WORKING PAPER | ISSUE 20/2023 | 14 DECEMBER 2023

SKILLS OR A DEGREE? THE RISE OF SKILL-BASED HIRING FOR AI AND GREEN JOBS

EUGENIA GONZALEZ EHLINGER AND FABIAN STEPHANY

For emerging professions, such as jobs in the field of artificial intelligence (AI) or sustainability (green), labour supply does not meet industry demand. In this scenario of labour shortages, our work aims to understand whether employers have started focusing on individual skills rather than on formal qualifications in their recruiting. By analysing a large time series dataset of around one million online job vacancies between 2019 and 2022 from the United Kingdom, and drawing on diverse literature on technological change and labour market signalling, we provide evidence that employers have started so-called 'skill-based hiring' for AI and green roles, as more flexible hiring practices allow them to increase the available talent pool. In our observation period the demand for AI roles grew twice as much as average labour demand. At the same time, the mention of university education for AI roles declined by 23 percent, while AI roles advertise five times as many skills as job postings on average. Our regression analysis also shows that university degrees no longer show an educational premium for AI roles, while for green positions the educational premium persists. In contrast, AI skills have a wage premium of 16 percent, similar to having a PhD (17 percent). Our work recommends making use of alternative skill building formats such as apprenticeships, on-the-job training, MOOCs (massive open online courses), vocational education and training, micro-certificates and online bootcamps to use human capital to its full potential and to tackle talent shortages.

Keywords: Future of Work, Labour Markets, Skills, Education, AI, Sustainability
JEL Class: C55, I23 J23, J24, J31

Fabian Stephany (fabian.stephany@bruegel.org) is a Non-resident Fellow at Bruegel and a Lecturer in AI & Work at the Oxford Internet Institute
Eugenia Gonzalez Ehlinger, Multiverse, London

This work is part of the Bruegel Future of Work and Inclusive Growth project. The authors are grateful for the feedback received on the project's 2023 seminar, and review by Estrella Gómez Herrera and Duygu Güner.

bruegel

Recommended citation:
Gonzalez Ehrlinger, E. and F. Stephany (2023) 'Skills or a degree? The rise of skill-based hiring for AI and green jobs, *Working Paper* 20/2023, Bruegel

1 Background

Are skills more relevant in the workplace than formal education? When it comes to hiring new employees, educational qualifications may play an important role from the perspective of an employer. But more and more attention is being focused on candidates' skills that may have been acquired outside formal education (Fuller, 2022; McKinsey, 2022; LinkedIn, 2022). The increasing importance of skills during hiring processes stems from the uneven pace at which formal education and the labour market are evolving, as well as from the prevalent challenges faced by companies in finding and retaining the right candidates if they limit themselves to only considering people with higher educational degrees in specific fields. Observational studies have also shed light on the fact that employers are more likely to adopt hiring strategies that focus on individual skills when the demand for talent far outstrips supply, for example, as seen in the unprecedented need for medical staff during the COVID-19 pandemic (Fuller, 2022).

The adoption of so-called 'skills-based hiring' also carries importance for emerging occupations, which may not have well-established or standardised higher education degree programmes tailored to their specific skills requirements. Examples of emerging occupations are those jobs that have gained in relevance as a consequence of the so-called *"twin transition"* (Paiho *et al*, 2023). The twin transition encompasses, potentially, two of the main drivers of change in the labour market: the growing digitalisation of economic processes and an economic shift towards greater environmental sustainability. The interplay between these two transitions creates unique synergies. By harnessing the power of AI, policy actors can analyse vast amounts of data, develop predictive models and optimise resource allocation, thus enabling more effective and efficient climate mitigation and adaptation strategies (Leal *et al*, 2022). AI can contribute to renewable energy systems by optimising energy generation and distribution, improving the efficiency of power grids and facilitating the integration of intermittent energy sources (Farzaneh *et al*, 2021). Additionally, AI algorithms can enhance climate modelling, helping to understand complex climate dynamics and predict future scenarios with greater accuracy. Furthermore, AI-powered solutions can optimise transportation systems, reduce emissions, and enable smarter urban planning (Son *et al*, 2023). The potential of AI in combating climate change is vast, and by leveraging its capabilities, a sustainable path forward for our planet can be forged. At the same time, AI has also been identified as a risk factor for reducing emissions. Widespread attention to the growing environmental impact of AI and its carbon footprint has been significantly stimulated by estimates of computational and electricity resources that are required to train selected AI models by machine-learning (ML) methods (Tamburini, 2022).

Despite the growing importance of skills-based hiring and its potential contribution to tackling skills shortages by increasing the size of the talent pool, to date, we know very little about it. Most prior scientific articles referring to employers' requirements focus on understanding the changing trends of skills demanded by employers, without comparing the value placed on skills versus formal education. These approaches are useful because they provide insight into the evolving demands of the labour market and enable the identification of emerging occupations and demanded skills (see Alekseva, 2021; Saussay, 2021; ILO, 2021). However, they often overlook the interplay between formal education and skills in the hiring process, simplifying the complex dynamic between formal degrees, work experience and skills through the lens of employers. We go beyond this by analysing a large time-series dataset of about one million online job vacancies in the UK between 2019 and 2022, which includes granular detail for every posting. We refer to the definition of skill-based hiring as *"... the practice of employers setting specific skill or competency requirements or targets (for hiring)"* (Butrica and Mudrazija 2022). Focusing on AI-related and green jobs allows us to explore the adoption of skills-based hiring in occupations that necessitate relatively novel skills, for which employers have previously reported skills shortages.

We ask the research question: *"Given the fast-growing excess demand, have employers started to apply skill-based hiring practices for AI and green jobs?"* We investigate if firms are trying to harvest the talent pool by putting stronger emphasis and remuneration on individual in-demand skills than on formal education requirements, resulting in the following hypotheses. For job advertisements in the domain of AI and green jobs, we theorise that we observe:

1. Below average mentioning of formal education requirements,
2. above average mentioning of individual skills, and
3. a premium in offering wages for skills in addition to formal education.

Furthermore, using statistical analyses and a regression model we are able to understand the association between higher education degrees and skills requirements with economic remuneration. Thus we are able to provide new insights on the shift of paradigms from a degree-focused to a skills-based labour market. Based on our unique dataset on employers' requirements in job advertisements, we find evidence that jobs requiring green and AI-related skills are rapidly increasing and demanding broader sets of skills. Our results show that vacancies demanding these novel skills are also associated with significant offering of wage premiums. Our findings also suggest that for AI roles, skill requirements surpass the wage impact of educational attainment.

This paper proceeds as follows. Section 2 provides the background literature. It describes our dataset and outlines the bottom-up approach we use to identify AI and green jobs, as well as the changing demand and supply on these two domains that might lead to a shift in hiring practices. Section 3 examines the aspect of human capital – central to our investigation – which is represented by formal education and skills. Here, we analyse and compare the educational and skills requirements and estimate their influence on wage premiums. Section 4 concludes with policy recommendations.

2 Tracking the twin transition in the UK

In this section, we describe the online job vacancies dataset, the granular-level information it contains and its limitations. We then describe the skills-level approach used, the list of AI and green skills that served as a guideline and the way we classified vacancies.

2.1 Online job vacancies

The primary data source used for this study is the online job vacancy (OJV) postings database provided by our project partner Lightcast, a labour market analytics firm[1]. Covering the period from January 2019 to December 2022, the Lightcast data encompasses a vast collection of one million job vacancies. These listings include essential details such as job titles, job locations, employer's name and industries. Moreover, the granularity of the dataset provides information regarding the desired characteristics of candidates, including a list of skills and the educational attainment. Additionally, for the UK, the Lightcast database contains data on the salaries advertised within these vacancies for about 38 percent of the sample. This information is not clustered across regions, industries or occupations (see Table A2). AI (29.8 percent) and green (33.5 percent) postings are just as likely as every other vacancy to contain wage information. Although these posted salaries may not reflect the accurate remuneration received by hired employees, they serve as an indicator of the companies' willingness to compensate for specific skill sets demanded in the job postings. A summary of the main characteristics used in this analysis can be found in Table A2 in the Appendix.

The vacancy data provides valuable and extensive insights into employer demands, but it has limitations. While we are able to analyse job vacancies, the candidate selection process is not fully transparent. Employers may consider criteria beyond those listed in postings throughout the selection process. Another significant limitation is that by looking solely at vacancies posted online we may overlook other means of acquiring talent in these domains, such as external contractors or in-house skills development among existing employees. Furthermore, as highlighted by Lancaster *et al* (2022), OJVs are biased towards certain occupations, sectors and industries. Some types of vacancies are heavily represented while others are not advertised, as shown in Table A2 in the Appendix.

2.2 A skills-based approach to identify AI and green jobs

The twin transition has entailed fundamental changes for the labour market. Yet, there is scarce systematic evidence on the transition's impact given its complexity and the lack of a universal taxonomy and definitions. Thus, researchers have studied emerging occupations and the labour market through a wide variety of approaches. Two of the main approaches used so far are 'bottom-up' and 'top-down'. Top-down approaches classify jobs based on their sectors or industries (OECD, 2023). By using this approach, we would consider anyone working for a clean-energy company to be working in a green job, even if their responsibilities do not involve any task related to sustainability or the

[1] https://lightcast.io/.

environment. On the opposite side, the bottom-up approaches define jobs based on the skills or tasks they require. In this case, an employee of an AI company would only be considered to be in an AI-related job if their responsibilities involved tasks to do with AI, such as training machine-learning models.

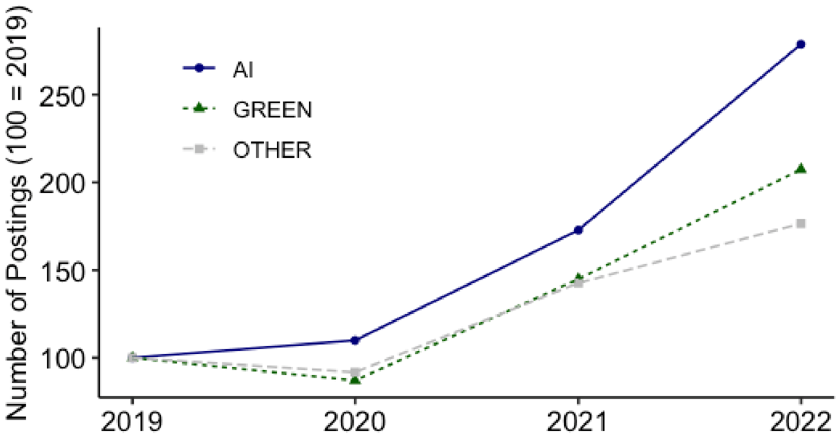
For the purpose of this study, we use a bottom-up (ie skill or task-based) approach to categorise AI-related and green jobs. Specifically, every vacancy that contained at least one AI skill was considered to be an AI job, and those considering at least one green skill were categorised as green, regardless of the sector. To carry out the categorisation, we used Lightcast´s skills taxonomy which classifies nearly 20,000 unique skills and which is unpacked in Burning Glass Technologies (2019). Overall, Lightcast has created and constantly updated a list of AI and green skills based on words commonly associated with AI and sustainability. Appendix items 1 and 2 contain the lists we utilised as a guideline to identify green and AI occupations. This methodological approach enables us to not only identify the jobs that are evidently green or AI-related but also those that are less obviously so. Moreover, it also allows for comparison of skills, levels of education demanded, and salaries between occupations demanding skills in the domains of the twin transition, and other occupations. Further, the methodology is flexible and could be easily applied across different countries and domains. An example of where information about salary, skills or formal education is extracted from an OJV is given in Figure A5 in the Appendix.

2.3 Demand: is the twin transition picking up pace?

Figure 1 shows the evolution of AI and green jobs over the period 2019-2022. We can see that businesses have rapidly increased the demand for employees with green and AI-related skills, both as an absolute number and as a proportion of the overall job vacancies. The data shows that the number of job postings requiring at least one AI skill has more than doubled (+155 percent) and increased significantly for green skill (+88 percent) in the past four years[2]. It is important to benchmark the growth in job openings demanding AI and green skills relative to the postings requiring other skills. While the number of job postings demanding other skills also grew in the past four years, this overall growth was significantly less distinct (+71 percent), especially when compared to postings that contain AI skills. These trends suggest that businesses in the UK are seeking to embrace the emerging technological advances to use AI across their businesses. They also suggest that employers are striving to adopt sustainable practices, or at least to meet the legal regulations regarding environmental impact.

[2] We define a job posting as AI-related or green if it asks for at least one of the AI and green skills provided by the Lightcast taxonomy and listed in our appendix.

Figure 1: UK labour demand for AI and green roles is growing faster than the average UK market



Note: Since 2019 we observe a clear increase in the demand for AI jobs (155 percent), higher than average market growth (71 percent) ('Other'). The demand for green jobs is rising similarly (88 percent) to the market average, but with slightly stronger growth since 2021.

Our findings are consistent with prior literature that shows that the impact of the twin transition in the labour market has become more evident in recent years, when specific events prompted and expedited the use of AI and the adoption of environmental policies. The COVID-19 pandemic of 2020, for example, increased the reliance on digital technologies (OECD, 2023) and pressured companies across all sectors to enhance their use of technology and data at a faster pace. Similarly, Russia's invasion of Ukraine in 2022 motivated many governments to boost alternative energy resources such as solar and wind energy in order to reduce gas imports from Russia (IEA, 2023). Figure 1 indicates that the so-called twin transition has been disrupting the needs of employers for the past four years.

2.4 Supply: is the workforce ready for the twin transition?

Our initial analysis suggests an accelerated rise in employers' demand for AI and green skills. While our current study focuses on the demand side, the literature consistently underscores that the workforce is not meeting the needs of the economy and that the demand for talent is far outreaching skills supply, particularly in novel domains. Francis-Devine and Buchanan (2023) highlight that employers have reported prevalent skills shortages, meaning people do not have the capacities needed in the labour market. These skills shortages present several economic and societal challenges. Further economic studies have shown that in the absence of skilled workers, businesses struggle to implement and develop new technologies, innovate and compete, which hinders economic development and exacerbates social inequalities (Strietska, 2007). Moreover, skills shortages polarise the labour market by limiting the number of high-paying jobs and restraining social mobility (UK Commission for Employment and Skills, 2014).

The UK is already facing imbalances in the labour market, with skills shortages posing significant difficulties in the midst of the twin transition. For example, while the government has focused on fostering AI and technology startups, leading to cities like Cambridge and London becoming AI global hubs, employers in these fields report a lack of proficient workers, in particular for advanced digital skills. Beyond that, the scarcity of digital skills has become a prevalent impediment to productivity and innovation. Approximations indicate that overall, the digital skills gap in the UK inflicts an economic loss of GDP growth of over £60 billion per year (Department for Digital, Culture, Media and Sport, 2022). Further studies suggest that the digital and AI skills shortage in the country is underpinned with a lack of skilled workers in sustainability. Serin (2021) showed that the insufficiency of green skills has been identified as a challenge in meeting the targets of reducing carbon emissions by 2050. This is consistent with a report published by PWC (2022) which revealed that a large share of employees with transferable skills for the renewable energy sectors are set to retire by 2030, leaving thousands of jobs at risk of going unfilled.

In this context, the success of the UK in the twin transition will depend on the capacity of the workforce to meet the needs of employers. Thus, understanding the skills demanded in the future of work in order to address them has become a pressing issue for policymakers, employers and educators across the country. Furthermore, given that this is not an isolated problem and a wide range of countries face similar skills mismatches, we can expect the increasing competitiveness to trigger a global competition for human capital, making the issue even more urgent.

3 Are UK firms shifting to skill-based hiring?

3.1 Skills: which capacities are needed?

The emergence of new jobs along with the disruption of existing ones will require workers to possess a different set of skills than those previously needed by employers (WEF, 2022). Our main research question revolves around the identification and quantification of the skills sought by employers amid the twin transition.

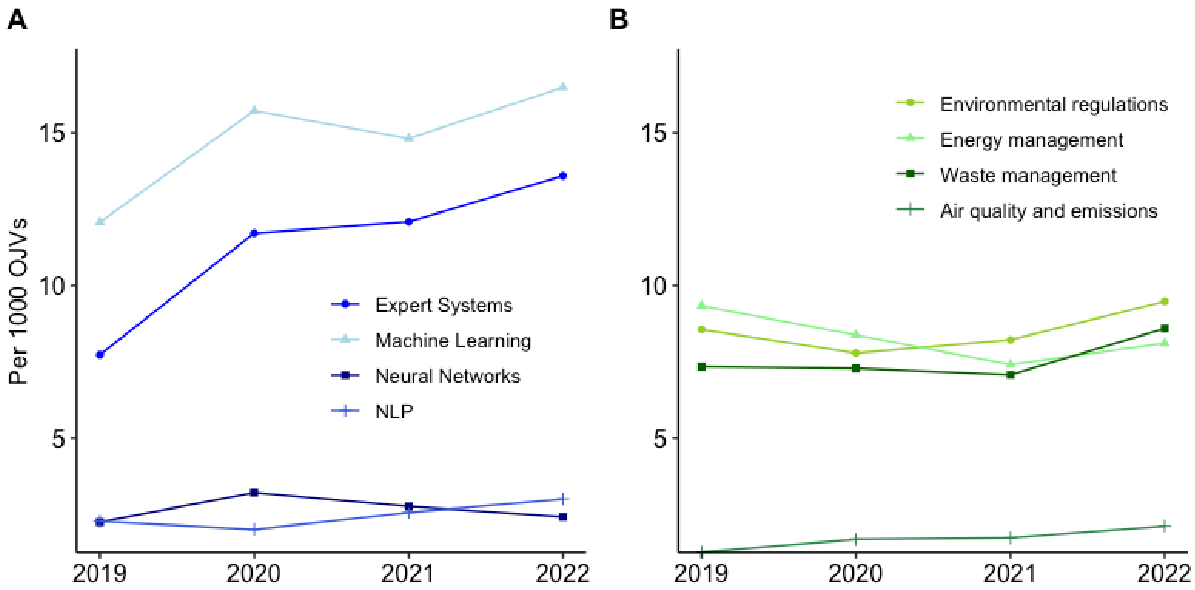
The literature suggests that potentially the main driver of change for the skills needed in the future of work is the accelerated pace at which technology is advancing. Businesses are increasingly pressured to rely on digital technologies, leading employers to look for candidates with strong digital skills. The UK government estimates that over 80 percent of job vacancies in the country currently require digital skills (Department for Digital, Culture, Media and Sport, 2022). But the impact of technology does not stop there. Beyond this, machines and AI have unlocked endless possibilities to increase efficiency, reduce costs and improve productivity (Tarafdar, 2021). Given the transformative power of AI and automation, many tasks within the labour market are increasingly exposed to forces of automation (Acemoglu, 2011). Rather than looking at the level of particular skills, this study aims to understand the *breadth* of skills demanded by firms. Ergo, we will focus on the skill intensity demanded by firms.

Recent advancements in AI have revived the idea that advancements in technology, including automation, would dramatically replace a large share of workers, putting them at high risk of unemployment. This fear is reminiscent of the current belief that the green transition will entail job displacement for workers in fossil fuel and high CO2 emission industries. However, recent research suggests that the impact of AI and the green transition on job vulnerability may not be as striking as has often been portrayed (OECD, 2023). Instead of jobs being completely automated, new estimates are that human–machine interaction will become ever more essential (Frey, 2019), meaning particular jobs will not disappear but instead be disrupted. Similarly, while there might be a decrease in the demand for workers in the fossil-fuel extraction and processing industry, the transition towards a green economy will result in the emergence of millions of jobs (ILO, 2023). Hence, while concerns around job displacements are understandable, employment opportunities will arise, which will demand workers to fulfil non-routine tasks (World Bank, 2016).

It is evident that the skills required by employers are being reshaped. By analysing job vacancies with the lists of skills generated by Lightcast, we found that employers are looking for a wide variety of skills related to the development and implementation of AI (see Figure 2). Building from Lightcast´s taxonomy and categorisation, AI-related skills can be grouped in: 'Expert Systems', 'Autonomous Driving', 'Machine Learning', 'Natural Language Processing', 'Neural Networks', 'Visual Image Recognition' and 'Robotics'[3]. By analysing OJVs data with this list it is evident that since 2019 the most demanded AI skills have consistently been around Machine Learning and Expert Systems, far outpacing the rest. This upward trend suggests that candidates with skills such as Torch or Supervised Learning skills are sought after within the labour market. That said, not all AI skills are equally sought after. The demand for skills around Autonomous Driving and Robotics has lagged behind, with demand remaining relatively low over the last four years.

[3] Please see the appendix for a detailed description.

Figure 2: Demand for AI skills (machine learning and expert systems) is rising



Note: (A) For the domain of AI work, we observe that the use of Expert Systems, such as IBM Watson, Chat GPT or Virtual Agents, has enjoyed a significant rise in demand. Similarly, OJVs in AI are asking for talent working with Machine Learning technologies. (B) In green jobs, it is particular skills in environmental regulations, energy and waste management that matter. The number of OJV postings mentioning these competencies has been growing steadily since mid-2020.

In parallel, the increasing pressure on companies to reduce their carbon footprints and boost sustainability has spurred the demand for green skills. Drawing from Lightcast's list of unique skills, the main groups of green skills demanded by companies to date can be grouped in: 'Environmental Regulation', 'Energy Management', 'Waste Management', 'Air Quality and Emissions', 'Conservation', 'Nuclear Energy', 'Energy Efficiency', 'Solar Energy', 'Clean Energy', 'Climate Change', 'Environmental Engineering and Restoration'. In contrast to the observed patterns in the demand for AI-related skills, the trajectories of demand for green skills are notably flatter (see Figure 2B), indicating comparatively more stable and consistent demand since 2019. Interestingly, all four groups of skills shown in Figure 2B picked up pace in 2021, including 'Air Quality and Emissions', which had been significantly less demanded in relation to other skills groups.

3.2 Education: does it still matter?

Traditionally, employers have relied on formal education qualifications as a way of identifying potential employees. Thus, higher educational credentials have tended to be positively associated with employment rates and earning advantages (Carbonaro, 2007; OECD, 2022). However, in recent years, this approach may have become less effective, as a large number of adults are acquiring their skills and experience through non-formal or informal education. Non-formal education refers to structured learning that takes place outside the traditional classroom environment, such as on-the-job training or apprenticeships, and informal education consists of unstructured learning, which takes place in everyday experiences, such as learning a new skill through a hobby or interest.

The dominance of non-formal and informal education among the working-age population means that many skills are not necessarily reflected in the workforce's formal qualifications (OECD, 2021). As a result, employers who focus exclusively on formal qualifications may be overlooking capable candidates who have gained valuable experience through non-traditional routes. To address this issue, many employers have reported that they are increasingly adopting a skills-based approach to recruitment, focusing on the specific skills of candidates, rather than relying solely on higher education degrees. For example, formal education is not mentioned in a posting or not requested as compulsory. Instead a precise set of skills is outlined and how these competencies contribute to success in the advertised position.

The correlation between education and employment rates has remained steady over recent decades. However, research shows that the significance of education credentials in the eyes of employers is influenced by external factors such as social shifts and economic disturbances. Some authors suggest that there has been a growing vertical demand for higher education credentials, as a result of the accelerated growth of educational opportunities and the proliferation of undergraduate degrees (Collins, 2019). Similarly, it has been found that in times when the number of vacancies is scarce compared to the pool of qualified candidates, employers are likely to add qualification requirements as the supply of educated candidates exceeds demand (Brown and Souto-Otero, 2020). In labour economics and sociology, this trend of adding a minimum level of education to jobs that would previously not require them, is referred to as *"degree inflation"* (Brown and Souto-Otero 2020). This trend was particularly visible during the economic disturbance between 2007 and 2010. Throughout the 2008 financial crisis, job postings demanding a bachelor's degree as a minimum level of education increased by more than 10 percent (Modestino *et al*, 2015).

On the opposite side of degree inflation, research suggests that skills shortages tend to encourage employers to seek an alternative to recruiting workers, namely skills-based hiring. For example, during the COVID-19 pandemic, when there was a significant lack of skilled medical workers, the number of job postings for medical staff requiring minimum education levels decreased (Fuller *et al*, 2022). By eliminating the minimum level of education from job postings, employers increase the talent pool and may be able to find more suitable candidates. The main focus of this article is to understand whether a similar phenomenon is now occurring with jobs demanding AI or green skills, for which there are no clear career paths and for which employers are struggling to find the right candidates.

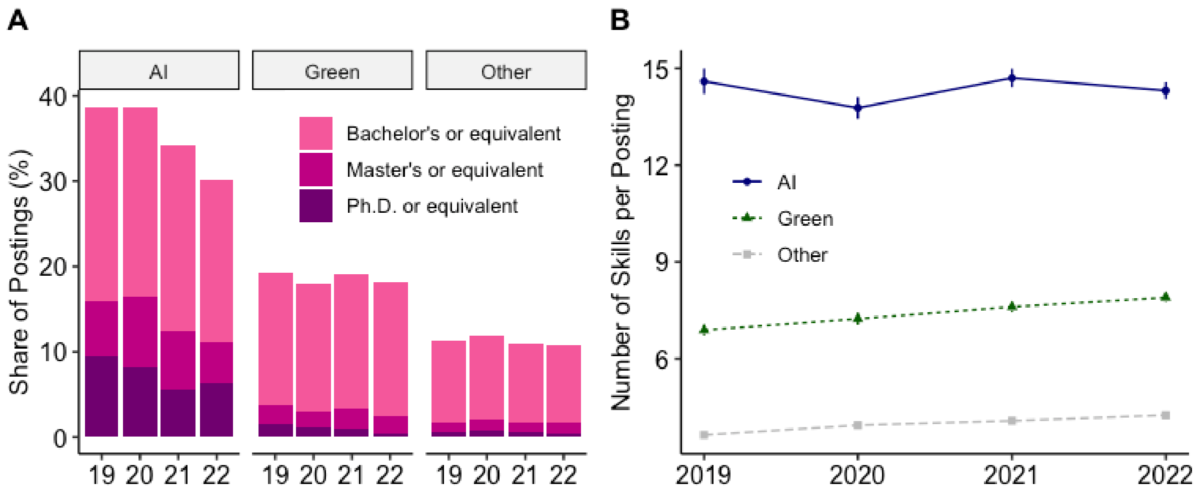
In the midst of the twin transition, focusing on formal education as a currency for employability opportunities seems to be insufficient. Several formal education degrees related to the domain of AI and green roles have been established only very recently in leading higher education institutions around the world (Chen *et al*, 2020; Muñoz-Rodríguez *et al*, 2020). Beyond education credentials, jobs in the twin transition also require a broad set of skills. Whilst education qualifications signal that individuals have become highly educated in certain domains, it may be the possession of specific skills and experience that will truly distinguish candidates. By enlisting skills in their job postings, employers can effectively identify candidates with a specific combination of technical and soft skills, ensuring a higher likelihood of successful job placements.

While supply and demand may influence the minimum levels of education demanded by employers, the nature of occupations can also lead employers to demand diverse education credentials. More specialised and complex occupations tend to require higher education degrees. Given the specialised nature of green and AI-related occupations, jobs in these fields are likely to require highly educated workers. In our data we find that formal education matters for the jobs of the twin transition (see Figure 3). In 2022, about 30 percent of all AI postings and 20 percent of all green jobs required at least a university degree, which is much higher than the 10 percent of all other advertisements that set this requirement. Here, as in the remainder of the analysis, the group 'other' contains all postings in our sample that have not mentioned any AI or green skills.

In particular, graduate (5 percent) and doctoral degrees (6 percent) are much more frequently mentioned in AI job advertisements than in the average OJV posting (at 1 percent and 0.5 percent, respectively). Green job postings have a slightly higher demand for formal education requirements, but mostly require a bachelor's degree. However, as we examine the mentioning of higher education over time, a different picture emerges. AI roles had higher formal education requirements in 2019 than in 2022. Between 2019 and 2022, the share of AI roles requiring at least a bachelor's degree dropped by nine percentage points. And while 10 percent of all AI roles asked for a PhD in 2019, this number had halved by 2022. Interestingly, this decline in the mentioning of higher education is not visible for green roles. So our first hypothesis, that there is a decrease in the mentioning of formal education requirements, is only partly confirmed. As our work does not apply an identification strategy, we cannot be sure that the observed decline in the mentioning of degrees is due to an excess demand for AI roles. However, as we do not observe a general declining trend in the overall labour market, we assume that employers mention formal education requirements less frequently for AI roles because of labour demand exceeding supply significantly in this domain.

AI and green vacancies demand a greater number of skills than postings on average. Figure 3B shows that AI and green OJVs ask for a larger set of skills than the average. Postings in AI demand on average around 15 skills and green postings about seven. On average, other postings require only four skills, meaning green occupations in the UK demand around twice as many skills as other jobs, and AI occupations demand more than three times as many skills. The more frequent mentioning of educational requirements (Figure 3A) and the high number of skills requested (Figure 3B) shows that AI and green jobs do not only require highly educated candidates but also that these jobs are more skill-intensive, meaning they demand proficiency across a wide variety of areas and the ability to apply a wide variety of skills across many tasks. Our data show that AI and green jobs are more skills intensive than the other jobs, which supports our second hypothesis.

Figure 3: AI and green roles are education- and skills-intensive



Note: (A) Jobs of the twin transition require higher levels of formal education. In 2022, about 30 percent of all AI postings and 20 percent of all green jobs required at least a university degree. Only 10 percent of all other advertisements set this requirement. However, the share of postings in AI requiring higher education is steadily declining. (B) On the other hand, AI and green OJVs ask for a larger set of skills. Postings in AI demand on average around 15 skills and green postings about seven. On average, other postings demand only four skills.

Including skills on job postings allows for consideration of skills developed outside formal education (Fuller, 2022) which currently represents the predominant way of learning among workers through non-formal and informal education. Data indicates that over 70 percent of workers learn through their job and interactions with others, compared to only 8 percent who are enrolled in formal education programmes (OECD, 2020). This is particularly relevant for technological skills, as they tend to be acquired on the job or through informal networks (Collins, 2019). In this context, focusing on skills may be paramount to identify and harness human capital to navigate the twin transition.

The skills demanded by firms have been the subject of extensive research. Numerous studies have analysed the demand for skills, the wage premium related to specific competencies (Stephany and Teutloff, 2024) and the correlation between skills and employment opportunities (see Acemoglu, 2011; Gofman, 2020; Deming, 2018). Many of these studies have found that as technology becomes pervasive across industries, developed economies are increasingly requesting more highly skilled workers, while reducing the number of low-skilled and routine jobs.

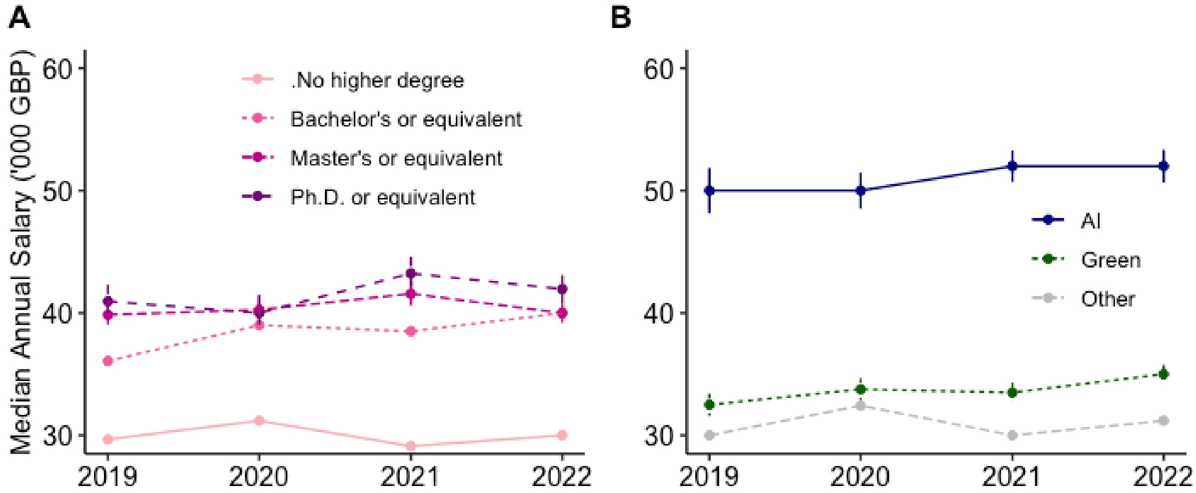
3.3 Salary: what is the economic premium of twin transition jobs?

In the last part of our analysis, we aim to understand and compare the relationship between the minimum level of education and the skills demanded with the remunerative outcomes. Generally, jobs that demand higher educational attainment or greater skill intensity tend to have sizable wage premiums. However, earning inequalities are not based solely on educational attainment or skill intensity; field of study and the type of occupation are also relevant factors that influence economic rewards (Carbonaro, 2007).

Previous literature has posited a strong correlation between economic compensation and the dynamics of skills availability and labour supply and demand (Autor, 2014). Consequently, wage premiums have been recognised as valuable indicators of potential skill shortages, recruitment challenges, and the value of specific skills (Stephany and Teutloff, 2024; Saussay *et al*, 2022). Studies on green and AI occupations have shown that these jobs offer higher economic rewards (Vona *et al*, 2019; Alekseva *et al*, 2021). This tendency in wage premia is consistent with the skills shortages reported by employers in these domains.

The novelty of this study is to delve into the variations in wages among different job vacancies and estimate the wage premium associated with AI and green skills. If jobs requiring AI skills are expected to yield higher productivity due to the application of these skills, it follows that such vacancies will offer a significant wage premium. Furthermore, we anticipate that the AI and green skills premium may differ across skill types. For instance, skills such as Machine Learning or Energy Management are in high demand and should therefore yield a higher economic return. On average, we see that wages in AI and green OJV postings are higher than in other job advertisements (see Figure 4B). In contrast to the premium of higher formal education (Figure 4A), we see that AI roles offer wages on a stable level and significantly higher than any role mentioning formal education can offer on average. However, it is worth noticing as a limitation of this work that we only observe offered salaries by the nature of the data. This means that the later negotiated salaries for the position advertised might differ from the wage levels considered in our analysis. While the salaries listed may not accurately reflect the actual compensation received by employed individuals, they serve as a reliable indicator of the company's willingness to pay for the specific skill set required for the vacant position.

Figure 4: AI roles offer to pay more than positions requiring a graduate degree

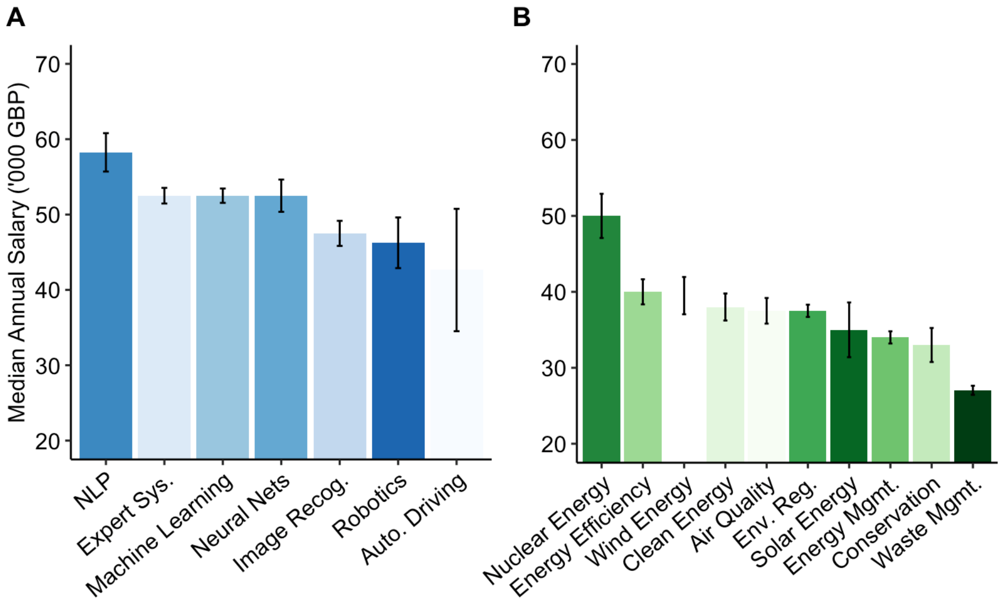


Notes: (A) Higher education has a significant premium on offered wages. Postings asking for a higher education degree offer around £40k as salary - about £10k more than postings without higher education requirements. (B) The offered wage premium for AI postings is even larger. Throughout the observation period wages in AI jobs are significantly higher than in other job postings (around £50k), while green postings (£33k) and other postings (£30k) offer lower wages (95 percent confidence intervals as shown).

Additionally, when examining the premium on specific skills more closely, we see that 'high-wage' skills are not necessarily those types of competences that are most strongly demanded. There is considerable variance in offered wages across skill domains. For the case of AI skills we observe that skills around Neural Networks[4] and Natural Language Processing (NLP) are associated with higher wage offerings than skills around Robotics or Autonomous Driving. For green skills, Nuclear Energy offers wages at the same level as AI jobs, but the offered wages decline for skills in the field of energy more generally, and they are lowest for Waste Management (see Figure 5). The premium of AI and green skills is also visible within occupational domains. For the case of AI, corporate managers with AI skills earn around 9 percent more than their less AI-savvy counterparts. This premium grows for Business and Public Service Professionals (18 percent) and peaks for Sales Managers with 21 percent. For green skills, premia within occupations are much lower. Sales Managers, for example, only earn around 1 percent more with green skills. However, the green premium is significant for Professionals in Textile and Printing with 9 percent on average (as shown in Figure A3 in the appendix).

[4] Computing systems inspired by the biological neural networks that constitute animal brains.

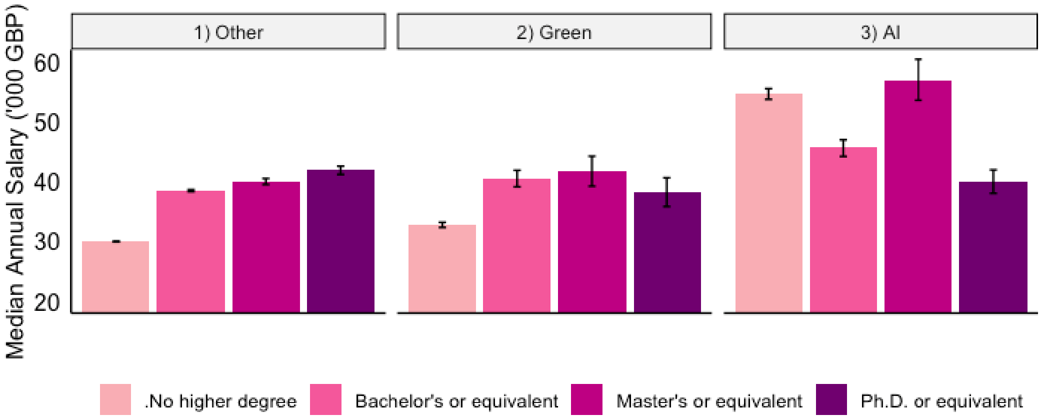
Figure 5: AI roles wanting NLP skills pay well; in green jobs, nuclear energy skills bring high rewards



Notes: There is considerable variance in offered wages across skill domains. (A) OJV postings asking for AI skills with Neural Networks or NLP offer a high salary, and higher than OJVs in Robotics or Autonomous Driving. (B) In the green domain, posts in Nuclear Energy have asking wages on the level of AI jobs. Asking wages are still relatively high in the field of Energy (Efficiency, Wind, Clean) and have the lowest economic value in Waste Management (95 percent confidence intervals as shown).

When distinguishing these wage differentials by educational requirements, we observe that much of the 'AI premium' might be driven by job offers for graduates (Figure 6). Here offered wages are significantly higher for OJVs around AI work than for green or any other job posting. For undergraduates, both AI and green jobs offer above average salaries, while for positions requiring a doctoral degree, we see no difference across the three types of job postings.

Figure 6: For AI roles, there is no clear premium for higher education



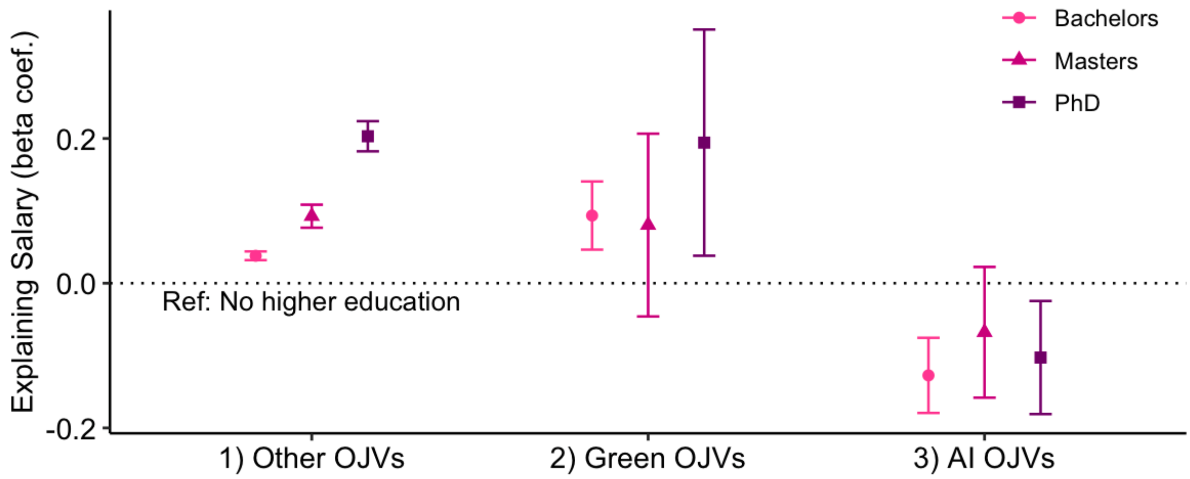
Notes: Educational wage premia change across domains. For average postings (lhs) offered wages rise steadily with the educational requirements. This pattern seems to be similar for green OJVs, too (middle), with the exception of stagnating premia for PhDs. However, for AI jobs (rhs), the picture changes entirely. Here, offered wages are significantly higher on average but the education gradient of premia has also disappeared: Postings without higher education requirements offer wages just as high as those asking for a masters degree and even higher wages than bachelor's or PhD postings (95 percent confidence intervals as shown).

In this last part of our analysis we contrast the premium for formal education across skill domains. To control for potential confounders, such as industry type, occupational sector or regional disparities, we run a regression model to explain wage premia for formal education across the AI and Green domains:

$$log(wage_i) = \beta_0 + \beta_1 * \rho_i + \beta_2 * \theta_i + \eta_i + \epsilon_i$$

The regression model explains the logarithmic asking wage of each posting (i) with a dummy for whether the post mentions at least one AI or green skill (ρ_i), a set of dummies for the level of education (θ_i), and fixed effects (η) for four years, twelve regions (NUTS 1), 16 industries (SIC 1), and 9 occupational groups (SOC 1). Average jobs offer wages that rise steadily with the minimum level of education required, showing a clear correlation between education and salaries. We observe a similar pattern for green OJVs, except for a stagnating premia for PhDs. However, the picture is completely different for AI jobs (see Figure 7).

Figure 7: The educational premium has disappeared for AI roles



Notes: When explaining offered wages with educational requirements in a regression model (see Appendix Table A1) we see a clear educational gradient of the average posting population (lhs): OVJs asking for a bachelor's degree offer wages four percent higher than postings without higher education requirements. This premium rises for postings requiring a masters (ten percent) or PhD degree (20 percent). The educational premia is somewhat similar, though less clear as a gradient, for green OJVs (middle). For AI postings (rhs), however, higher education premia are 'negative', as postings in the field of AI without higher education requirements offer higher wages than postings asking for a university degree (95 percent confidence intervals as shown).

On average, AI jobs offer a significantly higher wage but the education gradient vanishes. Vacancies that do not require a higher education degree offer wages as high as those offered for a master's degree and even higher than those demanding a bachelor's degree or PhD. These findings demonstrate that the ascendancy of wages does not depend solely on higher levels of education. Instead, within the AI domains, where human capital is scant and the jobs skills-intensive, the main characteristics sought and valued by employers are skills, with a limited focus on candidates' qualifications (detailed results of the regression model can be found in the Appendix in Table A2).

Table 1 summarises our regression model explaining offering wages. Here, we consider variation across time (four years), twelve regions (NUTS 1), 16 industries (UK SIC 1) and nine occupations (SOC 1). These characteristics are included in our model as Fixed Effects at all times, explaining around 35 percent of the variance in wages. In addition, we include educational controls and dummies for whether a posting has any AI or green skill. In our model, an educational gradient is visible. Higher educational attainment is associated with higher offering wages, as shown in models one, three and five. Similarly, we observe a premium for AI skills in models two and three. However, green skills do not show any wage premium, as shown in models four and five.

Table 1: AI skills have a wage premium comparable to a PhD

	log(Offered annual salary)					
Education						
Ref: No higher education						
Bachelor's or equivalent		0.04***		0.04***		0.04***
		(0.003)		(0.003)		(0.003)
Master's or equivalent		0.09***		0.09***		0.09***
		(0.01)		(0.01)		(0.01)
Ph.D. or equivalent		0.19***		0.17***		0.19***
		(0.01)		(0.01)		(0.01)
Skills						
Dummies						
AI			0.18***	0.16***		
			(0.01)	(0.01)		
Green					-0.01	-0.01
					(0.01)	(0.01)
Constant		10.02***	10.02***	10.02***	10.02***	10.02***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed Effects Controls						
4 Years	Yes	Yes	Yes	Yes	Yes	Yes
12 Regions (NUTS 1)	Yes	Yes	Yes	Yes	Yes	Yes
16 Industries (SIC 1)	Yes	Yes	Yes	Yes	Yes	Yes
9 Occupations (SOC 1)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	367,444	367,444	367,444	367,444	367,444	367,444
R^2	0.35	0.41	0.41	0.41	0.40	0.41
Adjusted R^2	0.35	0.41	0.40	0.41	0.40	0.41

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Notes: When explaining offering wages with a regression model, we consider variation across time (four years), space (12 NUTS 1), industry (16 UK SIC 1), and occupations (9 SOC 1). These characteristics are included in our model as Fixed Effects at all times, explaining around 35 percent of the variance in wages. In addition, we include educational controls and dummies for whether a posting has any AI or Green skill. In our model, an educational gradient is visible (Models 1, 3, 5) and similarly a premium for AI skills (Models 2, 3). However, green skills do not show any wage premium (Models 4, 5).

Overall, our findings indicate a shift from the usual focus on educational attainment as a means to a wage premium. For example, even when controlling for geographical, sectorial, occupational and educational variance, AI skills exhibit a wage premium on offering wages of 16 percent – similar to having a PhD (17 percent) and significantly higher than for a master's degree (9 percent). The study proves that the minimum level of education required within AI jobs wields diminished influence over the wage premium, which supports the idea that firms are undergoing a transformation within their recruitment practices, at least in AI jobs. Moreover, jobs demanding AI and green skills are more skills-intensive. Accordingly, this last part of our analysis delivers strong evidence in favour of our third hypothesis – that there is a premium in offering wages for skills in AI and green domains – at least for the case of AI roles.

In summary, our findings indicate that our hypotheses were, to certain extent, substantiated. First, our quantitative analysis showed a decrease in the emphasis on formal education across AI job postings and for PhD graduates. Second, our study showed that AI and green online job vacancies demand a larger number of skills, meaning they are more skills-intensive than the average job posting. Lastly, our analysis revealed a wage premium offered for AI skills, while the educational premium of university degrees is no longer visible once narrowing our analysis of AI job vacancies.

4 Conclusion and policy recommendations

Our work sheds light on the increasing demand for AI and green skills, and also on the specific requirements imposed by employers and the wage differences and premia associated with these skills. The findings show important trends and disparities between AI-related and green jobs, providing valuable insights for policymakers, educators, employers and job seekers.

Our analysis of one million OJVs reveals that during the past four years, the twin transition has boosted the demand for AI and green skills in the UK, reflecting the continuous efforts of firms to adopt AI and meet environmental sustainability targets. Our analysis further suggests that employers are seeking AI and green skills unevenly. While AI occupations have grown rapidly since 2019, the emergence of green jobs picked up pace only in 2021. Moreover, AI-related occupations require markedly higher levels of education and a larger number of skills, reflecting the complex nature of these roles. In turn, AI occupations offer significantly higher remuneration. Job postings demanding green skills were found to possess more similar skills and education requirements compared with the average of other roles. While they still demand a wide variety of skills, the requirements are less stringent compared to AI-related jobs. In line with that, while green vacancies still offer competitive remunerations, they have a less striking wage premium compared with other job postings. This may imply that up-to-date firms have started adopting a skills-based hiring approach for AI jobs, however, this shift in hiring practices has not been as pronounced for jobs requiring green skills.

Addressing our research question, we find indications that UK firms have indeed switched to a practice of skill-based hiring for occupations that demand AI and green skills. We see that the demand for AI and green positions has increased significantly in the four years of our observation period. We show that individual skills, rather than formal education requirements, have become the defining features of job advertisements for both AI and green roles. For the case of AI roles, our analysis shows that individual skills, in addition to educational attainment, help to explain the significant salary premium offered by AI roles. However, the educational premium – that is, offering higher wages with higher university degrees – has disappeared for AI roles entirely. Rather skills, like natural language processing or working with expert systems like ChatGPT, explain higher wage levels across industries and occupations.

Based on the findings of our analysis and previous policies and practices, several recommendations can be made to address these novel skills demands and navigate the twin transition. The labour market is dynamic and will continue to change. To better understand and address the changes, some organisations and policymakers, such as CEDEFOP, have started developing quantitative projections of expected trends in employment (CEDEFOP, 2022), which are complementary to national estimates. Forecasting skills demands plays a crucial role in fostering a proactive approach to monitoring and identifying new job types and the skills these will require. While efforts have started being made in this direction, policymakers, academia and employers should increasingly work together to recognise emerging occupations and anticipate employers' needs. This would allow relevant stakeholders to make better informed decisions and adapt their upskilling and reskilling strategies accordingly. An effective way of analysing the labour market is by examining online job vacancy data. As demonstrated in this paper, OJV data contains granular-level characteristics of job postings, which can provide valuable insights for key stakeholders. Governments can leverage OJV to align their educational, employment, economic and migration policies to the needs of the local labour market. Similarly, by identifying skills demands, firms can support their employees by providing opportunities that equip them with the skills needed to remain competitive.

As mentioned above, the literature suggests that the demand for green and AI skills is far exceeding supply, making it hard for employers to find candidates with the skills needed to navigate the twin transition. Therefore, it has become a pressing issue for the public and private sector to future-proof the workforce's skills. In order to ensure the workforce acquires the skills needed by the economy, it is essential to align and adapt education and training systems to emerging occupations. Given the weight placed by employers on university degrees, a good avenue for doing so might be through higher education. However, relying solely on higher education is likely to be insufficient as it disregards a significant portion of the working-age population and presents many challenges, such as overlooking skills acquired outside formal education, limiting the access to employability opportunities, and exacerbating socio-economic disparities. To ensure the adequacy of human capital to the current green and AI transitions, employers and governments should mainstream alternative skills development initiatives. There is a wide variety of avenues that could be implemented to develop skills for the twin transition outside of higher education, including apprenticeships, on-the-job training, MOOCs, vocational education and training, and bootcamps.

Some countries and employers have started leveraging these alternatives to boost the development of digital and green skills. The Netherlands, for example, currently offers workers over 45 with guidance on their job, as well as grants for training to SMEs in the ICT sectors, digitalisation or the green transition. Similarly, the Swedish government is currently providing older adults with digital skills training through the Digidel network and centres, which offer courses on digital communication and digital security (OECD, 2023). In parallel, many employers across the US and the UK, including Verizon and Citi, are providing their employees with the opportunity to develop data and digital skills through apprenticeships (Chopra-McGowan 2021), and many others are offering in-house training on how to leverage novel technologies.

Lastly, employers could benefit from resetting their hiring and talent management approaches. Up-to-date stakeholders from the private and public sectors have started this transformation, leading to the increasing prominence of skills-based recruitment. For example, the State of Maryland has removed the four-year college degree requirement for many state jobs, in order to promote inclusivity for individuals who have acquired skills through alternative paths. In the private sector, IBM is leading the way in modernising hiring approaches by making over 50 percent of their job openings in the US skills-based, rather than contingent on a traditional four-year degree, thus fostering a more open and inclusive job market (IBM, 2022). Given that education and industry will keep evolving at uneven paces, employers should progressively focus on candidates' skills rather than on their formal qualifications.

By requesting a specific level of education, employers may limit the number of candidates and overlook individuals who have developed skills through alternative paths such as on-the-job learning, online courses and social interactions. A skills-based hiring approach can increase the number of potential candidates, the variety of workers' social backgrounds and add diverse insights to the workforce. Additionally, in emerging fields such as AI and the green domains, where employers are struggling to find the right talent, attracting and recruiting candidates based on skills rather than formal education degrees may contribute to increasing the size of the talent pool and potentially, tackling skills shortages.

References

Acemoglu, D. and D. Autor (2011) 'Skills, tasks and technologies: Implications for employment and earnings', in *Handbook of Labor Economics* Vol. 4: 1043–1171, Elsevier

Alekseeva, L., J. Azar, M. Gine, S. Samila and B. Taska (2021) 'The demand for AI skills in the labor market', *Labour Economics* 71, 102002

Autor, D.H. (2014) 'Skills, education, and the rise of earnings inequality among the "other 99 percent"', *Science*, 344(6186): 843–851

Brown, P. and M. Souto-Otero (2020) 'The end of the credential society? An analysis of the relationship between education and the labour market using big data', *Journal of Education Policy* 35(1), 95-118

Butrica, B.A. and S. Mudrazija (2022) *Skills-Based Hiring and Older Workers*, Washington, DC: Urban Institute

Burning Glass Technologies (2019) *Mapping the Genome of Jobs: The Burning Glass Skills Taxonomy*

Carbonaro, W. (2007) 'The effects of education and cognitive skill on earnings: How much do occupations and jobs matter?' *Research in Social Stratification and Mobility* 25(1): 57-71

Chen, L., P. Chen and Z. Lin (2020) 'Artificial intelligence in education: A review', *Ieee Access* 8: 75264-75278

Chopra-McGowan, A. (2021) '5 Ways Companies are Addressing Skills Gaps in their Workforce', available at https://hbr.org/2023/06/5-ways-companies-are-addressing-skills-gaps-in-their-workforce

Collins, R. (2019) *The credential society: An historical sociology of education and stratification*, Columbia University Press

Cominetti, N., R. Costa, A. Eyles, K. Henehan and S. McNally (2022) *The Economy 2030 Inquiry. Train in Vain?* available at https://economy2030.resolutionfoundation.org/wp-content/uploads/2022/12/Train-in-Vain.pdf

Department for Digital, Culture, Media and Sport (2022) 'New Digital Strategy to make the UK a global tech superpower', UK Government Press Release, available at https://www.gov.uk/government/news/new-digital-strategy-to-make-uk-a-global-tech-superpower

Farzaneh, H., L. Malehmirchegini, A. Bejan, T. Afolabi, A. Mulumba and P.P. Daka (2021) 'Artificial intelligence evolution in smart buildings for energy efficiency', *Applied Sciences* 11(2), 763

Fouquet, R. and R. Hippe (2022) 'Twin transitions of decarbonisation and digitalisation: a historical perspective on energy and information in European economies', *Energy Research and Social Science* 91

Francis-Devine, B. and I. Buchanan (2023) *Skills and Labour Shortages*, available at https://commonslibrary.parliament.uk/research-briefings/cdp-2023-0001/

Gofman, M. and Z. Jin (2020) 'Artificial Intelligence, Human Capital, and Innovation', *Journal of Finance*, forthcoming, available at http://dx.doi.org/10.2139/ssrn.3449440

IBM (2022) 'Investing in the future of work: How IBM is tackling the credentials dilemma', available at https://www.ibm.com/blog/jff-horizons-and-workforce-development/

International Energy Agency (2023) 'Renewable power on course to shatter more records as countries around the world speed up deployment', available at https://www.iea.org/news/renewable-power-on-course-to-shatter-more-records-as-countries-around-the-world-speed-up-deployment

International Labour Organisation (2023) 'Greening with Jobs', available at https://www.ilo.org/weso-greening/#Intro-3

Kander, A., P. Malanima and P. Warde (2014) *Power to the People. In Power to the People*, Princeton University Press

Lancaster, V.A., D. Mahoney-Nair and N. Ratcliff (2021) 'Review of burning glass job-ad data', *Proceedings of the Biocomplexity Institute* 2021-013, Biocomplexity Institute

Lassébie, J. and G. Quintini (2022) 'What skills and abilities can automation technologies replicate and what does it mean for workers? New evidence', *OECD Social, Employment and Migration Working Papers* No. 282, OECD Publishing, Paris, available at https://doi.org/10.1787/646aad77-en

Leal Filho, W., T. Wall, S.A.R. Mucova, G.J. Nagy, A.L. Balogun, J.M. Luetz ... O. Gandhi (2022) 'Deploying artificial intelligence for climate change adaptation', *Technological Forecasting and Social Change* 180, 121662

McKinsey (2018) *Skills Shift: Automation and the Future of the Workforce*, available at https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce

Modestino, A.S. (2015) 'Middle skill workers in today's job market', in National Academy of Sciences Symposium on the Supply Chain for Middle-Skill Jobs: Education, Training and Certification Pathways (pp. 24-25)

Muñoz-Rodríguez, J.M., F. Sánchez-Carracedo, A. Barrón-Ruiz and S. Serrate-González (2020) 'Are we training in sustainability in higher education? Case study: Education degrees at the University of Salamanca', *Sustainability* 12(11): 4421

OECD (2022) *Education at a Glance Indicators*, available at https://www.oecd.org/education/education-at-a-glance/EAG2022_X3-A.pdf?_ga=2.121272584.1619592834.1687193801-1569189767.1681729219

OECD (2022) *Lifelong Learning for Adults*, available at https://www.oecd-ilibrary.org/sites/00dbdd06-en/1/3/4/index.html?itemId=/content/publication/00dbdd06-en&_csp_=f328ed2837bb980ebf7d72fc456ca435&itemIGO=oecd&itemContentType=book

Paiho, S., N. Wessberg, M. Dubovik, R. Lavikka and S. Naumer (2023) 'Twin transition in the built environment–Policy mechanisms, technologies and market views from a cold climate perspective', *Sustainable Cities and Society*, 98: 104870

PWC (2022) *The Energy Transition and Jobs*, available at https://www.pwc.co.uk/who-we-are/our-purpose/building-trust-in-the-climate-transition/supporting-a-fair-transition/the-energy-transition-and-jobs.html

Saussay, A., M. Sato, F. Vona and L. O'Kane (2022) 'Who's fit for the low-carbon transition? Emerging skills and wage gaps in job and data', available at https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2022/10/working-paper-381-Saussay-et-al.pdf

Serin, E. (2021) 'Will a shortage of green skills scupper the UK's net-zero plans?' available at https://www.lse.ac.uk/granthaminstitute/news/will-a-shortage-of-green-skills-scupper-the-uks-net-zero-plans/

Son, T.H., Z. Weedon, T. Yigitcanlar, T. Sanchez, J.M. Corchado and R. Mehmood (2023) 'Algorithmic urban planning for smart and sustainable development: Systematic review of the literature', *Sustainable Cities and Society*, 104562

Stephany, F. and O. Teutloff (2024) 'What is the price of a skill? The value of complementarity', *Research Policy* 53(1), available at https://doi.org/10.1016/j.respol.2023.104898

Strieska, O/ (2007) *Skills Shortage 'Building a European VET'*, Cedefop, available at https://www.cedefop.europa.eu/files/etv/Upload/Projects_Networks/Skillsnet/Publications/Striestka-skills_shortages.pdf

Tamburrini, G. (2022) 'The AI carbon footprint and responsibilities of AI scientists', *Philosophies*, 7(1): 4

Tarafdar, M., C. Beath and J. Ross (2019) 'Using AI to Enhance Business Operations', MIT Sloane Magazine, available at https://sloanreview.mit.edu/article/using-ai-to-enhance-business-operations/

UK Commission for Employment and Skills (2014) *The Labour Market Story: The State of UK Skills*, available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/344440/The_Labour_Market_Story-_The_State_of_UK_Skills.pdf

Vona, F., G. Marin and D. Consoli (2019) 'Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014', *Journal of Economic Geography* 19(5): 1021-1048

Appendix

Appendix List 1: List of skills used to identify AI skills

Artificial Intelligence:

Expert System, IBM Watson, IPSoft Amelia, Ithink, Virtual Agents, Artificial Intelligence.

Autonomous Driving: Autonomous Systems, Lidar, OpenCV, Path Planning, Remote Sensing.

Natural Language Processing (NLP): ANTLR, Automatic Speech Recognition (ASR), Chatbot, Computational Linguistics, Distinguo, Latent Dirichlet Allocation, Latent Semantic Analysis, Lexalytics, Lexical Acquisition, Lexical Semantics, Machine Translation (MT), Modular Audio Recognition Framework (MARF), MoSes, Natural Language Processing, Natural Language Toolkit (NLTK), Nearest Neighbour Algorithm, OpenNLP, Sentiment Analysis/Opinion Mining, Speech Recognition, Text Mining, Text to Speech (TTS), Tokenization, Word2Vec.

Neural Networks: Caffe Deep Learning Framework, Convolutional Neural Network (CNN), Deep Learning, Deeplearning4j, Keras, Long Short-Term Memory (LSTM), MXNet, Neural Networks, Pybrain, Recurrent Neural Network (RNN), TensorFlow.

Machine Learning: AdaBoost algorithm, Boosting (Machine Learning), Chi Square Automatic Interaction Detection (CHAID), Classification Algorithms, Clustering Algorithms, Decision Trees, Dimensionality Reduction, Google Cloud Machine Learning Platform, Gradient boosting, H2O (software), Libsvm, Machine Learning, Madlib, Mahout, Microsoft Cognitive Toolkit, MLPACK (C++ library), Mlpy, Random Forests, Recommender Systems, Scikit-learn, Semi-Supervised Learning, Supervised Learning (Machine Learning), Support Vector Machines (SVM), Semantic Driven Subtractive Clustering Method (SDSCM), Torch (Machine Learning), Unsupervised Learning, Vowpal, Xgboost.

Robotics: Blue Prism, Electromechanical Systems, Motion Planning, Motoman Robot Programming, Robot Framework, Robotic Systems, Robot Operating System (ROS), Robot Programming, Servo Drives/Motors, Simultaneous Localization and Mapping (SLAM).

Visual Image Recognition: Computer Vision, Image Processing, Image Recognition, Machine Vision, Object Recognition.

Source: Lightcast (2022) *AI Skills* https://aiskills.lightcast.io

Appendix List 2: List of skills used to identify green skills

Air quality and emissions

Air Permitting, Air Pollution Control, Air Quality, Air Quality Control, Air Sampling, Atmospheric Dispersion Modeling, Carbon Accounting, Carbon Footprint Reduction, Carbon Management, Carbon Monoxide Detectors, Continuous Emissions Monitoring Systems, Emission Calculations, Emission Reduction Projects, Emission Standards, Emission Testing, Emissions Controls, Emissions Inventory, Fugitive Emissions, Greenhouse Gas, Low Carbon Solutions, MACT Standards, National Emissions Standards For Hazardous Air Pollutants, Stack Emission Measurements, Vapour Recovery

Clean energy

Alternative Energy, Alternative Fuels, Biodiesel, Biodiesel Production, Biofuel Production, Biofuels, Biomass, Clean Technology, Geothermal Energy, Geothermal Heating, Methanol, Renewable Energy, Renewable Energy Development, Renewable Energy Markets, Renewable Energy Systems, Renewable Fuels

Climate change

Climate Analysis, Climate Change Adaptation, Climate Change Mitigation, Climate Change Programs, Climate Information, Climate Modeling, Climate Policy, Climate Resilience, Climate Variability And Change

Conservation

Conservation Biology, Conservation Planning, Environmental Impact Statements, Environmental Literacy, Environmental Protection, Environmental Risk Assessment, Environmentalism, Fish Conservation, Forest Conservation, Habitat Conservation, Habitat Conservation Plan, Low Impact Development, Marine Conservation, Rainwater Harvesting, Soil Conservation, Soil Genesis, Sustainability Planning, Threatened And Endangered Species Surveys, Water Conservation, Watershed Management, Wetland Conservation, Wetland Delineation, Wildlife Conservation, Wildlife Monitoring

Energy efficiency

Cooling Efficiency, Energy Analysis, Energy Conservation, Energy Conservation Measures, Energy Efficiency Analysis, Energy Efficiency Assessment, Energy Efficiency Improvement, Energy Efficiency Research, Energy Efficiency Services, Energy Efficiency Technologies, Energy Efficient Lighting, Energy Efficient Operations, Energy Modeling, Energy Saving Products, Energy-Efficient Buildings, Heat Recovery Steam Generators, Home Energy Assessment, LED Lamps, Renewable Portfolio Standard, Residential Energy Conservation, Residential Energy Efficiency

Energy management

Advanced Distribution Automation, Automatic Meter Reading, Biomass Conversion, Biorefinery, Electric Meter, Electric Utility, Energy Analysis System, Energy Audits, Energy Consumption, Energy Conversion, Energy Demand Management, Energy Forecasting, Energy Management, Energy Management Planning, Energy Management Systems, Energy Market, Energy Policy, Energy Production, Energy Project Management, Energy Supply, Energy Transformation, Energy Transport, Flow Assurance, Fuel Metering, Gas Meter Systems, Hydraulic Accumulators, Leadership in Energy and Environmental Design (LEED) Rating System, Load Shedding, Meter Reading, One-Line Diagram, Power System Simulator For Engineering, Public Utility, Resource Distribution, Smart Meter Installation, Smart Meter Systems, Sustainability Procedures, Transmission System Operator, Underground Utilities, Utility Cooperative

Environmental engineering and restoration

Biological Systems Engineering, Bioremediation, Ecological Engineering, Environmental Analysis, Environmental Contamination, Environmental Economics, Environmental Emergency, Environmental Field Services, Environmental Pollutants, Environmental Problem Solving, Environmental Program Management, Environmental Remediation, Environmental Technology, Environmental Toxicology, Geotextile, Land Reclamation, Landfill Design, Oil Containment Booms, Oil Skimmer, Oil Spill Contingency Plans, Pollution Control Systems, Reforestation, Remediation Systems, Restoration Ecology, Sanitary Engineering, Sediment Controls, Soil Contamination, Stream Restoration, Underground Storage Tanks (UST), Water Pollution, Wetland Restoration

Environmental regulations

Best Available Control Technology, California Environmental Quality Act (CEQA), Categorical Exclusions, Clean Water Act, Comprehensive Environmental Response Compensation and Liability Act (CERCLA), Emergency Planning And Community Right-To-Know Act, Endangered Species Act, Environmental Auditing, Environmental Compliance, Environmental Compliance Assessment, Environmental Due Diligence, Environmental Laws, Environmental Permitting, Environmental Protocols, EPA Regulations, Federal Insecticide Fungicide And Rodenticide Act, ISO 14000, ISO 14000 Series, ISO 14064, Marine Mammal Protection Act, Massachusetts Environmental Policy Act, National Environmental Policy Act, Natural Resources Law, Pollution Regulations, Resource Conservation And Recovery Act (RCRA), Restriction Of Hazardous Substances Directive, Safe Drinking Water Act, Spill Prevention Control And Countermeasure (SPCC), Total Maximum Daily Load, Water Law, Water Regulations Advisory Scheme

Nuclear energy

ANSI/ANS Standards, Monte Carlo N-Particle Transport Codes, Nuclear Core Design, Nuclear Criticality Safety, Nuclear Design, Nuclear Fuel, Nuclear Fuel Cycle, Nuclear Instrumentation Module, Nuclear

Navy, Nuclear Plant Design, Nuclear Power, Nuclear Reactor, Nuclear Safety, Nuclear Technology, RELAP5-3D, Roentgen, Scintillator

Solar energy

Commercial Solar Projects, Concentrix Solar, Passive Solar Building Design, Photodetector, Photovoltaic Systems, Photovoltaics, PVsyst, Solar Application, Solar Cell Manufacturing, Solar Cells, Solar Consulting, Solar Design, Solar Development, Solar Energy, Solar Energy Systems Installation, Solar Engineering, Solar Equipment, Solar Inverter, Solar Manufacturing, Solar Panel Assembly, Solar Panels, Solar Photovoltaic Design, Solar Products, Solar Roofs, Solar Systems, Solar Thermal Installation, Solar Thermal Systems, Solar Water Heating

Waste management

E-Waste, Electrocoagulation, Landfill, Landfill Gas Collection, Leachate Management, Municipal Waste Management, Plastic Recycling, Recycling, Sludge, Sludge Disposal, Solid Waste Management, Tire Recycling, Transfer Station, Trash Pickup, Waste Characterization, Waste Collection, Waste Disposal Systems, Waste Management, Waste Packaging, Waste Removal, Waste Sorting, Waste Tracking System, Waste Transport, Waste Treatment, Wastewater Treatment Plant Design

Water energy

Dam Construction, Hydraulic Structure, Hydroelectricity, Hydropower, WaterCAD

Wind energy

Wind Engineering, Wind Farm Construction, Wind Farm Design, Wind Farm Development, Wind Farming, Wind Power, Wind Turbine Maintenance, Wind Turbine Technology, Wind Turbines

***Figure A1**. When do we define OJVs as related to AI or green? For our analysis, we label a posting as AI or green once it asks for at least one skill from the respective domain. The reason for this decision is that the number of labelled postings would decline quickly if one were to set a higher threshold of two or more skills, see panel A. On the other hand, we notice that for both AI and green postings, the educational requirements (B) and the offered wages (C) increases with the number of respective skills required in the OJVs.*

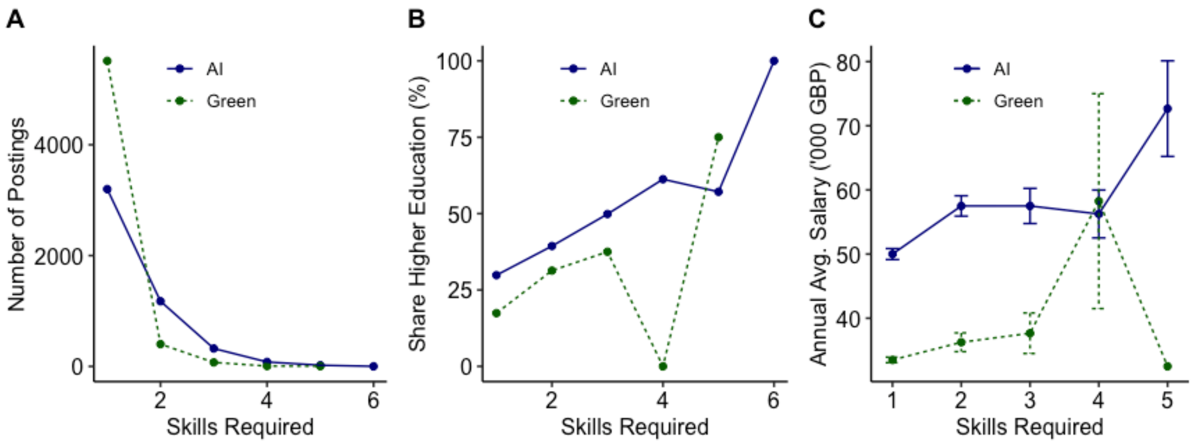


***Figure A2**. Roughly 37 percent (367,444) of all job postings in our analysis contain wage information. Wages are log-normal distributed and slightly right-skewed. Therefore, we consider the log-10 of wages for the subsequent analysis.*

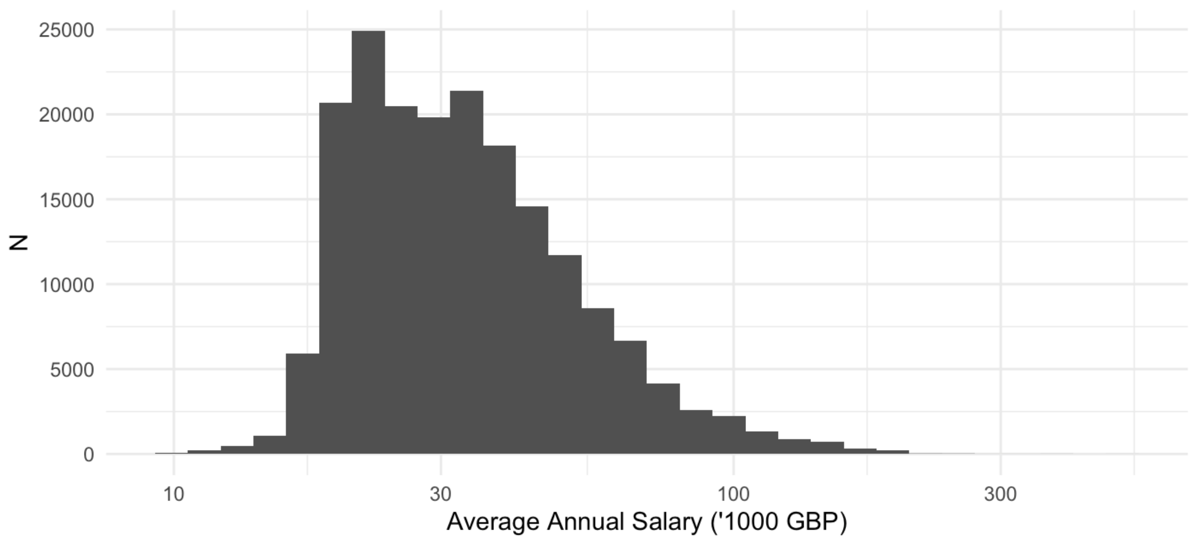


***Figure A3**. The premium of AI and green skills is also visible within occupational domains. (A) For the case of AI, corporate managers with AI skills earn around eight percent more than their less AI-savvy counterparts. This premium grows for Business and Public Service Professionals (18 percent) and peaks for Sales Managers with 21 percent. (B) For green skills, premia within occupations are much lower. Sales Managers, for example, only earn around one percent more with green skills. However, the green premium is significant for Professionals in Textile and Printing with nine percent on average (95% confidence intervals as shown).*

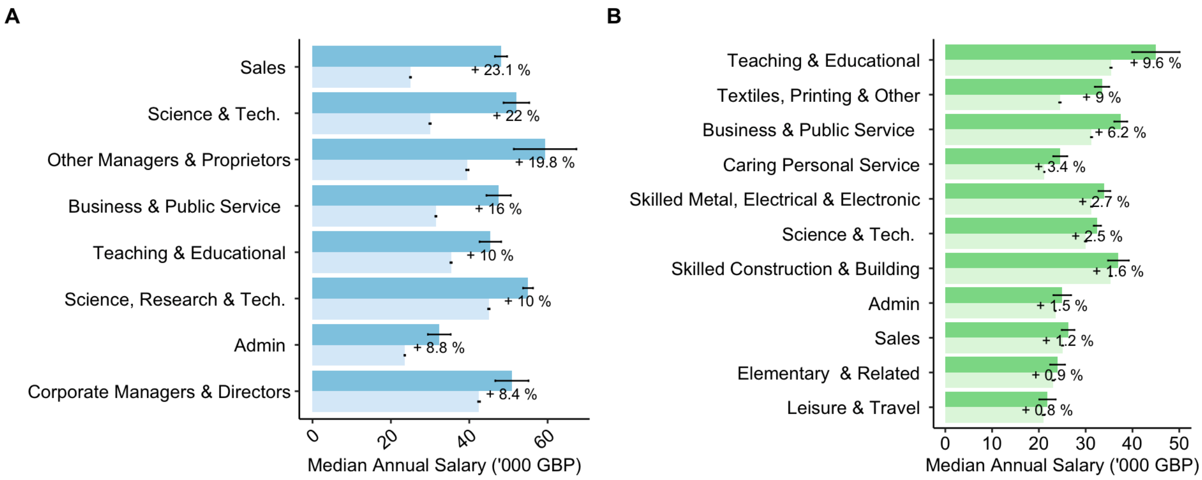


***Figure A4**. Both AI and green skills have a premium across the entire sample of OJVs. The premium is slightly lower for positions that do not require a university degree. For positions requesting a bachelors degree only AI skills are associated with higher offering wages. For graduate and postgraduate degree jobs, the AI and green skill premium disappears (95% confidence intervals as shown).*

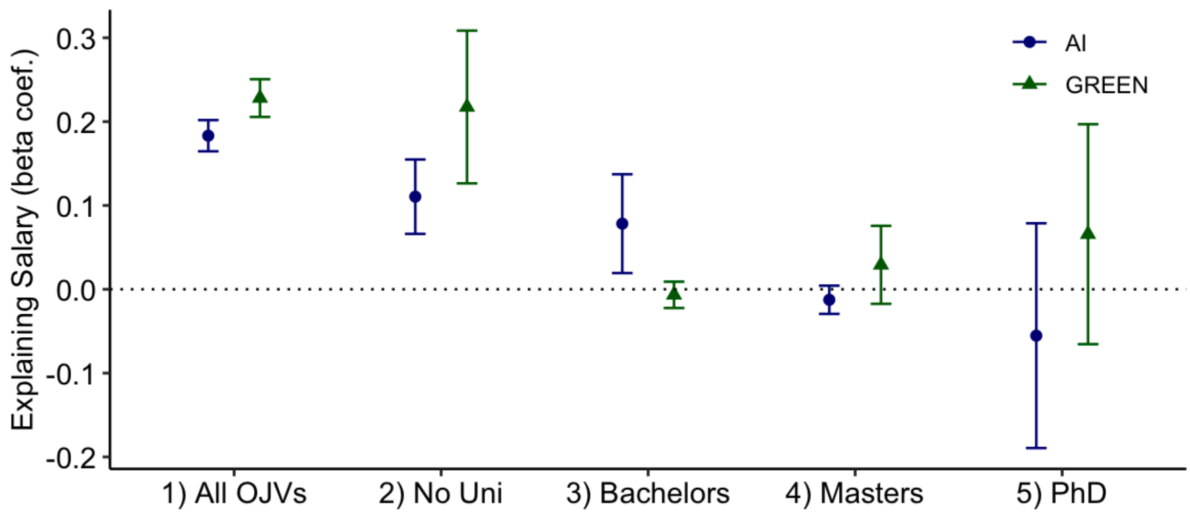


Figure A5. This is a job advertisement from the Greater London area. Information about the salary (highlighted in red), required education (blue), or skills (orange) had been extracted from all parts of the text of the posting, including headlines.

Machine Learning Engineer

[redacted] ★★★☆☆ 6 reviews

London

£48,237 a year - Fixed term contract

You must create an Indeed account before continuing to the company website to apply

Apply on company site

Role Responsibility

- Determining and refining machine learning objectives and run machine learning tests and experiments.
- Designing machine learning systems and self-running artificial intelligence software to automate predictive models.
- Solving complex problems with multi-layered data sets, as well as optimizing existing machine learning libraries and frameworks.
- Transforming data science prototypes and applying appropriate ML algorithms and tools.
- Proactively engaging with colleagues and maintain effective relationships and networks.

The Ideal Candidate

You will need demonstrable experience in and passion for machine learning and understanding of business user needs. You will have a Professional qualification or bachelor's degree in computer science, data science, mathematics, or a related field. You will have extensive knowledge of ML frameworks, libraries, data structures, data modelling, and software architecture. You should have an analytical mind and business acumen and be able to work competently and collaboratively as part of the Data & Insights Team and National Gambling Support Network providers and commissioners.

Table A1. We try to explain offering wages with educational attainment (reference is “no higher education requirement”) for all (but AI and green) postings in model 1 and for the subset of AI OJVs (model 2) and green OJVs (model 3). While the educational gradient is clearly visible in model 1, the premium for higher education disappears entirely for AI postings. Green postings do not show a clear gradient but nonetheless show a premium for bachelor’s and PhD degrees.

	log(Offered annual salary)		
	All Postings	AI	Green
Education			
Ref: No higher education			
Bachelor's or equivalent	0.04***	-0.13***	0.09***
	(0.003)	(0.03)	(0.02)
Master's or equivalent	0.09***	-0.07	0.08
	(0.01)	(0.05)	(0.06)
Ph.D. or equivalent	0.20***	-0.10**	0.19**
	(0.01)	(0.04)	(0.08)
Constant	10.02***	10.21***	10.17***
	(0.01)	(0.11)	(0.05)
Fixed Effects Controls			
4 Years	Yes	Yes	Yes
12 Regions (NUTS 1)	Yes	Yes	Yes
16 Industries (SIC 1)	Yes	Yes	Yes
9 Occupations (SOC 1)	Yes	Yes	Yes
Observations	367,444	2,866	4,022
R^2	0.41	0.39	0.35
Adjusted R^2	0.40	0.35	0.32

Note: **p<0.1,**p<0.05,***p<0.01*

Table A2. We see that OJV data is mostly representative of the UK labour force regarding geography, industries, and occupations. However, there are some notable exceptions: The capital, London, is slightly overrepresented in our data. This is also the region with the largest share of AI and Green postings. For industries, business admin and support services are significantly more prominent in OJV in contrast to motor trades, wholesale, and retail, which is underrepresented. Lastly, OJVs show more postings in professional occupations and less than average job offers for elementary occupations.

	Population (%)		Within Domain (%)		Wage Info
Regions (NUTS 1)	*Statistics**	*OJV Data*	*AI*	*Green*	*AVG: 37,5%*
East Midlands	7,3%	6,3%	0,6%	1,3%	53,7%
East of England	9,6%	8,4%	1,6%	1,2%	52,7%
London	14,4%	22,0%	3,0%	1,2%	46,1%
North East	3,7%	2,6%	0,7%	1,4%	50,5%
North West	10,9%	10,7%	0,9%	1,2%	52,6%
Northern Ireland	2,6%	2,0%	1,2%	1,2%	47,3%
Scotland	8,1%	6,9%	1,2%	1,8%	48,2%
South East	14,1%	14,3%	1,2%	1,2%	51,5%
South West	8,3%	8,2%	1,1%	1,6%	51,7%
Wales	4,4%	3,1%	0,5%	1,2%	52,9%
West Midlands	8,6%	8,6%	0,6%	1,3%	54,5%
Yorkshire and The Humber	8,0%	7,0%	0,6%	1,1%	51,6%
Industries (SIC 1)					
Agriculture, Forestry & Fishing (A)	1,7%	0,1%	3,7%	1,5%	25,3%
Mining, Quarrying & Utilities (B, D, E)	1,3%	0,9%	4,0%	10,9%	21,4%
Manufacturing (C)	7,5%	2,9%	2,2%	2,4%	20,6%
Construction (F)	5,0%	2,0%	0,8%	2,4%	26,0%
Motor Trades, Wholesale, Retail (G)	14,4%	5,9%	0,7%	0,7%	23,5%
Transport & Storage (inc Postal) (H)	5,0%	1,5%	2,3%	1,3%	29,6%
Accommodation & Food Services (I)	7,4%	3,1%	0,2%	1,0%	26,6%
Information & Communication (J)	4,3%	4,9%	5,1%	1,3%	22,4%
Finance & Insurance (K)	3,4%	2,8%	2,9%	1,0%	20,8%
Property (L)	1,9%	1,4%	1,3%	1,5%	32,8%
Professional, Scientific & Technical (M)	8,8%	7,2%	2,4%	2,7%	21,9%
Business Administration and Support Services (N)	8,7%	45,8%	1,2%	1,2%	42,2%
Education (P)	8,5%	3,8%	3,5%	1,3%	48,4%
Health (Q)	13,4%	12,0%	0,3%	0,4%	52,8%
Public Administration (O)	4,5%	3,2%	0,4%	2,2%	55,1%
Other (R,S,T,U)	4,3%	2,6%	0,7%	2,5%	26,5%
Occupations (SOC 1)					
Managers, directors and senior officials	10,8%	10,1%	0,9%	2,4%	35,3%
Professional occupations	20,1%	33,1%	2,1%	1,0%	38,4%
Associate professional and technical occupations	14,5%	17,7%	1,0%	1,4%	37,6%
Administrative and secretarial occupations	10,4%	9,3%	0,2%	0,6%	41,3%
Skilled trades occupations	10,1%	5,9%	0,6%	1,9%	36,2%
Caring, leisure and other service occupations	9,2%	7,3%	0,1%	0,9%	37,2%
Sales and customer service occupations	7,6%	7,9%	0,5%	0,8%	37,6%
Process, plant and machine operatives	6,4%	3,1%	0,5%	1,9%	39,6%
Elementary occupations	10,7%	5,6%	0,2%	1,3%	37,7%

**Source: Office for National Statistics*

bruegel

Bruegel, Rue de la Charité 33, B-1210 Brussels
(+32) 2 227 4210
info@bruegel.org
www.bruegel.org