Norway 7% - Finland 9% - Denmark 10% - Netherlands 7% - Belgium 12% - Germany	7% - Japan 6% - Korea 9% - Canada	AI and robotics.	Figures refer to the percentage of individuals facing high exposure (i.e. an automatability of at least 70%, based on tasks associated with occupations).

Figure A.1: Employment shares by gender by AI exposure and complementarity



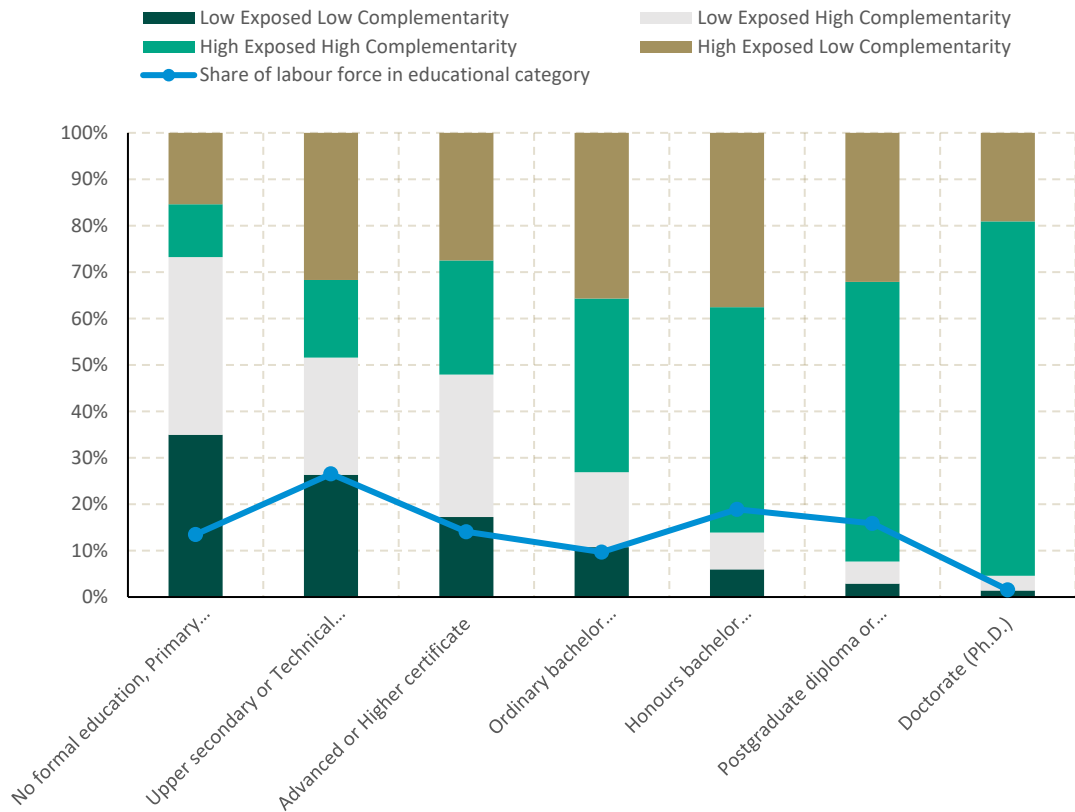
Source: Author's calculations

Figure A.2: AI exposure and complementarity by age cohort



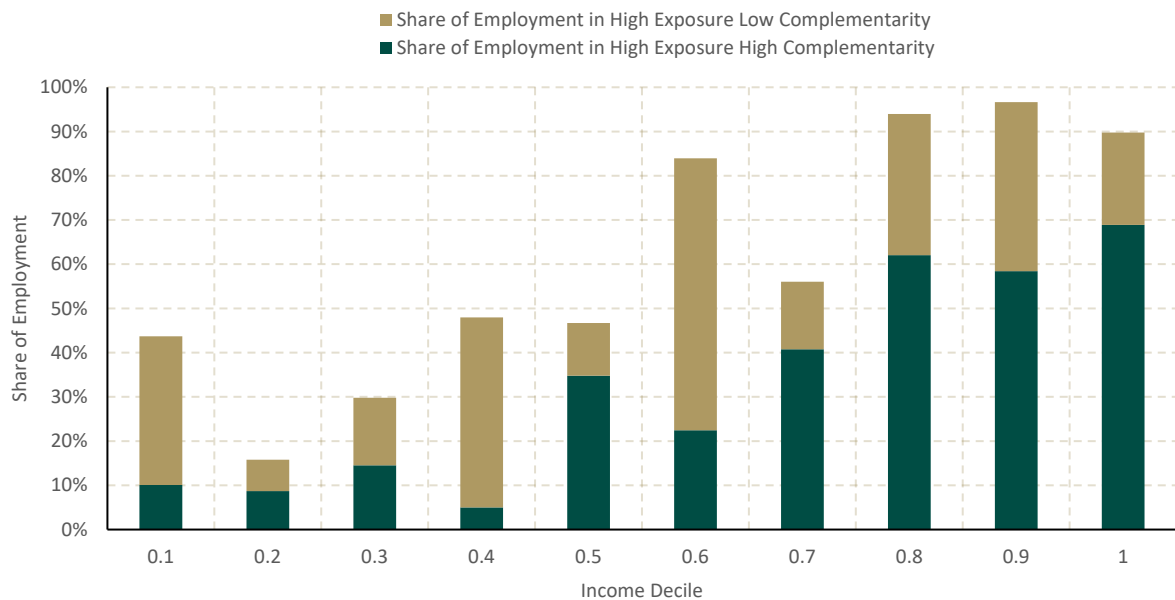
Source: Author's calculations

Figure A.3: AI exposure and complementarity by educational attainment



Source: Author's calculations

Figure A.4: AI exposure and complementarity by income decile



Source: Author's calculations

**FIRST VOTE OF THANKS PROPOSED BY JOHN FITZGERALD,
ECONOMIC AND SOCIAL RESEARCH INSTITUTE**

This is a very useful paper. As yet, there has been limited research on the possible implications for employment from the widespread adoption of AI. This paper fills a gap in our knowledge, providing detailed and robust analysis, helping us understand how the adoption of AI in Ireland and elsewhere may affect employment and potentially benefit the wider economy.

The paper divides jobs into four categories:

1. Those that will be affected by AI and may benefit from using it, increasing productivity (complementarity).
2. Those that will be affected but could be replaced by AI. This would increase output per person and reduce costs.
3. Those that will not be directly affected and will not be users of AI.
4. Those that will not be directly affected but could use AI.

The authors state “The results of our analyses indicate that 63% of employment in Ireland is relatively highly exposed to AI, with 30% of employment falling into the ‘at-risk’ category (or high-exposure, low-complementarity).” This is a high level of exposure. However, as the authors point out, many of these jobs may be users of AI rather than being merely replaced by AI. The authors also say that “Ireland also has a high share of persons working in high-complementarity roles. Approximately 53% of persons in Ireland work in roles which are highly complementary to AI, compared to 52% in the UK, and 50% in the US”.

An optimistic view of the implications of AI for the economy would see those sectors and workers for whom AI is “complementary” to their work raise output with unchanged inputs, raising productivity and potentially increasing output and returns for investors and those working in the sector.

An alternative pessimistic possibility is that AI, by replacing the work that many people currently do, would produce a major fall in employment. With similar output levels in the affected sectors, this would reduce the cost of producing a given good or service. In turn, there would be a demand response seeing output rise, partially offsetting the cut in labour input. The companies and countries that reaped the benefits of such a reduction in costs first could gain a competitive advantage and increase market share and output. Thus, the full implications of such changes need not necessarily be negative for the Irish economy.

Most of the jobs that might be at risk are for people with third level education. This cohort currently experiences low rates of unemployment in Ireland and elsewhere so, for those who lose their jobs as a result of AI, on current trends they are likely to find another job. The extent to which they suffer a loss of income from changing employment will depend on the extent to which their education was purely job specific or provided a broader education, fitting them for different roles. If those being redeployed find satisfactory employment, the effects of this change, combined with the increase in productivity in the firms directly affected, could increase output and national income. If successful redeployment does not take place, then the effects on the economy could be negative.

Looking at employment across the EU-27 since 2008, all of the increase in employment has been for people with third level qualifications, with major loss of jobs for those with lower levels of education.

	All jobs (000)	Third level (000)	First and Second level (000)
EU			
Total	16086	24567	-8482
Manufacturing	-1573	2932	-4504
IT	2432	2435	-3
Professional services	2466	2686	-220
Sub total	3325	8052	-4728
Public sector	6890	8307	-1417
Other	5871	8208	-2337

The question is whether this pattern will be affected by AI. Will time freed up by AI be redeployed within jobs or within sectors. To date there is no evidence that AI is leading to significant job losses for those with a good education.

Looking at what is happening globally, there is huge investment in developing the AI models, requiring massive energy input. The most obvious impact is the need to build and operate massive data centres to make AI models work. While Ireland has until recently been a focus for data centre investment, so that for a short period it had one of the biggest concentrations of centres in the world, this is going to change.

The problem with the latest data centres is that the computer chips needed to “train” the latest AI models require a dramatic increase in power, concentrated into a tight space. In turn, using all this power they use large amounts of water to keep them cool. The concentration of power, using the latest computer chips, together with their energy and water demands, are dramatically greater than those of existing Irish data centres.

Meta is building a centre in Louisiana that will require 2 GW of electricity generation, enough to power much of Ireland. These new data centres are on a scale way beyond anything operating in Ireland today and they even pose major challenges for the US economy. By 2028, US data centres could account for 12% of all electricity generated in the US, adding 3% to 4% to US greenhouse gas emissions and substantially increasing electricity prices across the US. There is no point in Ireland trying to compete in building these centres to train AI models, with the associated computing and energy infrastructure. The cost of energy in Ireland is too high. Ireland will be a user of AI and cannot try and produce it.

These investments in data centres to run AI, which are mainly taking place in the US, are massively expensive. This year the investment will amount to over 2% of US GDP. McKinsey estimates that by 2030 the cumulative cost of the investment needed to make AI work will be over 20% of US GDP. This raises a key question – will the investments pay off.

To make money on the investment, the income generated from this investment will first have to pay for all the computers and electricity generation and transmission equipment. The chips used may have a life of only three years. It will also have to pay for the energy consumed each year, and investors will also want a return on their investment. This means that by 2030 the AI models will need to generate income of well over 3% of US GDP, possibly even greater than 5%.

If the AI models are worth what they are costing, they would have to raise US productivity by at least 5% by 2030. This seems unlikely. Alternatively, they would need to replace well over 5% of all jobs in the US by 2030, which is even more unlikely. This raises serious concerns that the future value and profitability of investment in AI is exaggerated and, if this proves to be the case, the investment boom could prove to be a bubble. Bursting it could prove very disruptive for the world economy. The paper notes the negative effects on the Irish economy of just such a slowdown in the early 2000s when the “dotcom” bubble burst.

Policy implications

Ireland should not go after the data centre market. We could not handle the size of the latest investments. We are well fitted to use AI provided by cloud services, wherever in the world they are located. Having your data and models in a data centre down the road may have been appropriate 50 years ago, but today this is not necessary for many activities. As noted in the paper, we need to ensure that the educational system provides skills for a range of future occupations or vocations. People may need to be flexible moving jobs to where their skills are most valuably deployed. Already, third level education is doing a good job, fitting labour market entrants for a range of possible career paths. We have the highest share of STEM graduates per head of population of any EU member, around twice the EU average. (Other countries with high shares are Denmark, France and Finland.) This is a good start. We need to make good use of AI to enhance productivity and growth. Worrying too much about how it may change the labour market could see Ireland miss an opportunity.

This paper provides a very valuable basis for planning policy in Ireland to make the best use of the opportunities that AI may provide. However, if the world is currently exaggerating these opportunities, we could see serious disruption to the international economy in the next few years.

SECOND VOTE OF THANKS PROPOSED BY JAMES BROWNE, COMREG

I would like to thank the authors for a well-motivated and important contribution to the literature on this topic. The focus on Ireland makes this paper particularly important given the potential impact of AI on Ireland as a small open economy. The publication of this paper is also extremely timely. The media has recently focused on the negative impact of AI, using individual company job loss announcements to spread fear, even if many of these losses are due to regular labour migration. It is therefore useful that this paper makes the distinction between boosts (complements) and risks (job loss) from AI.

Of course, to realise these benefits and risks there are two requirements:

- the technological transformation must continue, the type and use of AI applications must continue to grow, and investment is needed for that. The idea of an investment bubble has been discussed frequently, and while the paper notes that a lag in adoption is expected for new technology, at some point monetisation will become a key priority to justify the valuations of large US firms.
- The outcomes also depend on adoption by firms. The paper makes this point clearly and shows that we may not see the full extent of the exposure for a while. A recent paper from the ESRI ‘Artificial Intelligence and Firm-Level Productivity: Early Evidence from a Small Open Economy’ supports this point. It uses data from the ICT survey from the CSO to show that adoption to date is low and the average productivity gains from AI are modest, delayed, and short-lived.

In terms of policy implications, there are two areas that I would like to mention:

- Firstly, I compared the points raised in the paper to some of the issues that Ireland’s National AI Strategy 2024 is aiming to address. The strategy was published in 2021 and redrafted in 2024 as it recognised the significant advancement in AI in that time period. The aim of the strategy is to act as a roadmap for how Ireland can leverage AI for productivity, addressing societal challenges, and delivering public services. There is significant overlap between what it covers and some of the points raised in the paper such as: an awareness campaign to encourage SME adoption, creating an environment for innovation and research, encouraging female participation, and conducting a study on the potential impacts of AI on key sectors of the Irish economy.
- Secondly, it is important to note the underlying infrastructure requirements for AI to fully benefit the economy – the National Broadband Plan ensures more equitable access to new technologies and offers the potential for more exposure to AI e.g. farming use cases. The paper covers the importance of meeting energy requirements and increased demand on the National Grid but does not mention other requirements.

Finally, one minor limitation of the paper is that the AI applications covered are from 2021. Given recent advances in AI, figures in the report could therefore be seen as a lower bound with more occupations now exposed to and complemented by new applications and use cases.