The effect of AI adoption on Personality Traits demand: evidence from Online Job Vacancies

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Abstract

This study examines the demand for Big Five personality traits in the UK labour market and their interaction with artificial intelligence (AI) adoption. Using text retrieval methods on 11.7 million online job vacancies (2017-2022), I find that 72 per cent of vacancies require at least one personality trait. Extraversion is most common (44 per cent), followed by Conscientiousness (34 per cent) and Openness (30 per cent). After accounting for occupational changes, personality demands remain mostly stable over time, with only Conscientiousness showing a decline (-2.1 percentage points) and Extraversion a modest increase (1.7 percentage points) by 2022. I use two approaches to study how AI affects personality demands. At the vacancy level, jobs requiring AI skills are more likely to demand Openness (7.2 percentage points) and less likely to demand other traits, even within the same firm and occupation. At the firm level, after companies adopt AI for the first time, they increase their demand for Openness (3.6 percentage points) across all subsequent hiring. These findings suggest that as firms adopt AI technologies, they increasingly value workers with traits associated with creativity and adaptability, both for AI-demanding positions and across their broader workforce.

Keywords: personality traits, artificial intelligence, Big Five, online job postings, labour demand, AI adoption, text analysis, UK labour market, staggered difference-in-differences

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1 Introduction

In the contemporary labour market, personality traits are recognised as important factors in employment outcomes. Research from the British Workplace Employment Relations Study shows that most employers use personality tests to complement performance or competency tests in their hiring processes (McGee & McGee, 2020). This practice suggests that employers value candidates' personality traits alongside their technical skills and competencies. The demand for personality traits has been linked to several factors, including the proliferation of information and communication technologies, the implementation of innovative work practices, and the transition from manufacturing to service-based employment (Borghans et al., 2014). However, the extent to which demand for specific personality traits has changed over time and how this demand varies between different occupations and firms remains an open question in the literature.

Moreover, the last decade has seen rapid advances in artificial intelligence (AI) and the availability of large datasets. This encompasses computational technologies such as machine learning algorithms, computer vision systems, natural language processing tools, and automated decision-making systems - distinct from the more recent generative AI models like ChatGPT. These AI technologies are increasingly being adopted in several industries, potentially reshaping labour markets and skill demands (Acemoglu et al., 2022; Babina et al., 2024; Webb, 2019). Alekseeva et al. (2021) document a substantial increase in AI-related job postings between 2010 and 2019, growing from 0.02 per cent to 0.16 per cent of all online job postings. Similarly, using employee resume data, Babina et al. (2024) find AI investments grew more than seven-fold from 2010-2018 across sectors, with AI-investing firms experiencing significant growth in sales and employment. This growth has been particularly pronounced in high tech sectors and firms with higher cash reserves, higher markups, and more intensive R&D activities. AI adoption is expected to significantly impact labour markets, potentially changing the skills and traits that employers value most.

Despite the recognised importance of personality traits and the rapid adoption of AI, little is known about how these two trends connect. Studies have separately examined the demand for personality traits and the growth of AI-related jobs, but there is a significant gap in our understanding of how AI adoption might influence the demand for specific personality traits across different occupations and industries. This gap is particularly relevant given AI's potential to automate or enhance various tasks, which could change the personality traits that employers require. As Johnson and Acemoglu (2023) observe:

> It is therefore not surprising that despite the spread of AI technologies, many companies are increasingly seeking workers with social, rather than mathe-

matical, or technical skills. At the root of this growing demand for social skills is the reality that neither traditional digital technologies nor AI can perform essential tasks that involve social interaction, adaptation, flexibility, and communication. (p.314)

This study addresses three key research questions: (1) What is the nature and extent of personality trait demands in the UK labour market, and how do these align with occupational characteristics? (2) How have personality trait demands evolved over time? (3) How does AI adoption relate to firms' demands for specific personality traits? The aim is to provide a comprehensive analysis of the relationship between AI adoption and demand for personality traits, offering insights into how the labour market is adapting to technological change. By examining these questions, I contribute to the ongoing discussion on the future of work and provide evidence-based insights for workforce development strategies.

To answer these questions, I use data from 11.7 million online job postings in the United Kingdom from 2017 to 2022, provided by Adzuna, a job vacancy aggregator. Unlike other vacancy aggregators, Adzuna includes complete unstructured job descriptions written by employers. I use advanced text analysis to identify personality trait requirements in job postings, along with measures of AI demand at both vacancy and firm levels. I complement this with occupational-level information from the UK Household Longitudinal Study (UKHLS) on self-assessed personality traits and firm-level details from Companies House and the Financial Analysis Made Easy (FAME) databases.

I find that 72 per cent of vacancies mention at least one word related to personality traits. Extraversion is the most frequently mentioned trait (44 per cent), followed by Conscientiousness (34 per cent), Openness (30 per cent), Emotional Stability (14 per cent), and Agreeableness (13 per cent)[1]. Notably, personality traits appear more often in job postings than soft skills (interpersonal competencies like communication and leadership), hard skills (technical capabilities such as data analysis and engineering), experience, seniority, and educational qualifications. I also find substantial variation in the demand for personality traits across occupations, with a higher predominance in Sales, Customer Service, Caring and Leisure-related roles.

When analysing time trends, I find that while raw personality trait demands have increased, most of these changes reflect shifts in the types of vacancies being advertised. After controlling for occupational and firm composition, only one significant trend emerges: a steady decline in Conscientiousness (-2.1 percentage points by 2022). I also find a modest increase in Extraversion (1.7 percentage points by 2022), which is significant in all years after 2017 except 2022.

[1] These are defined in Section 4.

The analysis of AI adoption reveals significant effects on personality trait demands, using both fixed effects and staggered difference-in-differences approaches. The fixed effects analysis shows that jobs requiring AI skills are significantly more likely to demand Openness (7.2 percentage points) but less likely to demand other traits, particularly Extraversion (-2.7 percentage points), Emotional Stability (-2.2 percentage points), and Conscientiousness (-1.7 percentage points). These findings align with theoretical predictions about AI complementing creative and adaptive capabilities while potentially replacing routine-oriented and interpersonal tasks (Johnson & Acemoglu, 2023).

The staggered difference-in-differences analysis compares firms that adopt AI at different points in time to examine how personality trait demands change following AI adoption. This approach tracks the same firms before and after they first adopt AI technologies, using firms that have not yet adopted AI as a control group. To ensure that treated firms (those adopting AI) and control firms are comparable in their observable characteristics, I employ entropy balancing, matching on pre-treatment personality trait demands, firm characteristics, and occupational composition. The results show modest but significant effects on overall personality trait demands, with firms increasing their demand for personality traits by 2.7 percentage points after AI adoption. The effect is strongest for Openness, with a 3.6 percentage point increase in demand following AI adoption, while Emotional Stability shows a decline of 2.6 percentage points. Importantly, these effects persist when excluding AI positions from the analysis, showing that AI adoption leads to changes in personality requirements across firms' entire workforce rather than only in AI-intensive roles. The consistency of the Openness effect across both empirical approaches strengthens confidence in AI's role in increasing demand for creative and adaptive traits.

This study contributes to the existing literature in several ways. First, it provides a comprehensive analysis of the demand for personality traits in the UK labour market using a large dataset of online job postings. This allows for a detailed understanding of how employers value different personality traits across occupations and industries, while validating these demands through assortative matching with workers' self-reported characteristics. Second, this study is unique in its temporal scope, analysing personality trait demands over 5 years (2017-2022), showing how they have evolved after accounting for changes in occupational composition. Third, my findings challenge the notion that formal qualifications are the primary focus of job advertisements, showing that personality traits appear in 72 per cent of vacancies compared to just 11 per cent mentioning educational requirements.

Fourth, this study makes new contributions to our understanding of how AI adoption affects labour demand by examining its relationship with personality traits, an aspect previously unexplored. While existing research has documented AI's impact on technical skill requirements (Acemoglu et al., 2022) and cognitive tasks (Babina et al., 2024), this study is the first to systematically analyse how AI adoption influences demands for widely-known measures of personality traits. Fifth, by using both fixed effects and staggered difference-in-differences analyses, this research provides causal evidence on how AI adoption shapes personality requirements, finding a strong complementarity between AI and traits related to creativity and adaptability. This suggests that as firms adopt AI technologies, they increasingly value workers' capacity for innovation and flexible thinking.

These insights have important implications for job seekers, educators and policy makers. The results suggest the need to consider personality development, particularly traits related to creativity and adaptability, alongside traditional skill acquisition in workforce preparation strategies. This is especially relevant as firms continue to adopt AI technologies, which appear to increase demand for these characteristics.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on personality traits in the labour market and recent developments in AI adoption. Sections 3 and 4 describe the data sources and methodology in detail. Section 5 examines the assortative matching between job requirements and worker characteristics. Section 6 presents the empirical framework. Section 7 presents the main results for the demand for personality traits and their interaction with AI adoption. Finally, Section 8 concludes and suggests directions for future research.

2 Literature Review

Personality traits, character attributes, soft skills, and social skills are often used interchangeably in the literature to reflect personal characteristics outside cognitive attributes. However, these terms connote different properties and levels of malleability (Heckman & Kautz, 2012; Woessmann, 2024). Soft skills and social skills represent dynamic attributes related to interpersonal and social competencies such as leadership, negotiation, teamwork, and communication. These are defined by the employer, locally relevant, generally considered learnable and modifiable through investments in training and work experience (Grugulis & Vincent, 2009; Matteson et al., 2016). Employers may select these during hiring or develop them in staff over time.

In contrast, personality traits and character attributes are more stable individual characteristics that remain relatively fixed after early adulthood (Cobb-Clark & Tan, 2011; Heckman & Kautz, 2012). They are also largely uncorrelated with cognitive skills (McCrae & John, 1992). Due to this stability, employers have stronger incentives to hire individuals who already possess required personality traits.

Economists have increasingly incorporated personality traits into their human capital analyses over recent decades. It is recognised that personality traits significantly explain differences in economic outcomes (Borghans et al., 2008; Heckman & Rubinstein, 2001). The "Big Five" personality traits—Openness, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability—have become a standard framework. This approach is based on the lexical hypothesis, which suggests that important personality traits become encoded in language, with more significant traits appearing as single words commonly used by individuals (Goldberg, 1990; John, 1990; McCrae & John, 1992).

Many studies show the impact of personality traits on labour market outcomes, including unemployment (Fletcher, 2013; Lindqvist & Vestman, 2011; Viinikainen & Kokko, 2012), occupational sorting (Borghans et al., 2014; Edin et al., 2022; Todd & Zhang, 2020) and career success (Judge et al., 1999; Seibert & Kraimer, 2001). Research suggests that personality traits affect workers' productivity and therefore wages (Woessmann, 2024), although these effects vary by gender and across the wage distribution (Collischon, 2020; Flinn et al., 2025; Gensowski, 2018; Heineck & Anger, 2010; Mueller & Plug, 2006; Nyhus & Pons, 2005). For example, emotional stability and agreeableness are linked to higher wages for women, while extraversion correlates with higher wages for men (Mueller & Plug, 2006; Nyhus & Pons, 2005).

Conscientiousness has emerged as a particularly strong predictor of job performance across various occupations (Barrick & Mount, 1991; Judge & Cable, 1997). Certain traits appear more valuable in specific job types; for instance, extraversion correlates strongly with performance in occupations requiring interpersonal attributes, such as management or sales (Barrick & Mount, 1991). Gensowski (2018) found that personality traits, particularly openness to experience and extraversion, have significant effects on lifetime earnings, with these effects varying between different levels of educational attainment. Collischon (2020) used unconditional quantile regressions to show that the returns to personality traits vary across the wage distribution, with larger effects observed at higher wage quantiles. Rohrbach-Schmidt et al. (2023) found that the relationship between personality traits and wages varies significantly with job task requirements, with extraversion and emotional stability associated with higher wages, while agreeableness and openness tend to correlate with lower wages within occupations.

2.1 Measuring Personality Demands in Labour Markets

Traditionally, personality traits have been measured through surveys and psychological tests administered to individuals. These assessment instruments are constructed based on the lexical hypothesis described earlier, where trait-descriptive adjectives from natural language are systematically analysed and grouped through factor analysis to identify underlying personality dimensions. Questionnaires like the NEO-PI, the Big Five, and similar instruments present respondents with standardised statements derived from this lexical approach, asking them to rate how accurately these statements describe their typical behaviours and feelings.

Recent advances in big data and text analysis have opened new ways to measure personality traits at scale. Deming and Kahn (2018) pioneered the use of online job postings to measure skill demands, including social skills that closely relate to certain personality traits. This approach, while offering unprecedented scale and detail, also presents challenges in terms of representativeness and interpretation (Hershbein & Kahn, 2018). These challenges include potential selection bias in which jobs appear in online platforms, with casual, freelance, or certain industry-specific roles being underrepresented. More fundamentally, personality trait mentions in job advertisements reflect employer demands rather than worker characteristics—capturing what employers believe they need or what they strategically emphasise to attract certain applicants (Abraham et al., 2024).

Building on this methodological foundation, researchers have developed sophisticated methods to extract personality-related information from job advertisements, ranging from keyword-based approaches to advanced machine learning techniques (Khaouja et al., 2021; Lovaglio et al., 2018; Turrell et al., 2019). Brenčič and McGee (2023a, 2023b) employed a knowledge engineering method to identify personality-related terms in online job advertisements, providing insights into employers' demand for specific traits across different occupations and tasks. Their findings using a two-week database from Monster.com reveal that in the US, 54% of job advertisements make at least one reference to personality traits, with employers primarily demanding workers who are extroverted (31%), conscientious (26%), and open-to-experience (21%).

Studies examining temporal changes in personality trait demands have revealed interesting trends. Evidence suggests that the labour market has increasingly rewarded character skills over time, particularly related with extraversion and agreeableness (Deming, 2017; Weinberger, 2014). This trend has been attributed to technological change and the growing importance of teamwork in the workplace. Analysis of skill demands in the UK labour market has shown an increasing use of both analytical and interpersonal skills over time, with changes occurring mainly within occupations rather than between them (Dickerson & Morris, 2019). More productive firms tend to have higher skill requirements in their job postings, including those related to social skills and personality traits (Deming & Kahn, 2018), suggesting that personality trait demands may vary systematically between firms and labour markets.

2.2 Artificial Intelligence and Labour Market Transformation

Artificial intelligence (AI) has emerged as a transformative force in the labour market, with potential far-reaching implications for skill demands and job characteristics. Recent years have seen a significant increase in AI-related job postings, particularly in high-tech sectors and firms with higher cash reserves, higher markups, and more intensive R&D activities (Acemoglu et al., 2022; Alekseeva et al., 2021; Schmidt et al., 2024). This trend extends beyond the tech sectors, with AI adoption spreading through major industries including finance, manufacturing, retail and healthcare services (Babina et al., 2024; Choi & Leigh, 2024).

The impact of AI on the labour market is complex. Research shows that high-wage occupations and those with higher educational requirements tend to be more exposed to AI than low-wage occupations (Webb, 2019). However, this exposure does not straightforwardly translate into negative employment effects. While AI may substitute for certain tasks and potentially displace workers, research suggests it can create new tasks that complement human skills (Acemoglu & Restrepo, 2019). Supporting this complementarity hypothesis, Babina et al. (2024) find that AI-investing firms experience faster growth in both revenue and employment. The terminology of AI used in all these studies, as well as here, refers to non-generative AI, which was released to the public in 2022.

Studies have found that exposure to AI is associated with a shift in job postings toward non-routine analytical and interpersonal skills (Alekseeva et al., 2021), suggesting that as AI takes over more routine and codifiable tasks, there may be increasing demand for uniquely human skills that are harder to automate. Analysis of AI-related job postings has shown that in addition to technical skills, there is a growing emphasis on skills related to communication, problem solving, creativity, and teamwork (Squicciarini & Nachtigall, 2021). These skills are closely associated with certain personality traits, suggesting that as AI adoption increases, there may be growing demand for personality traits that complement AI capabilities.

The increasing importance of "character" skills in the labour market, as documented by several studies (Deming, 2017; Deming & Kahn, 2018), may be partially driven by the need for workers who can interact effectively with AI systems and bridge the gap between technical capabilities and human needs. This trend aligns with observations that neither traditional digital technologies nor AI can fully replace essential tasks involving social interaction, adaptation, flexibility, and communication (Johnson & Acemoglu, 2023).

2.3 Research Gap and Study Contribution

The literature highlights the importance of personality traits in determining labour market outcomes and the growing impact of artificial intelligence on skill demands. However, there remains a significant gap in our understanding of how AI adoption influences the demand for specific personality traits across different occupations and firms. While existing research has provided valuable insight into the relationship between personality traits and labour market outcomes, there is a need for more comprehensive studies that examine how this relationship may be changing over time, particularly in response to technological advancements like AI.

This study aims to bridge this gap by using a large-scale dataset of online job postings to examine the evolving demand for personality traits in the context of increasing AI adoption. By analysing the demand for personality traits over a five-year period and investigating its interaction with AI adoption, this study seeks to provide a more comprehensive understanding of the evolving role of personality in the labour market.

3 Data

This paper uses data from Adzuna, a job vacancy aggregator[2]. Adzuna's algorithms collect information on open vacancies posted across different online platforms. The UK Office of National Statistics (ONS) uses Adzuna data to produce a weekly vacancy indicator.

Adzuna's data limitations are common to other online vacancy aggregators: the scope of online job advertisements does not fully capture all job adverts in the UK. Representative biases could arise from specific jobs that are not posted in online marketplaces. Casual or freelance work may be advertised using different methods, such as word of mouth, newspapers, local advertising, or in-shop windows. Comparing the 2021 data with the 2021 Census exhibits occupational composition differences at the 1-digit SOC level. Associate Professional & Technical occupations and Caring & Leisure roles have greater representation in online vacancies, while Administrative, Managerial, and Process & Machine Operative roles have lower representation. Table A.1 in Appendix A compares Adzuna's 2021 occupational distribution with the 2021 UK Census at 3-digit SOC level.

Adzuna provided a database without duplicate advertisements for the same week from the same online source, such as job.uk, jobsincare.co.uk or cv-library.co.uk[3]. According to Adzuna's representatives, their point-in-time estimates are more comprehensive than *Burning Glass Technologies (BGT)*, the most widely cited online vacancy aggregator. While Adzuna collects data from job boards, BGT's collection focuses on individual company websites, resulting in fewer vacancies.

Studies using BGT, such as Deming and Kahn (2018), Hershbein and Kahn (2018), Acemoglu et al. (2022), and Schmidt et al. (2024), highlight its structured information as an advantage. By contrast, Adzuna's unprocessed data, while more difficult to manage, offers

[2] I am grateful to Urban Big Data Centre for granting the licence to use the Adzuna database under Data Sharing Agreement number 678175.

[3] I further cleaned potential duplicate vacancies published in other sources or with different vacancy IDs but identical company, location and descriptive text. A step-by-step explanation of this procedure is in Appendix B.

valuable benefits. The raw job description text allows for flexible dictionary construction, which is essential for identifying personality-trait wording. It also enables more thorough data preprocessing, allowing the extraction of skills, education, and experience criteria directly from job descriptions. Access to the complete advertisement text makes it possible to study trait mentions both within and across advertisements.

When collecting job advertisements, Adzuna stores information from the web page and creates several key variables, including job title, offered salary, posting date and site, contract type (permanent or temporary), location, and whether the job is part- or full-time. I added information extracted from the job descriptions. Specifically, I cleaned the wage variable, job schedule, and contract type, and recoded job locations to the two-digit *Nomenclature des Unités territoriales statistiques* (NUTS) level. I also created indicators for soft and hard skills requirements[4], education, experience, seniority, and bonus availability. Adzuna's vacancy identifier allows tracking of advertisements over time, regardless of posting site.

Since Adzuna lacks standard occupational codes, I implemented a machine learning algorithm created by Turrell et al. (2019) to classify advertisements into 3-digit Standard Occupation Codes (SOC). The algorithm categorises advertisements based on their title, description, and industry. Using Companies House data, a public dataset of UK-registered companies, I matched Adzuna's companies to obtain Standard Industrial Codes (SIC), keeping only private companies whose names uniquely matched.Advertisements from recruitment agencies or non-private institutions lack industry codes, which are needed for the Turrell et al. (2019) algorithm and were therefore removed (reducing the sample by 45 per cent) and those without SIC codes (further reducing the sample by 56 per cent).

Finally, this study only uses vacancies with posted wages. A common criticism of wage data from online job advertisements is that they often target lower-skilled workers or positions that need to be filled urgently (Banfi & Villena-Roldan, 2019; Brenčič, 2012). Batra et al. (2023)'s meta-analysis highlights the scarcity of wage information, which is often only available in broad ranges, limiting its reliability as a proxy for actual wages. This scarcity is more evident in high-wage occupations and large private firms. After removing recruitment agencies and advertisements not matching Companies House, the dataset contained wage information for 46 per cent of vacancies. This is twice the proportion found in studies using job boards that don't aggregate sources (24.8 per cent in *monster.com* (Brenčič, 2012); 13.3 per cent in *trabajando.com* (Banfi & Villena-Roldan, 2019); 20 per cent in *careerbuilder.com* (Marinescu & Wolthoff, 2020); and 24.3 per cent in *xmrc.com*

[4]For soft skills, these include *communication skills, critical thinking, language skills, leadership, interpersonal skills, negotiation skills*, among others. For hard skills, I coded *administrative skills, data analysis, design skills, engineering, legal analysis, sales skills, customer service*, among others. The complete list is in Appendix B.

(Kuhn & Shen, 2023). The final database contains 11.7 million vacancies from 128,559 companies.

I complemented the job vacancy data with information at both occupational and firm levels. For occupations, I obtained data on gender and migrant proportions, average education, seniority, age, and tenure from the UK Household Longitudinal Study (UKHLS), a household panel survey. The UKHLS also asks individuals to self-assess their personality using the Big Five framework, allowing me to compare personality trait demands in job vacancies with workers' self-reported traits in different occupations. Appendix B provides detailed explanations of the additional data sources, cleaning process, variable construction, refinement of Adzuna's categories, and the Turrell et al. (2019) algorithm. At the firm level, I matched Adzuna data with the FAME database to identify publicly listed companies.

4 Methodology

The most widely used framework for studying personality traits in psychology is the Big Five. These five dimensions are Conscientiousness, Openness to experience, Extraversion, Agreeableness, and Emotional Stability[5]. This framework is based on the lexical hypothesis, which suggests that important personality characteristics become encoded in language over time. The words people use to describe themselves and others reflect important personality dimensions. In job advertisements, this is especially relevant as employers likely use words associated with valued personality traits, and job seekers recognise and respond to these trait-related terms when applying.

Researchers built and refined the taxonomy using factor analysis to group the many adjectives describing personality in natural language into these five traits (John, 1990). The Big Five follows the structure proposed by Goldberg (1990), McCrae and John (1992), and John (1990), who developed the initial work of Cattell (1943).

The Big Five structure has been validated across different languages and cultures (Borghans et al., 2008; King et al., 2005). This cross-cultural consistency has led to its widespread use in economics research, following key papers linking personality types to economic outcomes such as educational attainment, job selection, productivity and earnings (Almlund et al., 2011; Borghans et al., 2008; Heckman, 2011).

Each of the Big Five traits includes specific characteristics (Costa Jr & McCrae, 1992; Goldberg, 1990; Stanek & Ones, 2023):

- *Conscientiousness* relates to being organised, responsible, and diligent, with self-discipline and achievement drive.

[5]Emotional Stability is commonly described as the opposite of Neuroticism.

- *Openness-to-experience* refers to an interest in new aesthetic, cultural, or intellectual experiences, showing a desire for cognitive exploration.
- *Extraversion* involves an outward orientation towards social interactions and activities, associated with sociability and positive attitude.
- *Agreeableness* appears in cooperative and unselfish behaviour that promotes harmonious interactions.
- *Emotional Stability* refers to consistency in emotional responses without rapid mood changes.

In this study, I use the Big Five framework to analyse personality trait demand in the UK labour market. By identifying words linked to each trait in job advertisements, I measure employers' demands for specific personality characteristics and examine how these vary across occupations and time.

4.1 Personality traits retrieval

As Lovaglio et al. (2018) outline, there are two main approaches to identify job advertisement requirements: *knowledge engineering* and *machine learning techniques*. Knowledge engineering involves manually defining rules to classify text, while machine learning uses an inductive process to automatically build classifiers.

This study uses the Knowledge Engineering method, which aligns with the theoretical foundations of the Big Five personality taxonomy.

This approach allows me to directly use established personality psychology research to identify relevant trait descriptors. When analysing job advertisements, this method offers two key advantages. First, it keeps trait identification true to the Big Five framework, avoiding semantically related but conceptually different terms that might be incorrectly included by open-vocabulary methods like machine learning. This reduces the risk of identifying traits through broad synonyms with ambiguous meanings. Second, it provides a clear and replicable method for identifying trait-related language in job postings, which helps interpret results in the context of labour markets.

My methodology builds on previous research using similar approaches. Deming and Kahn (2018) and Alekseeva et al. (2021) used Knowledge Engineering to search for various skills and character attributes in job postings. Brenčič and McGee (2023b) and Brenčič and McGee (2023a) also used knowledge engineering to identify personality-related terms in online job advertisements. While Brenčič and McGee (2023b) focused mainly on personality-trait words in a small dataset, and Brenčič and McGee (2023a) expanded this by examining traits across different job tasks, my research examines the relationship with AI demand and provides deeper analysis of job, occupation, and firm attributes.

To identify personality traits, I use a Boolean retrieval approach. A job posting is labelled as requiring one of the Big Five personality traits if it includes at least one keyword from a dictionary related to traits in its job requirements or job title[6]. The demand for each trait is then measured at an aggregate level as the percentage of job postings containing trait-related words, similar to Alekseeva et al. (2021) for AI skills and Draca et al. (2022) for remote work.

To mitigate the risk of false positives in trait retrieval (Brenčič & McGee, 2023b), I used a two-step approach. First, I compiled dictionaries from authoritative works in the field, including Goldberg (1990), Costa Jr and McCrae (1992), Goldberg (1992), McCrae and John (1992), John (1990), Saucier (1994) and Heckman and Kautz (2012). For four of the Big Five traits, I used only adjectives from these established dictionaries. However, for Emotional Stability, I supplemented the dictionary with additional job-relevant terms[7]. Second, I refined these dictionaries through manual analysis to ensure that, in job vacancy contexts, the words actually referred to employee or job characteristics.

I analysed the context of each dictionary word using natural language processing tools. For each word, I examined up to eight rounds of 100 randomly selected sentences from job advertisements containing the word. I analysed the 10 words before and after each trait-related term. This process identified words with multiple meanings, such as *flexible* or *trust*, which could refer to work schedules rather than personality traits. I modified terms in contexts not referring to worker or team characteristics before dictionary matching. For example, I replaced phrases like "flexible hours" with "flx hours" and "national trust" with "national tst" to avoid false positives. I repeated this process of checking contexts and redefining false matches until no spurious matches appeared in samples of 100 advertisements.

I removed words that, regardless of context, did not refer to personality traits in job vacancies, such as *modest, conventional, deliberate, order, aesthetic, deep, relaxed* or *comfortable*. These terms were excluded because they typically described job conditions, physical environments, or general preferences rather than specific personality character-

[6] Marinescu and Wolthoff (2020) found that job titles have crucial information and play a more important role than wages in explaining the number and quality of applicants. Titles often indicate hierarchy, experience and specialisation.

[7] Psychology literature predominantly uses neuroticism-related language, which resulted in fewer suitable terms for measuring Emotional Stability in job contexts. I therefore added job vacancy terms closely related to Emotional Stability requirements, including *fortitude, pressure, resilience, unflappability, patience, conflict, and tense situations.* Terms like *fortitude, resilience, unflappable and patience* refer to positive behavioural traits, while *pressure, conflict, and tense situations* appear in phrases where applicants must work well *under pressure*, in *conflictive* environments, or handle *tense situations*, demonstrating emotional stability requirements.

istics that employers seek in candidates—for instance, "comfortable salary" or "relaxed atmosphere" do not indicate personality requirements but rather job attributes. Table 1 contains the terms used for each of the Big Five and the source they were retrieved from.

Table 1: **Dictionary of Personality Traits**

Agreeableness	**Extraversion**	**Conscientiousness**	**Emotional Stability**	**Openness**
affection (4, 5)	adventurous (3, 5, 7)	ambitious (2, 7)	at ease (3)	artistic (3 - 7)
agreeable (all)	assertive (1, 3 - 7)	careful (6)	calm (2, 3, 5)	bright (3, 6)
altruist (5, 7)	bold (3, 6)	competence (5, 7)	emotional (all)	clever (5)
amiable (1)	candour (1)	conscientious (all)	hostil (5, 7)	creative (1 - 3, 6)
considerate (3, 6)	confident (7)	decisive (1)	fearful (6)	curious (1, 2 - 5, 7)
cooperative (1, 3, 5 - 7)	courage (1)	dependable (1, 5)	tempered (2, 5, 6)	ideas (5, 7)
courteous (1)	daring (3, 6)	dutiful (7)	fortitude (ads)	imaginative (2 - 7)
empathy (1)	energetic (1, 3 - 7)	efficient (1, 4 - 7)	pressure (ads)	independent-mind (5)
forgiving (4, 5, 7)	enthusiastic (4, 5, 7)	hardwork (2, 3)	resilience (ads)	ingenious (5)
gentle (5)	expressive (1)	logic (1)	tense (4, 5)	innovative (3, 6)
good-nature (2, 5)	extraverted (all)	neat (3, 7)	unflappable (ads)	insightful (1, 4, 5)
helpful (3, 5, 6)	forceful (5)	organised (1, 3 - 7)	patience (ads)	intellectual (1, 5, 6)
kind (3 - 6)	friendly (7)	painstaking (5)	pressure (ads)	intelligent (1, 3, 5)
naturalness (1)	fun (2)	persevering (2)	-	introspective (3, 6)
pleasant (3, 5, 6)	gregarious (1, 5, 7)	persistence (1)	-	inventive (5)
sensitive (5)	humour (1)	planful (4, 5)	-	openness (all)
straight-forward (5, 7)	optimist (1)	precise (1, 5)	-	original (2, 4)
sympathetic (3 - 7)	outgoing (4, 5)	prompt (3, 6)	-	prefer variety (2)
trust (2, 3 - 7)	outspoken (5)	punctual (1, 2)	-	reflective (3)
unselfish (3, 5, 7)	passionate (2)	reliable (4, 5)	-	sharp (5)
warm (1, 3, 5 - 7)	playful (1)	responsible (3 - 5)	-	unconventional (5, 7)
	pro-active (2 - 7)	striving (5, 7)	-	wide interests (4, 5, 7)
	sociable (5, 7)	systematic (3, 7)	-	witted (5)
	spontaneous (1)	thorough (3 - 5, 7)	-	-
	talkative (1 - 6)		- -	-

Notes: The numbers denote which dictionaries the words are mentioned in. The numbers correspond to the following dictionaries: (1) Goldberg (1990); (2) Costa Jr and McCrae (1992); (3) Goldberg (1992); (4) McCrae and John (1992); (5) O. P. John et al. (1999); (6) Saucier (1994); (7) Heckman and Kautz (2012)

4.1.1 Examples of Classification

Table 2 shows two job vacancies and their classification using the Boolean retrieval approach.

Table 2: **Two examples of job vacancies and the boolean indicator.**

Vacancy 1

Our comprehensive training will give you the skills and knowledge you need, so our main focus is that you are professional, ***kind*** *and* ***empathetic*** *to the needs of our service users. You will need to be* ***even-tempered****, willing to carry out personal hygiene tasks and be dedicated to providing outstanding levels of care.*

Vacancy 2

This chef apprenticeship offers a fantastic opportunity to learn and develop your skills and knowledge in a busy commercial kitchen. You will need to have a ***passion*** *for food and a good work ethic. You will need to be* ***organised*** *and have the ability to work under pressure. You must maintain a* ***pro active*** *attitude, seek to improve your skills and achieve personal development.*

Boolean categorization

Personality Trait	Vacancy 1	Vacancy 2
Agreeableness	1	0
Conscientiousness	0	1
Extraversion	0	1
Openness	0	0
Emotional Stability	1	0

4.2 AI demand retrieval

To measure AI skills demand in job postings, I use text analysis based on work by Acemoglu et al. (2022), Babina et al. (2024) and Choi and Leigh (2024). These studies use different methods to identify AI-related terms. Babina et al. (2024) and Choi and Leigh (2024) employ a co-occurrence approach using pre-classified skills in BGT data[8]. Acemoglu et al. (2022) uses a dictionary-based method. I expand on the dictionary-based approach, which works better for raw text analysis.

I extended the AI skills list from Acemoglu et al. (2022) and Babina et al. (2024) to include more AI-related terms. I grouped similar technology terms to ensure comprehensive retrieval of AI-related content in job postings. For example, when searching for *machine learning* requirements, I also searched for related specific techniques such as *cross-domain learning, federated learning,* and *reinforcement learning*, treating all these terms as indicators of machine learning skill demands. To expand the term list, I manually

[8] Babina et al. (2024) and Choi and Leigh (2024) identify AI skills by calculating how often skills appear alongside core AI terms ("Machine Learning", "Artificial Intelligence", "Natural Language Processing", and "Computer Vision") in BGT job postings. Skills frequently appearing with these core terms are classified as AI-related. This method uses BGT's pre-classified skill categories, unavailable in raw job posting text.

examined 100 advertisements for each term from Acemoglu et al. (2022) and Babina et al. (2024), analysing surrounding AI-related skills or tools. The complete list of skills from each source and text replacements is in Appendix B.

This manual review process, though more time-consuming than the co-occurrence method used by Babina et al. (2024) or Choi and Leigh (2024), serves a similar purpose of identifying related AI terms in context. Since Adzuna provides raw text rather than listed skills, a co-occurrence approach would consider all vacancy words rather than just skills, making it less reliable for identifying AI terms. By examining over 2,000 vacancies with AI-related content, my approach identified additional AI tools and software packages that might not be included in structured databases like BGT. I carefully ensured these terms were specific to AI and excluded broader IT functions.

5 Assortative Matching Exercise

To validate my text-based approach for identifying personality trait demands, I first test whether these demands align with workers' actual characteristics in the same occupations. If job advertisements effectively signal personality requirements, we should see assortative matching—occupations with higher demands for specific traits should employ workers who score higher on those same traits in surveys. This analysis also helps confirm that personality-related language in job postings reflects genuine trait requirements rather than just differences in advertising styles.

I compare trait requirements in job advertisements with workers' self-reported traits from the UK Household Longitudinal Study (UKHLS)[9].

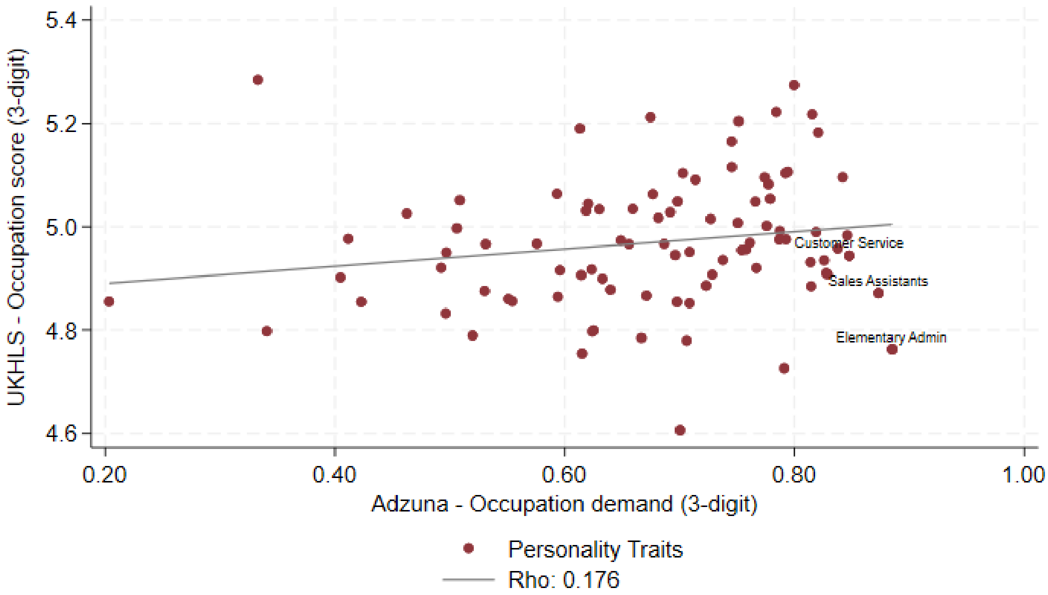
The scatter plots in Figure 1 show positive assortative matching for most personality traits: occupations with high trait demands tend to employ workers who report higher scores in those same traits. This correlation is particularly strong for Agreeableness (ρ = 0.464). The top 10 occupations with the highest self-reported Agreeableness scores demand this trait in 18 per cent of their vacancies on average, while the bottom 10 occupations demand it in only 5 per cent. The occupation with the highest trait demand (39.1 per cent of vacancies) also ranks among the top quartile for self-reported scores, exemplifying this strong assortative matching between job advertisement requirements and workers' self-reported traits[10].

[9] These range from 1 to 7, where 1 means *does not apply to me at all* and 7 means *applies to me perfectly*. Workers' self-assessments are averaged to create occupation-level mean scores for each trait.

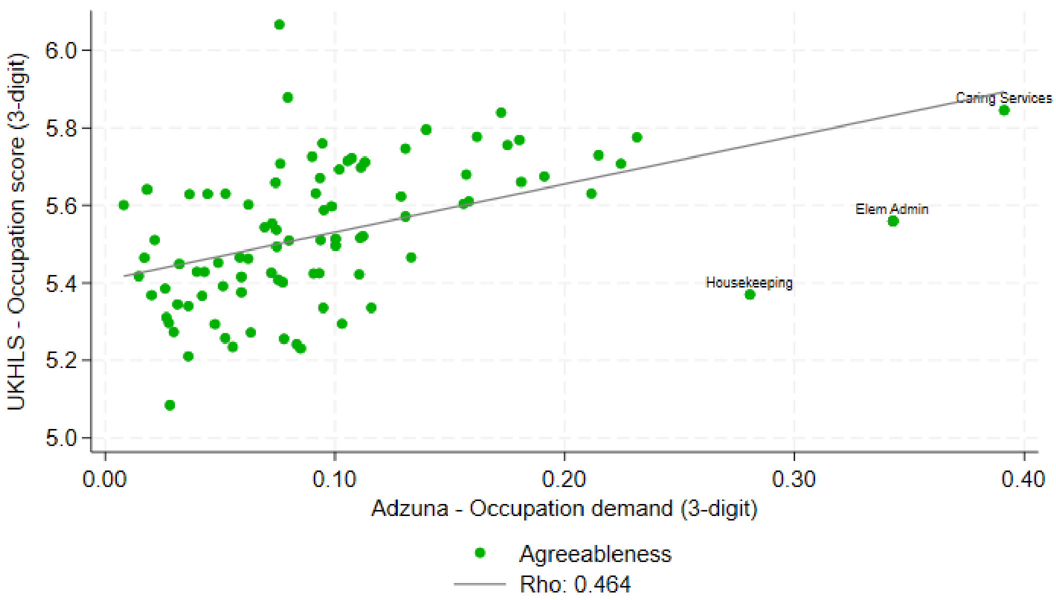
[10] Linear probability regressions without controls show that one standard deviation increase in the average occupation score for overall personality traits raises the probability of an advertisement mentioning any personality trait by 2.3 per cent, Agreeableness by 8.9 per cent, Conscientiousness by 0.1 per cent, Emotional Stability by -4.4 per cent, Extraversion by 8.9 per cent and Openness by 4.5 per cent. The regression output is in Table A.4, Appendix A.

Figure 1: Scatter-plot between mean trait's standardized scores in UKHLS and share of vacancies that mention Personality traits in Adzuna.

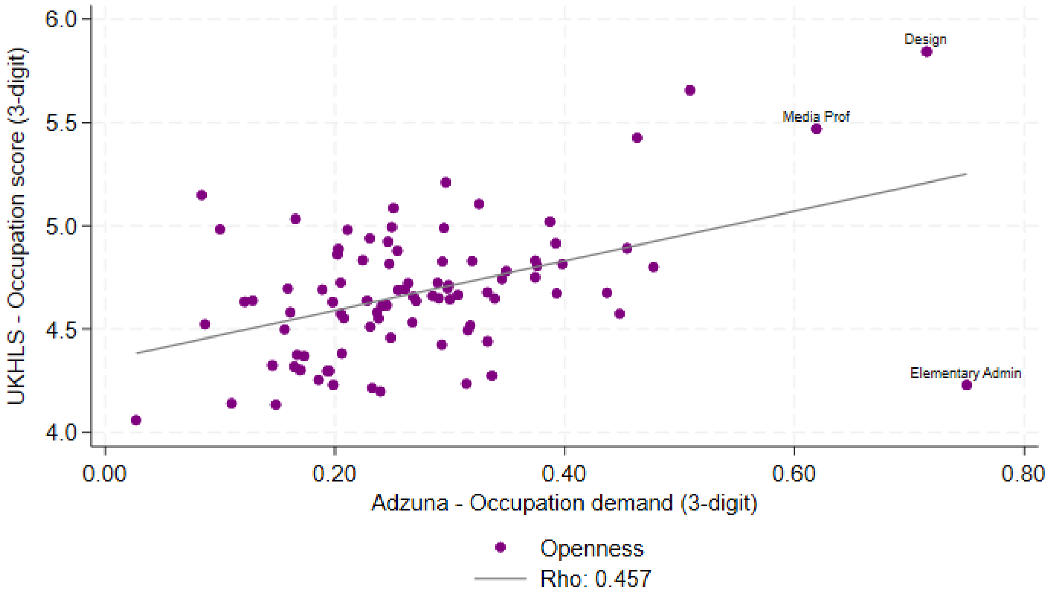
(a) All Personality Traits



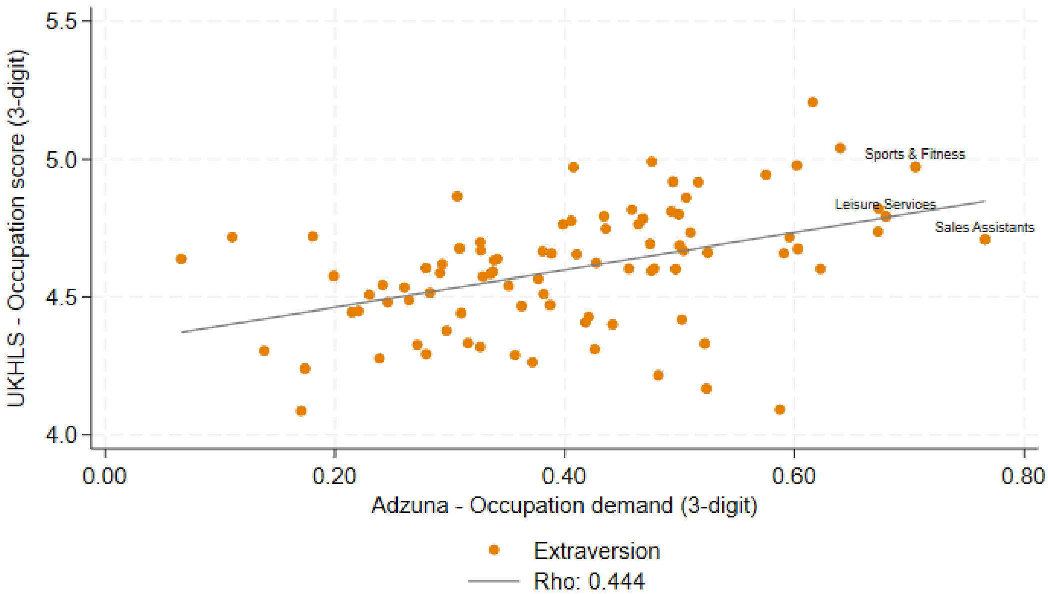
(b) Agreeableness



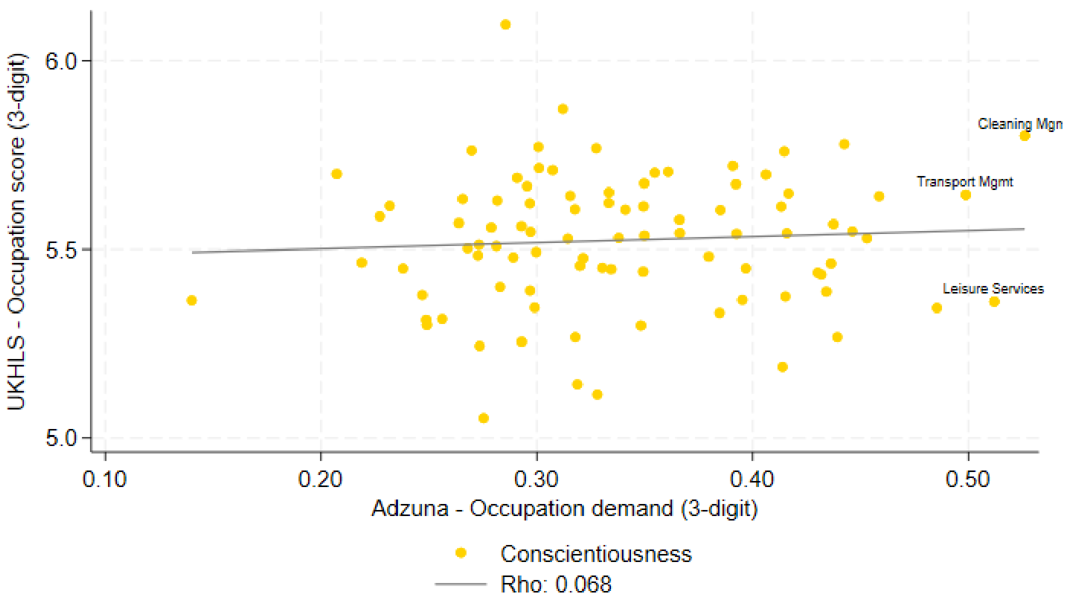
(c) Openness



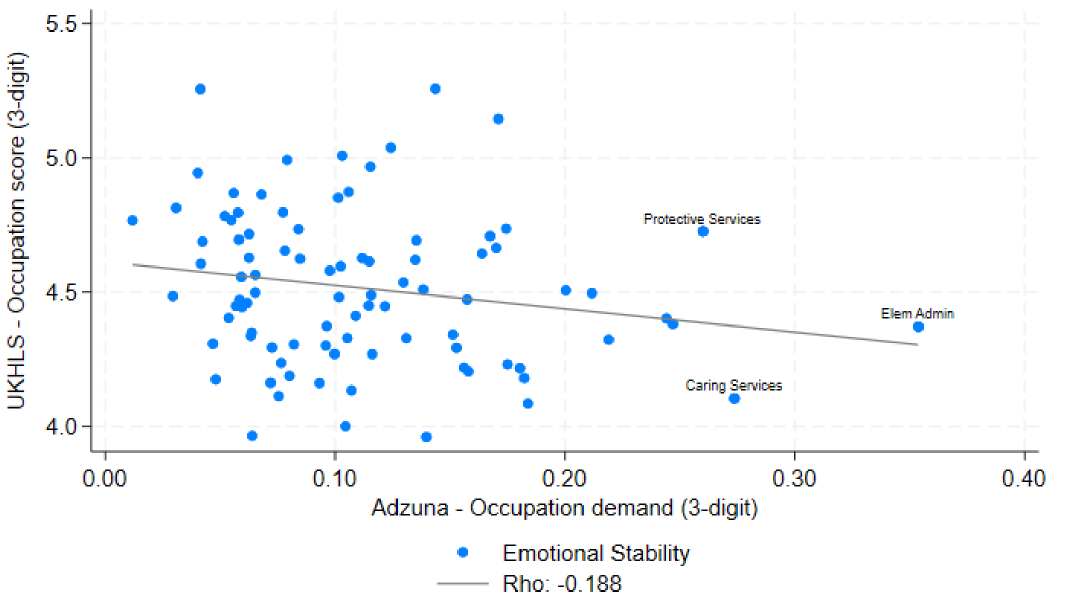
(d) Extraversion



(e) Conscientiousness



(f) Emotional Stability



Notes: Author's creation using UKHLS and Adzuna.

The relationship varies across traits and occupations. For Openness, occupations with the highest demands (exceeding 60 per cent of vacancies) also exhibit correspondingly high self-reported scores, reflecting the creative nature of these roles. This pattern reinforces the validity of using job postings to measure personality trait requirements.

Emotional Stability presents an exception to the assortative matching pattern. While some occupations frequently demand Emotional Stability (over 25 per cent of vacancies), the highest self-reported scores appear in different occupation groups entirely. This discrepancy likely stems from two measurement issues. First, job postings emphasise situational requirements (e.g., "ability to work under pressure"), while self-reported scores reflect broader personality tendencies. Second, the self-reported scores come from UKHLS questions about neuroticism that were inversely transformed to approximate Emotional Stability. This transformation may not capture the same construct that employers seek when requesting emotional stability, as employers may use different terminology or find it difficult to articulate these requirements in job postings.

To understand which occupation-level characteristics relate to each traits demand, I estimate a linear probability model following Equation 1:

$$P(Trait_i = 1) = \alpha + \beta_0 + \beta_1 Z_k + \beta_2 S_k + \beta_3 X_i + \delta_l + \theta_t + \phi_j + \epsilon_i \quad (1)$$

where Z_k is a vector of UKHLS occupation-level characteristics including gender composition, education levels, migrant share and mean worker age, S_k represents the standardised UKHLS trait score for occupation k, and X_i captures job posting characteristics such as advertisement length and other requirements. The model includes location (δ_l), time (θ_t), and firm (ϕ_j) fixed effects to account for geographic, temporal, and employer-specific factors that might affect trait demands.

Table 3 shows how occupation-level characteristics influence trait demands. Workforce education level shows a consistent negative relationship with trait demands: occupations with more university graduates are less likely to mention personality requirements (-0.8 to -1.9 percentage points across traits). Female-dominated occupations show higher demands for Extraversion (2.6 percentage points) and Emotional Stability (2.1 percentage points). Occupations with more migrant workers show mixed effects: positive for Emotional Stability (0.7 percentage points) and Openness (1.6 percentage points), but negative for Conscientiousness (-0.9 percentage points). Age composition negatively affects both overall personality traits (-1.1 percentage points) and Extraversion (-1.6 percentage points).

Table 3: Assortative matching: Occupation characteristics effects on PT demand

	(1) P(All P.T.)	(2) P(Agree.)	(3) P(Consc.)	(4) P(Emot.)	(5) P(Extra.)	(6) P(Open.)
Women share	0.017***	−0.015	−0.006	0.021**	0.024***	−0.002
	(0.006)	(0.013)	(0.004)	(0.011)	(0.004)	(0.005)
Degree share	−0.014**	−0.019**	−0.012**	−0.012**	−0.008*	−0.010**
	(0.007)	(0.009)	(0.005)	(0.005)	(0.004)	(0.004)
Migrant share	−0.001	0.000	−0.009**	0.007***	−0.002	0.016***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Management share	−0.001	0.005	0.005	−0.002	−0.009*	−0.001
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Age mean	−0.009**	−0.007	−0.002	0.001	−0.016***	0.004
	(0.005)	(0.005)	(0.006)	(0.003)	(0.004)	(0.004)
Tenure mean	−0.009	−0.016	0.010	0.007	−0.008**	−0.003
	(0.008)	(0.012)	(0.007)	(0.005)	(0.003)	(0.006)
R^2	0.346	0.357	0.274	0.283	0.339	0.326

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 9888315$. “Any P.T.” refers to Any Personality Trait, “Consc.” to Conscientiousness, “Open.” to Openness, “Agree.” to Agreeableness, “Extra.” to Extraversion, “Emot.” to Emotional Stability. All variables refer to the occupation-level 2011-2017 UKHLS standardized value. Regression controls for the standardised UKHLS trait score, traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Location, year and firm fixed effects. SE clustered at the firm level. Author’s creation using Adzuna and UKHLS.

6 The model

I use two complementary models in this analysis: a high-dimensional fixed effects linear probability model[11] and a staggered difference-in-differences approach[12].

Personality-related words in job advertisements may correlate with unobserved characteristics that could bias estimates. For instance, personality trait demands might relate to occupation-specific skill requirements, industry practices, or local labour market conditions. Firms that emphasise certain personality traits might also offer different compensation structures, working conditions, or advancement opportunities. Even within the same occupation and location, firm-specific HR practices could influence both job posting language and actual job requirements.

This model controls for these sources of unobserved heterogeneity across multiple dimensions, reducing potential bias. I also account for observable job characteristics that might correlate with personality demands, including contract type, work schedule, seniority level, required education, experience, and performance-based compensation. By isolating within-location, within-occupation, and within-firm variation while controlling for these observable characteristics, this method reduces bias in estimates of how personality requirements relate to other job characteristics, particularly AI demand.

I examine whether personality traits appear together in job postings and how they

[11] Implemented using the STATA command *reghdfe* from (Correia, 2016).
[12] Implemented using the STATA *csdid* command from (Callaway & Sant’Anna, 2021).

relate to other job requirements, I estimate:

$$P(Trait_i = 1) = \beta_0 + \beta_1 X_i + \delta_l + \theta_t + \phi_j + \gamma_k + \epsilon_i \tag{2}$$

where X_i is a vector of job posting characteristics including the demand for other personality traits, δ_l are location fixed effects, θ_t are month-year fixed effects, ϕ_j are firm fixed effects and γ_k are occupation fixed effects. To measure how these relationships change over time, I use a variation of Equation 2 where I replace month-year fixed effects with year dummies:

$$P(Trait_i = 1) = \beta_0 + \beta_1 X_i + \sum_{t=2018}^{2022} \alpha_t Year_t + \gamma_k + \phi_j + \epsilon_i \tag{3}$$

where $Year_t$ are dummy variables (with 2017 as the base year). The coefficients α_t capture the evolution of personality trait demands over 2018-2022, after accounting for changes in job requirements, occupational composition, geographical variation, and firm-specific practices.

To study how technological change affects personality demands, I examine the relationship between AI adoption and personality requirements[13]. This analysis is relevant given AI's rapid adoption across industries and the interest on how AI might complement or substitute for human traits. While research has examined AI's impact on technical skill requirements (Acemoglu et al., 2022) and cognitive tasks (Babina et al., 2024), little is known about its effects on personality trait demands. Johnson and Acemoglu (2023) suggest firms adopting AI technologies might increasingly value workers with personality characteristics that complement AI capabilities. To test these relationships, I estimate:

$$P(Trait_i = 1) = \beta_0 + \beta_1 X_i + \beta_2 AI_i + \delta_l + \theta_t + \phi_j + \gamma_k + \epsilon_i \tag{4}$$

where X_i is a vector of job posting characteristics, δ_l are location fixed effects, θ_t are time fixed effects, ϕ_j are firm fixed effects and γ_k are occupation fixed effects. I show how AI coefficients change when incrementally introducing each fixed effect.

While the fixed effects analysis shows how AI adoption relates to personality demands, I complement this with a staggered difference-in-differences strategy that uses variation in the timing of firms' first AI adoption, following Callaway and Sant'Anna (2021)'s methodology for multiple time periods.

This approach's key innovation is using never-treated and not-yet-treated units as controls, which helps avoid bias from treatment effect heterogeneity in traditional two-way fixed effects models. For each firm, I identify the day they first post a job advertisement

[13] All specifications use Linear Probability Models. While these have known limitations such as predicted probabilities potentially outside the [0,1] range, this approach offers easier interpretation and avoids the incidental parameter problem in non-linear models with multiple fixed effects (Greene, 2004).

requiring AI skills as their treatment timing, allowing me to construct quarter, half-year and annual treatment variables. This staggered adoption design compares changes in personality trait demands between firms adopting AI at different times while using both never-treated and not-yet-treated firms as controls. A key assumption for this identification strategy is that there is almost no adoption of AI before 2017, which I show in Section 7.2.

Let $Y_{i,t}$ denote the proportion of vacancies requiring a personality trait at time t for firm i. Let $G_{i,g} = 1$ indicate that firm i is first treated in period g. Following Callaway and Sant'Anna (2021), the group-time average treatment effects are:

$$ATT(g,t) = E[Y_{i,t}(g) - Y_{i,t}(0)|G_i = g] \tag{5}$$

where $Y_{i,t}(g)$ represents the proportion of vacancies requiring a personality trait when first treated in period g, and $Y_{i,t}(0)$ represents the proportion had the firm not adopted AI. Under the parallel trends assumption, this parameter is identified by:

$$ATT(g,t) = E[Y_{i,t} - Y_{i,g-1}|G_i = g] - E[Y_{i,t} - Y_{i,g-1}|G_i \in G_{comp}] \tag{6}$$

where G_{comp} consists of not-yet-treated units. For pre-treatment periods, G_{comp} includes all cohorts not yet treated at time t, rather than only those not treated at time g[14]. The estimation uses the doubly-robust inverse probability weighted estimator with standard errors clustered at the firm level.

The model is estimated using three specifications: a base specification without controls, a specification that includes pre-treatment covariates as control variables, and a specification that uses entropy balancing weights. Let X_i^{pre} denote the vector of pre-treatment covariates for firm i, which includes: (1) the average pre-treatment demand for personality traits and skills, (2) pre-treatment firm characteristics (firm size measured by number of employees, profit and whether the firm is publicly quoted), and (3) pre-treatment occupational composition at the 1-digit SOC level. The covariates specification includes X_i^{pre} directly in the estimation, functioning as a regression adjustment approach. The entropy balancing specification instead constructs weights w_i for control units such that the weighted distribution of X_i^{pre} in the control group matches the distribution in the treated group in both mean and variance. These weights are estimated using Hainmueller (2012)'s method, targeting first and second moments of the pre-treatment covariates[15].

This model addresses several identification threats. First, it avoids the "negative

[14] This distinction in the comparison group construction for pre-treatment periods is implemented using the `asinr` option in the `csdid` command.

[15] Unlike propensity score methods that model the probability of treatment assignment, entropy balancing directly reweights control units to achieve exact balance on specified moments of pre-treatment covariates, without requiring an intermediate propensity score estimation step.

weights" problem in TWFE models by using clean comparison groups. Second, entropy balancing addresses concerns about selection into AI adoption based on observable characteristics by ensuring treated and control firms are comparable across pre-treatment covariates. Third, using both never-treated and not-yet-treated comparison units maximises statistical power while maintaining comparison group integrity.

While balancing weights ensure treated and control firms are comparable across covariates before treatment, the DiD framework accounts for time-invariant unobserved differences between firms, time-varying unobservables affecting groups differently, and potential dynamic selection occurring post-treatment. This allows for parsimonious estimation while accounting for selection on observables through matching procedures.

I test the parallel trends assumption validity by examining pre-treatment effects, which should be statistically indistinguishable from zero if the assumption holds. I also use event study plots to visualise both pre-treatment trends and post-treatment effects over time.

The data are analysed at the firm-period level, with each observation representing a firm's average personality trait demands in a given period (year, half-year or quarter). Although the original data are weekly, aggregating to longer periods allows more precise treatment timing identification while maintaining sufficient observations for each firm and minimising anticipation effects. The staggered adoption timing combined with matching on pre-treatment characteristics helps address endogeneity concerns about firms' decisions to adopt AI technologies.

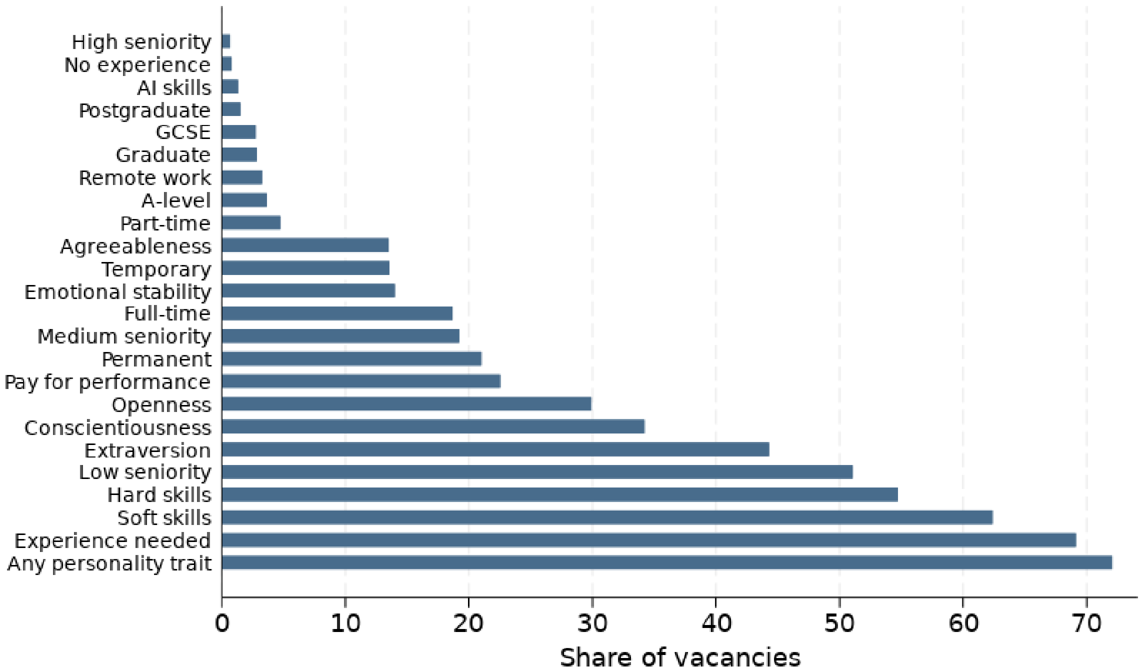
Together, the fixed effects and staggered DiD models provide complementary evidence on how personality demands in job advertisements respond to firm AI adoption, capturing both immediate within-firm effects and dynamic changes in requirements following adoption.

7 Results

Analysis of 11.7 million UK job advertisements shows that 72 per cent contain at least one personality trait-related word (Table A.2 in Appendix A). Extraversion appears most frequently, in 44 per cent of advertisements, followed by Conscientiousness (34 per cent), Openness (30 per cent), Emotional Stability (14 per cent), and Agreeableness (13 per cent). Figures A.1 to A.5 in Appendix A show the terms within each trait dictionary. For Extraversion, "passion" and "friendly" are most common. For other traits, the most frequent terms are "innovative" and "flexible" (Openness), "efficient" and "ambitious" (Conscientiousness), "work under pressure" and "emotional" (Emotional Stability), and "warm" and "trustful" (Agreeableness).

Personality traits appear more often in job postings than traditional human capital measures (Figure 1). Soft skills and hard skills are mentioned in 62 per cent and 55 per cent of advertisements, while experience appears in 69 per cent and seniority in 70 per cent. Only 11 per cent explicitly mention education requirements - roughly the same percentage that mention being passionate. This low figure aligns with recent research by Bone et al. (2024), who found that only about 12 per cent of UK job postings explicitly state formal educational requirements[16]. While education requirements might be implied through job titles, occupational categories, or task descriptions, employers clearly choose to emphasise personality characteristics in their recruitment.

Figure 1: Frequency of Job Requirements



Notes: Author's creation using Adzuna.

Personality trait demands vary systematically across occupations[17]. Administrative and customer-facing roles show the highest trait demands: Elementary Administration (88.6 per cent), Sales Assistants and Retail Cashiers (87.3 per cent), and Customer Service (85.3 per cent). In contrast, manual and construction-related occupations show much lower demands: Elementary Construction (20.2 per cent), Metal Forming and Welding

[16]This low education demand is specific to the UK online labour market and contrasts with nearly 50 per cent in US online vacancies (Stahle, 2024). Several factors may contribute to this difference, including different recruitment practices between countries and variations in how education requirements are communicated during hiring. While formal qualifications might be verified later in the recruitment process, there may also be an emerging shift toward skills-based hiring in certain sectors (Bone et al., 2024).

[17]Demand for each 3-digit SOC group is shown in Table A.3 in Appendix A.

Trades (33.1 per cent), and Building Finishing Trades (33.9 per cent). This pattern aligns with theories about the importance of non-cognitive attributes in jobs requiring frequent interpersonal interaction (Deming, 2017).

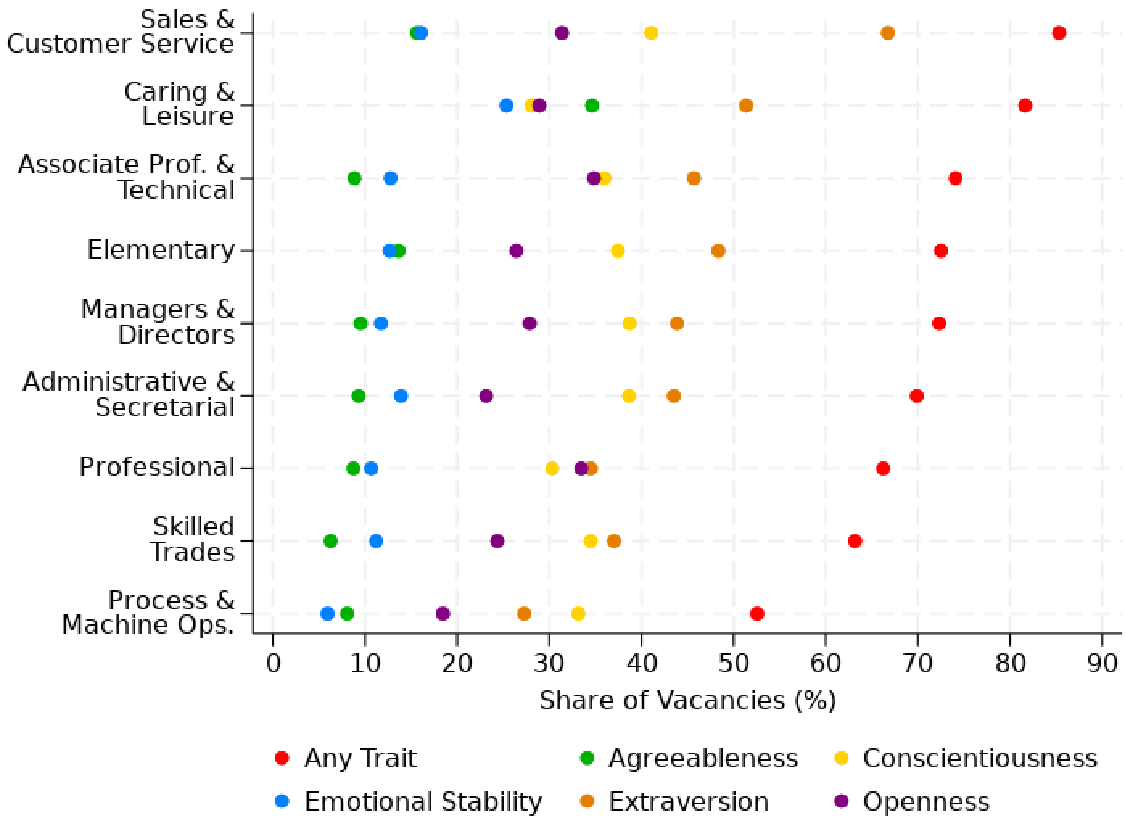
Analysis at the major occupational group level (1-digit SOC code) reveals clearer patterns in both overall trait demands and specific trait preferences (Figure 2). Sales and Customer Service occupations have the highest overall trait demands (85.3 per cent), with particular emphasis on Extraversion (66.8 per cent) and Conscientiousness (41.1 per cent), reflecting needs for both social interaction and organisational skills. Caring and Leisure Services follow with 81.7 per cent overall trait demand and show the highest requirements for Agreeableness (34.7 per cent) and Emotional Stability (25.3 per cent) among all groups, consistent with the empathetic and emotionally demanding nature of care work. Associate Professional and Technical occupations show balanced demands across traits, with notably high requirements for Openness (34.9 per cent), suggesting the value placed on adaptability and creativity in these roles.

In contrast, Process and Machine Operatives show the lowest overall trait demands (52.6 per cent), with particularly low requirements for Emotional Stability (5.9 per cent) and Openness (18.5 per cent). Roles focused on routine technical tasks place less emphasis on personality characteristics, although Conscientiousness remains relatively important (33.1 per cent) even in these occupations, reflecting the general need for efficiency and attention to detail across job types.

These occupational variations in trait demands align with task-based job design and skill-biased technological change frameworks. Jobs involving complex social interactions or non-routine cognitive tasks show higher demands for personality traits, while those focused on routine or manual tasks show lower requirements. This supports the literature on the growing importance of social and personality characteristics in an increasingly service-oriented economy (Borghans et al., 2014).

Further analysis shows these occupational patterns align with skill requirements. When ranked by hard skill requirements (Figure A.6a in Appendix A), occupations show relatively stable demands for Extraversion (average 41 per cent) and Conscientiousness (average 34 per cent), suggesting these traits are valued regardless of technical skill intensity. However, Openness demand increases notably in occupations with more hard skill requirements, rising from an average of 24 per cent in the bottom 20 occupations to over 34 per cent in the top 20 hard-skill intensive occupations, reflecting the need for adaptability and creativity in complex technical jobs. When occupations are ranked by soft skills requirements (Figure A.6b in Appendix A), there is a clear positive relationship for most traits. Extraversion demand shows the strongest increase, rising from 28 per cent in the bottom 20 to over 45 per cent in the top 20 soft skill-intensive activities.

Figure 2: Personality Trait demand by 1-digit SOC group



Notes: Author's creation using Adzuna.

Openness and Conscientiousness also show positive trends, though less pronounced. While certain traits (like Extraversion and Conscientiousness) are broadly valued across the skill spectrum, others serve specific functions depending on occupational characteristics: Openness complements occupations with greater technical skills, while the full range of personality traits becomes increasingly important as jobs require more interpersonal interaction. These relationships are formally tested in Equation 2.

7.1 Personality Traits demand and their evolution

7.1.1 Complementarities in Trait Demands

Understanding how personality traits are demanded together provides insight into how employers conceptualise the multidimensional nature of personality in the workplace. Research has studied individual personality traits' effects on labour market outcome, such as Flinn et al. (2025) finding that conscientiousness and emotional stability predict job stability, and Gensowski (2018) showing openness and extraversion affect lifetime earnings. However, little is known about how these traits are demanded in combination. This analysis helps show whether employers see certain personality characteristics as complementary or substitutable, similar to the relationship between cognitive and social skills identified by Deming (2017).

Table 4 shows the relationships between different personality trait requirements. The results show significant complementarities in trait demands, even after controlling for occupation fixed effects and other job characteristics. Job postings mentioning one personality trait are consistently more likely to mention others, though relationship strengths vary across trait pairs.

Both Conscientiousness and Extraversion show positive relationships with other traits: advertisements mentioning Conscientiousness are 5 percentage points more likely to demand Extraversion and 4.1 percentage points more likely to demand Openness. Those mentioning Extraversion are significantly associated with all other traits, with effects ranging from 4.5 to 8.4 percentage points. The strongest complementarities are between Extraversion and Emotional Stability (8.4 percentage points), Openness (7.8 percentage points), and Agreeableness (7.8 percentage points).

These complementarity patterns suggest employers tend to demand clusters of traits rather than isolated characteristics. These relationships persist even after controlling for occupation and firm fixed effects, indicating that trait clustering reflects broader requirements rather than just occupational differences or firm-specific HR strategies. This aligns with Rohrbach-Schmidt et al. (2023), who found that trait combinations are valued differently in specific job contexts.

Table 4: Coefficients between traits demands

	(1) P(Agree.)	(2) P(Consc.)	(3) P(Emot.)	(4) P(Extra.)	(5) P(Open.)
Agreeableness		0.015 (0.014)	0.048** (0.019)	0.078*** (0.021)	0.020** (0.009)
Conscientiousness	0.007 (0.007)		0.027*** (0.010)	0.050*** (0.010)	0.041*** (0.008)
Emotional Stability	0.043*** (0.015)	0.050*** (0.018)		0.084*** (0.016)	0.009 (0.012)
Extraversion	0.037*** (0.008)	0.050*** (0.010)	0.045*** (0.011)		0.067*** (0.006)
Openness	0.011** (0.005)	0.048*** (0.009)	0.006 (0.007)	0.078*** (0.007)	
R^2	0.364	0.281	0.287	0.342	0.331

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 9888315$. "Consc." refers to Conscientiousness, "Open." to Openness, "Agree." to Agreeableness, "Extra." to Extraversion, "Emot." to Emotional Stability. Regressions control for traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Location, year, occupation and firm fixed effects. SE clustered at the occupation and firm level. Author's creation using Adzuna.

7.1.2 Relationship with Other Job Requirements

Beyond understanding trait combinations, examining how personality traits relate to other job requirements reveals how employers package worker attributes. Deming and Kahn (2018) provides evidence about strong associations between cognitive and social skills in job postings. However, little is known about how specific job requirements relate to the Big Five in actual hiring. Understanding these patterns shows how firms combine personality demands with other requirements to create job profiles, as suggested by Brenčič and McGee (2023b).

Table 5 shows the relationships between personality trait demands and other job requirements, controlling for occupation, location, month-year and firm fixed effects. The results reveal systematic patterns in how employers combine personality traits with other job characteristics.

The most important finding is that soft skills requirements strongly predict personality trait demands, with advertisements mentioning soft skills being 7.3 percentage points more likely to demand personality traits overall. This relationship is consistent across all Big Five traits, with effects ranging from 2.6 percentage points for Extraversion to 4.4 percentage points for Conscientiousness. Hard skills requirements show weaker but still positive associations (2.1 percentage points overall). This pattern confirms that employers view personality traits as complementary to interpersonal capabilities rather than technical competencies, supporting Woessmann (2024)' argument about modern workplace skill combinations.

Advertisement length emerges as the strongest predictor of trait demands: a one per cent increase in length raises the probability of mentioning any personality trait by 26 pe cent, indicating that detailed job descriptions systematically include more personality requirements. Pay-for-performance schemes reveal strategic trait emphasis, increasing Extraversion demands by 3.7 percentage points while reducing Openness demands by 1.7 percentage points. This suggests firms align personality requirements with their incentive structures, with performance-based compensation favouring assertive traits over creative ones.

Organisational hierarchy systematically shapes trait demands. High seniority positions are 5.4 percentage points more likely to mention personality traits overall, while entry-level positions emphasise Conscientiousness (2.1-2.3 percentage points increase for low and medium seniority). Remote work reduces overall trait demands by 1.3 percentage points, and temporary positions show negative associations with Conscientiousness (-1.4 percentage points) and Openness (-1.6 percentage points), indicating that stable, office-based positions drive personality requirements.

Table 5: Correlation with other job requirements

	(1) P(All P.T.)	(2) P(Agree.)	(3) P(Consc.)	(4) P(Emot.)	(5) P(Extra.)	(6) P(Open.)
Soft skill	0.073***	0.017	0.044***	0.032**	0.026**	0.032***
	(0.007)	(0.013)	(0.007)	(0.015)	(0.012)	(0.007)
Hard skill	0.021**	−0.013*	0.019**	−0.002	0.024**	0.008
	(0.009)	(0.007)	(0.009)	(0.008)	(0.011)	(0.007)
Remote work	−0.013**	−0.008	−0.013	−0.005	−0.009	0.010
	(0.006)	(0.006)	(0.014)	(0.005)	(0.012)	(0.015)
Pay for performance	0.016**	0.006	−0.005	0.004	0.037***	−0.017**
	(0.006)	(0.010)	(0.008)	(0.007)	(0.009)	(0.007)
Advert's lenght	0.260***	0.063***	0.168***	0.095***	0.156***	0.176***
	(0.009)	(0.005)	(0.009)	(0.020)	(0.009)	(0.012)
Offers negotiable salary	−0.004	−0.008**	−0.001	−0.008**	−0.002	−0.002
	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)
Temporary job	−0.018***	−0.000	−0.014**	0.002	0.005	−0.016**
	(0.006)	(0.006)	(0.007)	(0.005)	(0.008)	(0.008)
Permanent job	−0.000	−0.000	−0.005	−0.002	0.011*	0.004
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.006)
Full time job	−0.003	−0.003	−0.010**	0.005	−0.000	−0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
Part time job	0.013*	0.019	−0.017	0.007	0.001	0.010
	(0.007)	(0.016)	(0.020)	(0.016)	(0.017)	(0.008)
High seniority	0.054***	0.018	0.025	0.018	0.015	−0.028
	(0.016)	(0.018)	(0.018)	(0.018)	(0.019)	(0.022)
Medium seniority	0.025**	−0.005	0.023*	−0.009	0.007	−0.011*
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.006)
Low seniority	0.019	−0.009	0.021*	−0.006	0.002	−0.015***
	(0.014)	(0.010)	(0.012)	(0.009)	(0.008)	(0.005)
GCSE	−0.006	−0.011	0.012	0.030***	0.003	−0.027**
	(0.011)	(0.011)	(0.013)	(0.008)	(0.015)	(0.011)
A-level	−0.014	0.007	−0.009	−0.004	−0.018	−0.007
	(0.011)	(0.010)	(0.010)	(0.009)	(0.014)	(0.008)
Bachelor's degree	0.023**	−0.014***	0.029**	−0.011	0.022**	0.024***
	(0.011)	(0.004)	(0.014)	(0.012)	(0.009)	(0.007)
Posgraduate degree	−0.012	−0.012*	0.009	−0.018	−0.022*	0.023
	(0.009)	(0.007)	(0.023)	(0.027)	(0.011)	(0.027)
Request experience	−0.008	−0.011	−0.002	−0.006	−0.010	−0.014**
	(0.006)	(0.008)	(0.007)	(0.010)	(0.009)	(0.006)
No experience needed	−0.028	0.006	−0.060*	−0.004	−0.008	−0.033
	(0.043)	(0.026)	(0.032)	(0.020)	(0.040)	(0.028)
R^2	0.349	0.364	0.281	0.287	0.342	0.331

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 9888315$. "Any P.T." refers to Any Personality Trait, "Consc." to Conscientiousness, "Open." to Openness, "Agree." to Agreeableness, "Extra." to Extraversion, "Emot." to Emotional Stability. Regression controls for traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Location, year, occupation and firm fixed effects. SE clustered at the occupation and firm level. Author's creation using Adzuna.

Educational requirements reveal distinct trait patterns that reflect job complexity. Bachelor's degree requirements increase demands for Conscientiousness (2.9 percentage points), Extraversion (2.2 percentage points), and Openness (2.4 percentage points) while reducing Agreeableness demands (-1.4 percentage points). In contrast, GCSE-level positions emphasise Emotional Stability (3.0 percentage points) but reduce Openness demands (-2.7 percentage points). The strongest education effect occurs for no-experience positions, which are 6 percentage points less likely to demand Conscientiousness, suggesting that personality requirements substitute for work experience in signalling candidate quality.

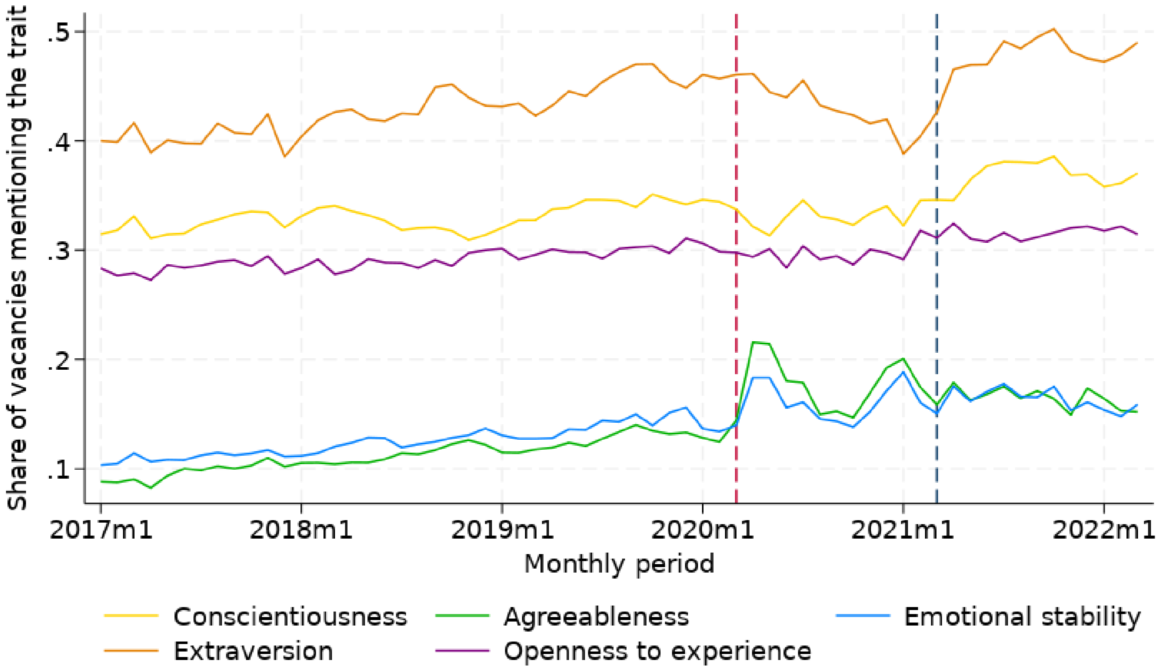
These findings reveal that personality trait demands reflect strategic employer choices rather than random job posting variation. Soft skills requirements and detailed job descriptions strongly predict trait mentions, while organisational factors (seniority, incentive structures, employment arrangements) systematically shape which traits employers emphasise. Educational requirements create distinct trait profiles, with higher education levels associated with greater emphasis on analytical and interpersonal traits. Together, these patterns demonstrate that personality demands are embedded within broader job design decisions and organisational practices.

7.1.3 Changes over time

Examining how personality trait demands change over time helps us understand evolving work and skill requirements in modern labour markets. These changes may reflect both economic structural shifts and changing employer preferences, especially during periods of technological change and economic disruption. This analysis covers 2017 to 2022, a period marked by the COVID-19 pandemic and accelerated workplace digitalisation.

With substantial increases in AI adoption during this period (Schmidt et al., 2024), analysing these trends provides context for understanding how technological change might affect personality requirements. The raw data shows increasing demand for personality traits (Figure 3). The share of vacancies mentioning at least one personality trait rose from 68 per cent in 2017 to 76 per cent in 2022. However, this overall change hides considerable variation across traits and time.

Figure 3: Change over time of the demand for personality traits.



Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

To analyse how personality trait demands have evolved, I use the Linear Probability Model from Equation 3 to estimate time effects while progressively adding controls for job characteristics, location, industry, occupation, and firm fixed effects. Figures A.7 to A.12 in Appendix A show the monthly evolution of coefficients for each trait as these controls are added, revealing how compositional factors shape the observed patterns.

Table 6 shows how the estimated effect of 2022 (compared to 2017) changes with different controls and fixed effects. The basic specification shows significant differences across most traits, but as fixed effects are added, many become statistically insignificant. In the most comprehensive model, only Conscientiousness shows a significant decline (-2.1 percentage points), while Extraversion maintains a positive trend (1.7 percentage points) that approaches significance.

Controlling for compositional changes is particularly important during the COVID-19 period. The data shows a shift in occupational composition: Caring Personal Services increased sharply from about 10 per cent of vacancies in early 2020 to over 30 per cent by mid-2020, before stabilising at around 15 per cent in 2021-22. Other major occupational groups like Customer Service, Business Professionals, and Sales remained relatively stable, fluctuating between 5-10 per cent throughout the period (see Figure A.13 in Appendix A). This rise in care-related vacancies helps explain some observed changes in trait demands.

Table 6: Effect of 2022 vs 2017 on Personality Traits: Progression across model specifications

	(1) Basic	(2) +Location	(3) +Industry	(4) +Occupation	(5) +Firm
Personality Traits	-0.002***	-0.001	-0.004	-0.005	-0.014
	(0.001)	(0.001)	(0.009)	(0.009)	(0.009)
Agreeableness	0.020***	0.018***	0.014	0.013	0.003
	(0.000)	(0.000)	(0.012)	(0.010)	(0.009)
Conscientiousness	-0.005***	-0.006***	-0.011	-0.016	-0.021**
	(0.001)	(0.001)	(0.012)	(0.010)	(0.011)
Emotional Stability	0.001***	0.000	-0.002	-0.001	0.006
	(0.000)	(0.000)	(0.008)	(0.008)	(0.008)
Extraversion	0.009***	0.013***	0.013	0.013	0.017
	(0.001)	(0.001)	(0.012)	(0.009)	(0.012)
Openness	-0.019***	-0.020***	-0.018	-0.012	-0.003
	(0.001)	(0.001)	(0.012)	(0.010)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes
Location FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No
Occupation FE	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
R-squared range	[0.082, 0.181]	[0.083, 0.181]	[0.103, 0.203]	[0.118, 0.223]	[0.280, 0.364]

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients show the effect of 2022 relative to the baseline year 2017. All regressions include controls for traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option.

For example, the apparent increase in Agreeableness (2.0 percentage points in the basic specification) disappears completely once the full set of fixed effects is included (0.3 percentage points, non-significant), suggesting it was driven by the increased proportion of caring roles rather than changing requirements within occupations.

Occupational fixed effects produce the largest mediating effect across all traits, as shown by the shift from column (3) to column (4) in Table 6. This highlights the importance of occupational composition in driving trait demand patterns. However, the negative effect for Conscientiousness and the positive trend for Extraversion persist across specifications, suggesting these reflect genuine shifts in trait demands within occupations and firms.

After accounting for compositional changes in location, occupation, and firm, Table 7 shows the estimated year effects relative to 2017 for the full period. Conscientiousness shows a gradual decline, becoming significantly negative by 2022. Extraversion shows a consistent positive trend, with significant increases during 2019-2021 (ranging from 1.7 to 2.8 percentage points). Emotional Stability shows temporary positive effects during 2021 (1.1 percentage points), while Openness and Agreeableness show no significant time trends after controlling for composition.

Table 7: Year effect on each Personality Trait. Baseline: 2017

	(1) P(All P.T.)	(2) P(Agree.)	(3) P(Consc.)	(4) P(Emot.)	(5) P(Extra.)	(6) P(Open.)
2018	−0.003	0.002	−0.010	0.004	0.009	0.002
	(0.004)	(0.004)	(0.008)	(0.004)	(0.006)	(0.005)
2019	−0.003	0.003	−0.012	0.011	0.017*	0.006
	(0.006)	(0.007)	(0.010)	(0.007)	(0.009)	(0.007)
2020	0.001	0.012	−0.014	0.009	0.028**	−0.000
	(0.008)	(0.013)	(0.011)	(0.007)	(0.012)	(0.007)
2021	−0.005	0.018	−0.016	0.011*	0.022*	−0.001
	(0.008)	(0.016)	(0.010)	(0.007)	(0.012)	(0.008)
2022	−0.014	0.003	−0.021**	0.006	0.017	−0.003
	(0.009)	(0.009)	(0.011)	(0.008)	(0.012)	(0.009)
R^2	0.349	0.364	0.280	0.286	0.341	0.331

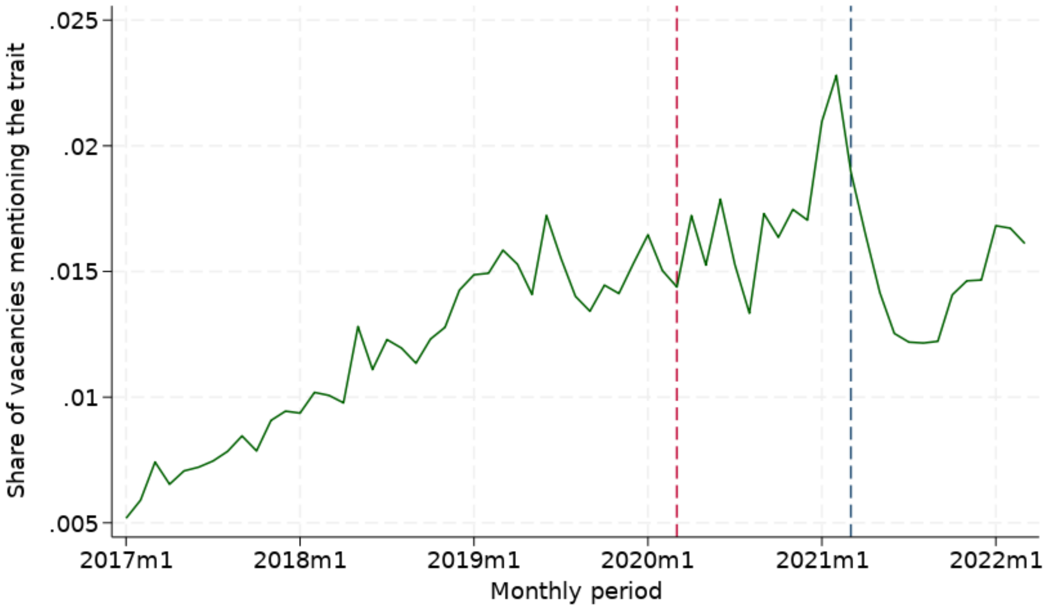
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $N = 9888315$. "Any P.T." refers to Any Personality Trait, "Consc." refers to Conscientiousness, "Open." to Openness, "Agree." to Agreeableness, "Extra." to Extraversion, "Emot." to Emotional Stability. Regression controls for traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Location, occupation and firm fixed effects. SE clustered at the occupation and firm level. Author's creation using Adzuna.

7.2 AI demand and Personality Traits

This section examines how artificial intelligence adoption relates to firms' demands for personality traits. While research has documented AI's impact on technical skill requirements (Acemoglu et al., 2022) and cognitive tasks (Babina et al., 2024), little is known about how AI adoption affects demands for specific personality characteristics. As Johnson and Acemoglu (2023) observe, firms adopting AI technologies might increasingly value workers with personality traits that complement AI capabilities, particularly those involving social interaction, adaptation and communication.

In the Adzuna dataset, 1.3 per cent of advertisements mention AI-related skills, with an increasing trend over time (Figure 4). This demand started at 0.75 per cent in 2017, peaked at 2.3 per cent in early 2021—coinciding with the end of Covid-19 restrictions—before stabilising around 1.5 per cent. This modest but growing trend matches findings from Schmidt et al. (2024), who report that AI-hiring intensity in the UK peaked at the end of 2020 before returning to pre-COVID levels.

Figure 4: Change over time of AI-skills demand



Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

AI-demanding vacancies strongly require technical capabilities, with 91.3 per cent requiring hard skills compared to 54.2 per cent in non-AI positions. Software skills are the most frequently co-demanded proficiency (59.2 per cent), followed by engineering skills (45.3 per cent) and data analysis capabilities (35.1 per cent). While technical skills dominate, these positions also need substantial interpersonal capabilities, with communication skills (29.3 per cent), teamwork (16.4 per cent) and problem-solving abilities (13.8 per cent) frequently appearing alongside AI requirements (Figures A.14 and A.15 in Appendix A). This aligns with research by Squicciarini and Nachtigall (2021), who found that skills related to communication, problem-solving, creativity, and teamwork increasingly appear alongside software-related and AI-specific competencies in job postings. However, AI requirements remain specialised - among positions requiring software skills, only 8.5 per cent demand AI capabilities, while for engineering and data analysis positions these figures are 7.3 per cent and 5.5 per cent respectively. This suggests that while AI skills complement other technical capabilities, they represent a distinct technical requirement.

AI-demanding and non-AI-demanding positions show strong differences in personality requirements (Table 8). Openness demand is substantially higher in AI-demanding positions (52.1 per cent versus 29.6 per cent), indicating that employers value adaptability and creative thinking alongside AI skills. This aligns with Alekseeva et al. (2021), who identified increased demand for creative and adaptive skills in AI-intensive jobs. Conversely, AI-demanding positions show lower demands for Agreeableness (6.2 per cent versus 13.6 per cent), Conscientiousness (29.9 per cent versus 34.2 per cent), Emotional Stability (7.8 per cent versus 14.1 per cent), and Extraversion (35.2 per cent versus 44.4 per cent). Interestingly, the overall demand for soft skills and personality traits remains relatively stable between AI and non-AI positions (62.8 per cent versus 62.4 per cent for soft skills, and 73.1 per cent versus 72.1 per cent for personality traits), suggesting that AI adoption could reshape the specific personality traits demanded rather than reducing the overall importance of non-technical attributes.

Table 8: Demand for Personality Traits and Skills in vacancies by their AI demand, in percentages

Demands AI	Hard	Soft	All P.T.	Agree.	Consc.	Emot.	Extra.	Open.
Yes	91.3	62.8	73.1	6.2	29.9	7.8	35.2	52.1
No	54.2	62.4	72.1	13.6	34.2	14.1	44.4	29.6

Notes: “Hard” refers to Hard Skills, “Soft” to Soft Skills„ “Any P.T.” to Any Personality Trait, “Consc.” to Conscientiousness, “Open.” to Openness, “Agree.” to Agreeableness, “Extra.” to Extraversion, “Emot.” to Emotional Stability. Author’s creation using Adzuna.

While the overall demand for AI skills in job advertisements is modest, this figure masks substantial variation across occupations. AI requirements are most prevalent in Natural and Social Science Professionals jobs (10.1 per cent of vacancies), followed by IT and Telecommunications Professionals (9.2 per cent) and Engineering Professionals (5.9 per cent). These figures suggest that AI skills have become significant in hiring requirements for knowledge-intensive sectors, particularly those involving research, data analysis, and technical development, similar to patterns identified by Babina et al. (2024). The relatively high demand in Natural and Social Science Professionals (10.1 per cent) is particularly noteworthy, indicating AI’s growing importance beyond purely programming domains, possibly reflecting increased use of AI tools in research methodologies and data analysis across scientific disciplines.

AI-demanding vacancies are concentrated in specific occupations. While AI skills are demanded across the 90 3-digit SOC occupational categories, 78 per cent of all AI-demanding vacancies appear in just five occupations, with IT and Telecommunications Professionals alone accounting for 49.1 per cent. This is followed by Business, Research and Administrative Professionals (10.3 per cent), Engineering Professionals (7.2 per cent), Legal Associate Professionals (6.2 per cent) and Electrical and Electronic Trades (5.1 per cent). This concentration aligns with Schmidt et al. (2024), who identified Information and Communication, Finance and Insurance, and Professional, Scientific and Technical Activities as the most AI job-intensive sectors across all countries studied. This concentration suggests that skills required to implement artificial intelligence remain primarily within specialised roles. Without accounting for occupation fixed effects, the analysis of AI’s relationship with personality traits would be heavily influenced by the characteristics and requirements of these dominant sectors.

To examine how AI adoption relates to personality trait demands while accounting for potential confounding factors, I estimate:

$$P(Trait_i = 1) = \beta_0 + \beta_1 X_i + \beta_2 AI_i + \delta_l + \theta_t + \epsilon_i \tag{7}$$

where X_i is a vector of job posting characteristics, δ_l represents location fixed effects, and θ_t captures time fixed effects. The vector X_i includes job posting characteristics: soft and hard skills requirements, education levels, seniority, experience, contract type, work schedule, bonus availability and advertisement length. The variable AI_i is a dummy equal to 1 when the advertisement mentions any AI-related skill.

This comparison with detailed controls addresses potential confounding factors. Some firms might systematically demand more personality traits, locations might have different conditions affecting trait demands, and requirements might vary over time or across occupations. Also, the relationship between AI and personality traits might stem from correlations with other job requirements rather than a direct relationship. The extensive controls and fixed effects help isolate the specific relationship between AI adoption and personality trait demands[18].

Table 9 shows the relationship between AI adoption and personality trait demands across different specifications. The baseline specification (column 1) reveals substantial heterogeneity in how AI relates to different traits. While the overall effect is modestly positive (1.0 percentage point), this masks strong opposing forces: a large positive association with Openness (22.5 percentage points) counterbalanced by negative relationships with other traits, particularly Extraversion (-9.2 percentage points) and Agreeableness (-7.4 percentage points).

Adding job requirement controls (column 2) substantially alters these relationships, while including time and location fixed effects (columns 3-4) produces modest changes. After controlling for hard and soft skills, experience, seniority, and contract types, the overall effect becomes negative (-2.7 percentage points), suggesting the initial positive relationship was driven by AI positions requiring more comprehensive skill sets. At the trait level, this shift reflects both a reduction in the positive effect on Openness (from 22.5 to 16.3 percentage points) and stronger negative associations with Conscientiousness

[18] For example, in the most comprehensive model, consider two software developer positions advertised by Google in London during September 2018: one requiring Conscientiousness and another not mentioning it. Even in this narrow comparison, the positions might differ in other requirements—one might require more experience or offer different contract terms. By controlling for these job-specific characteristics while including fixed effects, I can isolate how AI requirements relate to the probability of demanding Conscientiousness, keeping constant occupation, location, time, and firm factors, as well as other job posting attributes.

(from -4.3 to -7.5 percentage points) and Extraversion (from -9.2 to -11.2 percentage points). These changes likely reflect the high correlation between personality traits and other job requirements—particularly hard skills, which are substantially more prevalent in AI-demanding positions.

After including firm and occupation fixed effects, the effect of AI adoption on personality trait demands remains consistently positive—whether controlling for firm (1.1 percentage points), occupation (2.1 percentage points), or both (1.6 percentage points). Trait-level analysis reveals substantial heterogeneity. Even in the most demanding specification with all fixed effects (column 7), AI adoption shows a strong positive relationship with Openness (7.2 percentage points) but negative associations with other traits, particularly Extraversion (-2.7 percentage points), Emotional Stability (-2.2 percentage points), and Conscientiousness (-1.7 percentage points). The positive effect on Openness is more than twice the size of any negative effect, suggesting that AI adoption leads to a reallocation of emphasis across personality traits rather than a wholesale reduction in personality requirements. These patterns align with theories about AI complementing creativity and adaptability while potentially substituting for interpersonal and routine-oriented traits. This view is supported by Acemoglu et al. (2022), who found that AI exposure is associated with a shift toward non-routine analytical skills, and by Alekseeva et al. (2021), who documented that AI-intensive jobs increasingly require creative problem-solving abilities alongside technical competencies.

Including firm fixed effects (column 5) substantially reduces coefficient magnitudes compared to specifications without firm controls (columns 1-4), suggesting that firm-specific practices explain a large portion of the relationship between AI and personality demands. The effect is particularly strong for Openness, where the coefficient drops from 16.5 to 8.0 percentage points, and for Extraversion, decreasing from -11.1 to -3.8 percentage points. This reduction indicates that much of the raw correlation between AI adoption and personality demands reflects systematic differences across firms rather than AI adoption itself.

When controlling for occupation fixed effects instead (column 6), the coefficients show a different pattern. While still smaller than the raw correlations, the occupation-only specification maintains stronger effects than the firm fixed effects model, particularly for Openness (11.9 percentage points) and Conscientiousness (-3.7 percentage points). This suggests that occupational requirements explain less of the variation in AI-personality trait relationships than firm characteristics. The way firms implement AI appears to have a stronger influence on personality demands than occupation-specific patterns of AI adoption.

These relationships persist in the most comprehensive specification with both firm and occupation fixed effects (column 7). The coefficients generally decrease further, with Openness showing a 7.2 percentage point effect and other traits showing modest negative associations ranging from -1.3 to -2.7 percentage points. This leads to a positive overall effect (1.6 percentage points), as the strong complementarity with Openness outweighs the more modest negative associations with other traits. These results suggest two key insights: first, both firm practices and occupational requirements play important roles in mediating AI-personality relationships; second, there exists a fundamental complementarity between AI adoption and demand for Openness that persists even after controlling for both firm and occupation characteristics. The fact that firm fixed effects produce a larger reduction in coefficients than occupation fixed effects suggests that firm-level decisions about AI adoption and implementation may be more crucial in shaping personality requirements than occupation-specific technological constraints.

The analysis reveals complex relationships between AI adoption and personality trait demands across multiple empirical specifications. While AI-demanding positions initially appear to require more personality traits overall, once accounting for job characteristics and fixed effects, we find evidence of significant reallocation in personality demands. As Johnson and Acemoglu (2023) argue, AI tends to automate routine cognitive tasks while increasing demand for human attributes like adaptability and creativity—which aligns with the finding of increased demand for Openness, alongside modest reductions in demands for traits related to interpersonal interaction and routine task execution. This pattern is consistent with Autor (2014)'s observations on how technological change tends to "amplify the comparative advantage of workers in supplying problem-solving, adaptability and creativity" (p. 2), while substituting for more routine activities. The magnitude of these effects varies substantially with the empirical specification, with firm-specific practices explaining a larger portion of the variation than occupational requirements, echoing Deming and Kahn (2018)'s work on the importance of firm heterogeneity in skill demands.

Table 9: Impact of AI on Personality Traits

	(1) Baseline	(2) +Controls	(3) +Time	(4) +Location	(5) +Firm	(6) +Occ	(7) All FE
Panel A: Overall Effect							
All Personality Traits	0.010***	-0.012***	-0.012***	-0.011***	0.011	0.021***	0.016**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.005)	(0.007)
Panel B: Effects by Trait							
Agreeableness	-0.074***	-0.028***	-0.031***	-0.033***	-0.015***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.004)
Conscientiousness	-0.043***	-0.065***	-0.064***	-0.064***	-0.023***	-0.038***	-0.017**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.009)	(0.009)
EmotionalStability	-0.063***	-0.044***	-0.046***	-0.047***	-0.027***	-0.026***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.010)	(0.007)
Extraversion	-0.092***	-0.082***	-0.082***	-0.083***	-0.034***	-0.038***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.007)
Openness	0.225***	0.141***	0.143***	0.143***	0.073***	0.111***	0.067***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.014)	(0.013)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No	Yes
Occupation FE	No	No	No	No	No	Yes	Yes
R-squared range	[0.001, 0.012]	[0.080, 0.121]	[0.082, 0.122]	[0.084, 0.123]	[0.273, 0.351]	[0.105, 0.169]	[0.281, 0.364]
N observations	11662124	11662124	11662124	9923701	9888315	9923701	9888315
N firms	128559	128559	128559	117229	81843	117229	81843

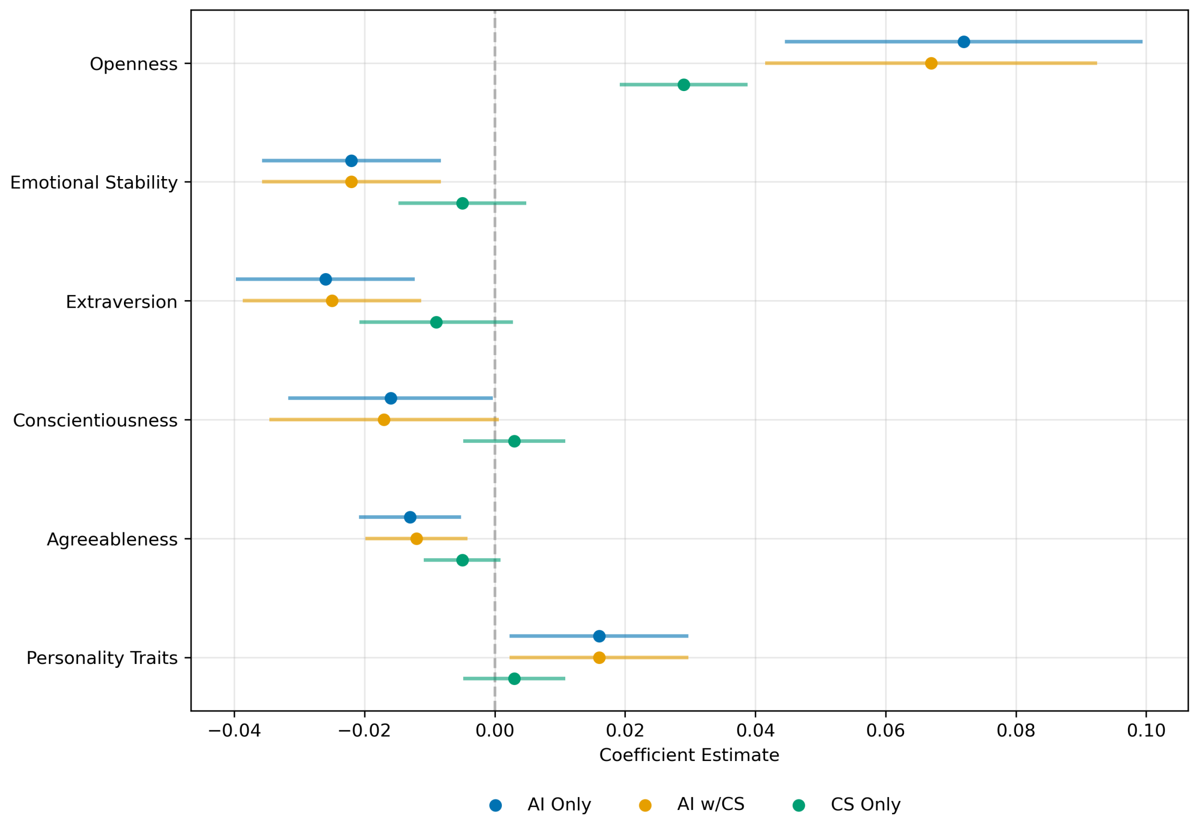
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column and coefficient represents a different specification with progressively added controls and fixed effects. The R-squared range shows the minimum and maximum values across the six trait regressions for each specification. All regressions include computer skills controls and standard controls (traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option). Standard errors are clustered at the occupation and firm level in specifications (5)-(7).

7.2.1 Robustness: Distinguishing AI from General Computer Skills

A potential concern is that the identified effects of AI skills might simply reflect broader technological requirements rather than AI-specific demands. To address this, I examine whether general computer skills requirements drive the results. I define computer skills as job requirements related to software development and data analysis capabilities within the broader hard skills category. This includes 1,911,086 vacancies, 12 times more than those demanding AI skills. Table A.5 presents estimates excluding computer skills controls, while Table A.6 shows the effects of computer skills—instead of AI—on personality traits.

The comparison shows significant differences between AI and computer skills effects. Without controlling for computer skills, the AI coefficient on overall personality traits is 1.6 percentage points ($p < 0.05$), similar to the main specification. However, examining trait-specific effects shows that computer skills alone generate substantially weaker relationships. As shown in Figure 5, while both AI and computer skills show positive associations with Openness, the AI effect (7.2 percentage points) is more than twice the magnitude of the computer skills effect (2.9 percentage points). This difference is statistically significant, with $p < 0.01$ in the most demanding specification with all fixed effects (Table A.7).

Figure 5: Effects on Personality Trait demand: AI vs Computer Skills



Notes: Author's creation using Adzuna.

The other traits show no significant effect in the computer skill specification. Formal tests comparing AI and computer skills coefficients reject coefficient equality for all traits except Agreeableness in the full specification. This is because AI and computer skills have very small impacts on Agreeableness (-1.13 vs -0.5 percentage points). Additionally, when testing the difference in AI coefficients when removing computer skills controls (Table A.8 in Appendix A), we cannot reject equality of means in the occupation and firm fixed effects estimations. This placebo exercise strengthens confidence in the main results by showing that AI adoption influences personality requirements through channels distinct from general technological skill demands. The substantially larger effects of AI, particularly for Openness, suggest that the identified relationships reflect specific features of AI technology rather than simply correlating with broader computer skill requirements.

7.3 From Vacancy-Level to Firm-Level Effects

The vacancy-level analysis shows that firm-specific practices play a crucial role in mediating the relationship between AI adoption and personality trait demands, with firm fixed effects producing larger coefficient reductions than occupational controls. This suggests that firm-level decisions about AI adoption and implementation may be more important in shaping personality requirements than occupation-specific technological constraints. To further investigate these firm-level dynamics, I conduct two complementary analyses that differ conceptually from the previous fixed effects estimation.

While the vacancy-level analysis examines how personality requirements differ between AI and non-AI positions within firms, the firm-level approach focuses on how firms' overall hiring patterns change when they demand AI technologies. First, I examine changes in the average personality requirements across all vacancies posted by firms in months when they also recruit for AI positions. Second, I analyse changes in the volume of vacancies requiring different personality traits, providing insight into potential substitution patterns between AI and non-AI roles.

Table 10 presents the firm-level analysis of personality requirements. The results align with the vacancy-level findings. After controlling for average job characteristics, location, industry, and occupational composition (Column 5), firms posting AI vacancies show a significant reduction in overall personality requirements (-3.0 percentage points, $p < 0.01$). There is a substantial increase in demands for Openness (3.4 percentage points, $p < 0.01$) alongside reductions in requirements for other traits, particularly Extraversion (-4.3 percentage points, $p < 0.01$) and Conscientiousness (-3.6 percentage points, $p < 0.01$).

When including firm fixed effects (Column 6), many of these effects become smaller but remain consistent in their sign. For instance, the effect on Openness remains positive and statistically significant (1.8 percentage points, $p < 0.01$), while the negative effects on

Extraversion and Emotional Stability persist (-1.1 percentage points for both, $p < 0.01$). This within-firm analysis suggests that as firms adopt AI, they systematically adjust their personality requirements across all vacancies. The persistence of these patterns at the firm level suggests that AI adoption relates to broader changes in firms' desired worker characteristics rather than just requirements specific to AI positions.

Table 11 examines how AI posting relates to the volume of vacancies requiring different personality traits. The results confirm the changes in firms' hiring patterns. After controlling for average job characteristics, industry, location, and occupational composition (Column 5), firms posting AI vacancies show a significant reduction in positions requiring personality traits overall (-5.6 vacancies, $p < 0.01$), despite a large increase in total vacancies (80.3 vacancies, $p < 0.01$). This pattern is consistent across all traits except Openness: firms significantly reduce vacancies requiring Agreeableness (-13.5 vacancies), Emotional Stability (-5.6 vacancies), Extraversion (-3.6 vacancies), and Conscientiousness (-1.7 vacancies). In contrast, they increase positions requiring Openness (7.4 vacancies, $p < 0.01$).

The within-firm analysis (Column 6) shows smaller but still substantial effects, with firms significantly increasing total vacancies (30.5 vacancies, $p < 0.01$) when posting AI positions. The model also confirms that firms continue to increase positions requiring Openness (3.6 vacancies, $p < 0.01$) while reducing Agreeableness-demanding positions (-5.8 vacancies, $p < 0.01$).

Interestingly, firms posting AI vacancies also show a substantial reduction in non-AI demanding positions (-4.5 vacancies in Column 5 and -2.8 vacancies in Column 6, both $p < 0.01$), suggesting significant substitution between AI and non-AI roles in their hiring patterns. This result aligns with Acemoglu et al. (2022) and Choi and Leigh (2024).

Table 10: Impact of AI on Personality Traits: Firm-Month Level Analysis

	(1) Baseline	(2) +Controls	(3) +Location	(4) +Industry	(5) +Occupation	(6) +Firm
Panel A: Overall Effect						
All Personality Traits	0.006***	-0.049***	-0.051***	-0.044***	-0.030***	-0.001
	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)	(0.002)
Panel B: Effects by Trait						
Agreeableness	-0.031***	-0.025***	-0.025***	-0.018***	-0.010***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)
Conscientiousness	-0.015***	-0.057***	-0.056***	-0.051***	-0.036***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.003)
EmotionalStability	-0.029***	-0.041***	-0.040***	-0.035***	-0.021***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)
Extraversion	-0.053***	-0.068***	-0.071***	-0.068***	-0.043***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)
Openness	0.153***	0.066***	0.058***	0.053***	0.034***	0.018***
	(0.002)	(0.002)	(0.002)	(0.008)	(0.006)	(0.003)
Controls	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
R-squared range	[0.000, 0.005]	[0.067, 0.237]	[0.068, 0.238]	[0.082, 0.248]	[0.091, 0.264]	[0.476, 0.574]
N observations	728161	728161	701816	701814	701814	651808

Notes: Analysis conducted at firm-month level. Standard errors in parentheses, clustered at firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a different specification with progressively added controls and fixed effects. Column (6) includes firm fixed effects, capturing within-firm variation in personality trait demands associated with AI adoption. All regressions include computer skills controls. Regressions with controls include traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option.

The comparison between proportions and counts of personality-demanding vacancies shows consistent patterns in firms' hiring strategies during months of AI adoption. Both specifications show negative effects across all traits except Openness. For instance, firms reduce both the share of vacancies requiring Extraversion (-4.3 percentage points) and their absolute numbers (-3.6 vacancies). The effect on Openness stands out for its consistency in the opposite direction: firms increase both the share of vacancies requiring this trait (3.4 percentage points) and the absolute number of such positions (7.4 vacancies). The firm fixed effects analysis confirms these patterns, showing that they persist even when examining within-firm changes over time. This robust pattern reinforces the complementarity between AI adoption and demand for adaptive and creative characteristics, while suggesting substitution away from other personality traits and non-AI vacancies.

Table 11: Impact of AI Adoption on Vacancy Counts: Firm-Month Level Analysis

	(1) Baseline	(2) +Controls	(3) +Location	(4) +Industry	(5) +Occupation	(6) +Firm
Panel A: Effect on Personality Trait Demanding Vacancies						
All Personality Traits	-5.999***	-6.254***	-6.353***	-6.073***	-5.646***	-0.836
	(0.534)	(0.558)	(0.572)	(1.941)	(1.935)	(0.830)
Panel B: Effects by Trait						
Agreeableness	-13.316***	-13.486***	-13.776***	-13.579***	-13.521***	-5.811***
	(1.239)	(1.301)	(1.335)	(4.897)	(4.925)	(2.059)
Conscientiousness	-2.179***	-2.159***	-2.145***	-2.101	-1.742	0.495
	(0.608)	(0.632)	(0.649)	(1.602)	(1.653)	(0.916)
Emotional Stability	-5.914***	-5.894***	-5.999***	-5.822*	-5.616*	-2.415
	(1.046)	(1.098)	(1.127)	(3.009)	(3.071)	(1.778)
Extraversion	-4.549***	-4.309***	-4.325***	-4.269**	-3.624*	-0.681
	(0.836)	(0.871)	(0.894)	(2.104)	(2.182)	(1.165)
Openness	7.504***	7.348***	7.499***	7.593***	7.421***	3.563***
	(0.655)	(0.677)	(0.694)	(2.163)	(2.168)	(0.786)
Panel C: Effects on Non-AI Vacancies						
Non-AI Vacancies	-4.574***	-4.525***	-4.583***	-4.602***	-4.463***	-2.768***
	(0.058)	(0.056)	(0.057)	(0.317)	(0.279)	(0.092)
Controls	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
R-squared range	[0.348, 0.906]	[0.350, 0.907]	[0.350, 0.907]	[0.352, 0.907]	[0.352, 0.907]	[0.573, 0.950]
N observations	728161	728161	701816	701814	701814	651808

Notes: Analysis conducted at firm-month level. The dependent variables are counts of vacancies. Panels A and B show effects on the number of vacancies demanding personality traits. Panel C shows effects on total vacancies and non-AI vacancies. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a different specification with progressively added controls and fixed effects. Column (6) includes firm fixed effects, capturing within-firm variation in vacancy patterns associated with AI adoption. All regressions control for total number of vacancies.

7.4 Staggered Difference-in-Differences Analysis

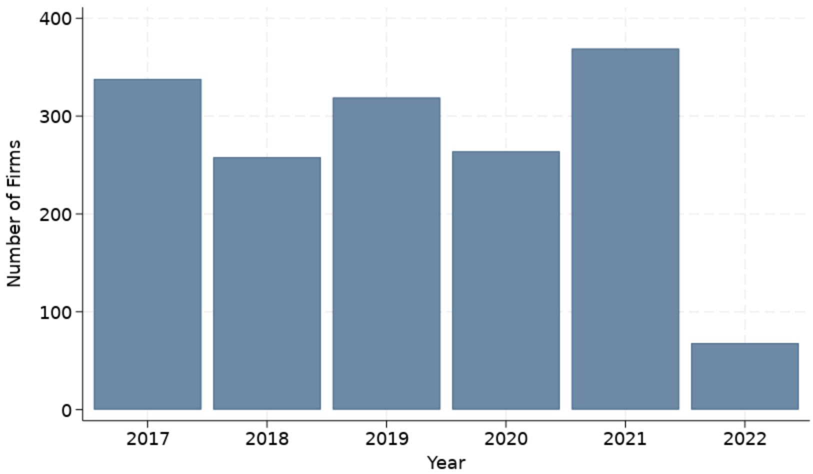
These firm-level findings motivate a deeper investigation of the causal effects of AI adoption on personality demands. While the fixed effects analyses show strong correlations between AI adoption and personality requirements, they cannot fully address potential endogeneity in firms' AI adoption decisions. Firms might adopt AI precisely when planning to reorganise their workforce or shift skill requirements. To provide causal evidence on how AI adoption affects firms' personality trait demands, I use a staggered difference-in-differences strategy that exploits variation in the timing of firms' first AI adoption. This approach captures organisational changes that might occur after firms begin integrating AI skills, even in positions not directly requiring them.

Following Callaway and Sant'Anna (2021)'s methodology, I identify for each firm the first time they post a job advertisement requiring AI skills. This creates a staggered treatment design where firms adopt AI at different times. To ensure comparability between treated and control firms, I implement three specifications: a base specification without pre-treatment controls, a specification with pre-treatment covariates, and entropy balancing. The covariates specification includes pre-treatment characteristics as control variables in the estimation, functioning similarly to a regression adjustment approach where observable differences between treated and control firms are accounted for through linear controls. The entropy balancing specification instead reweights the control group to match the treated group on both the mean and variance of pre-treatment characteristics, creating a balanced pseudo-population before estimation. Both approaches match on pre-treatment personality trait demands (specifically, the average demand for the trait being analysed in the pre-treatment period), pre-treatment firm characteristics (firm size and profit), and pre-treatment occupational composition at the 1-digit SOC level. Entropy balancing is the preferred specification as it ensures better balance across the full distribution of covariates rather than just controlling for their linear effects.

This approach offers advantages over the standard two-way fixed effects (TWFE) difference-in-differences model. First, preliminary analysis showed substantial treatment effect heterogeneity across adoption timing, with later adopters (2021-2022) having different effects compared to early adopters (2018-2019), which TWFE cannot properly account for. Second, while TWFE relies primarily on never-treated firms as controls, the staggered design uses the more comparable group of not-yet-treated firms, better accounting for selection into treatment timing. These features make the staggered design particularly suitable for studying the dynamic effects of AI adoption on personality trait demands.

Of the 128,559 firms in the database, only 1,610 posted vacancies demanding AI skills. These AI-adopting firms collectively posted 61,431 AI-related job advertisements, indicating that firms demanding AI skills tend to post multiple relevant positions rather than single vacancies. This staggered adoption pattern creates variation in treatment timing essential for the difference-in-differences approach. Firms adopting AI in 2017 (21 per cent of adopters) are considered "always treated" in the yearly analysis, while those adopting in subsequent years (2018-2022) form distinct treatment cohorts (Figure 6). Since the data extends only to March 2022, adoption figures for this year are censored, representing just 4.2 per cent of total adopters. This temporal distribution allows identification of treatment effects while accounting for potentially heterogeneous impacts across different adoption periods, which would not be possible with a standard two-way fixed effects estimation.

Figure 6: Number of firms adopting AI by year



Notes: Author's creation using Adzuna.

The entropy balancing results at the yearly aggregation show modest but significant effects. As shown in Table 12, firms increase their overall personality trait demands by 2.7 percentage points ($p < 0.05$) following AI adoption. Looking at individual traits, the effect is strongest for Openness, with a significant increase of 3.6 percentage points ($p < 0.10$). Emotional Stability shows a significant decline of 2.6 percentage points ($p < 0.05$), while effects on other traits remain small and statistically insignificant. The covariates specification shows similar patterns, with a 2.0 percentage point increase in overall personality traits ($p < 0.05$) and a larger effect on Openness (4.9 percentage points, $p < 0.01$). The base specification without controls produces smaller and generally insignificant effects, highlighting the importance of accounting for pre-treatment differences between treated and control firms.

Table 12: ATT Estimates: Year Aggregation

	Entropy Balance	Base	Controls
Panel A: Overall Effect			
All Personality Traits	0.027**	0.004	0.020**
	(0.014)	(0.006)	(0.009)
Panel B: Effects by Trait			
Openness	0.036*	0.021***	0.049***
	(0.021)	(0.007)	(0.014)
Agreeableness	-0.015	-0.002	-0.005
	(0.016)	(0.005)	(0.009)
Conscientiousness	-0.001	0.007	0.009
	(0.019)	(0.007)	(0.012)
Emotional Stability	-0.026**	-0.005	-0.011
	(0.012)	(0.005)	(0.009)
Extraversion	0.001	0.003	-0.007
	(0.020)	(0.007)	(0.013)
Pre-trend Test P-values			
All PT	0.930	0.563	0.097
Openness	0.196	0.081	0.161
Agreeableness	0.086	0.325	0.131
Conscientiousness	0.022	0.826	0.446
Emotional Stability	0.331	0.446	0.358
Extraversion	0.716	0.584	0.341

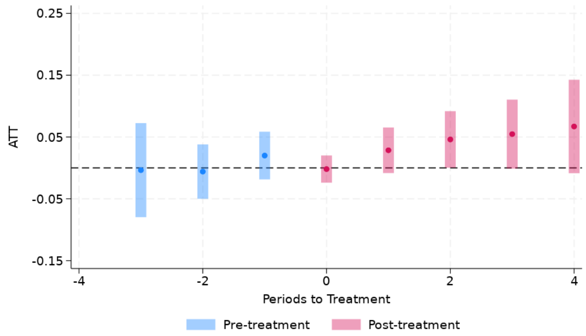
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table compares ATT estimates using three different estimators at year level. Standard errors in parentheses, clustered at the firm level. Pre-trend test p-values from chi-square test of joint significance of pre-treatment coefficients.

The event study plots in Figure 7 show the dynamic effects of AI adoption on trait demands using the entropy balancing specification. For overall personality traits (panel a), pre-treatment trends remain flat and close to zero, followed by a gradual increase in the treatment effect over time, becoming more pronounced three to four years after adoption. The pattern for Openness (panel d) shows the most consistent positive trajectory, with the effect building steadily in the post-treatment period and reaching approximately 7 percentage points by the fourth year after adoption. For Emotional Stability (panel f), the pattern shows a decline in the post-treatment period. The patterns for Agreeableness (panel b), Conscientiousness (panel c), and Extraversion (panel e) show relatively stable trends with confidence intervals including zero throughout most of the post-treatment period, consistent with the insignificant average treatment effects for these traits.

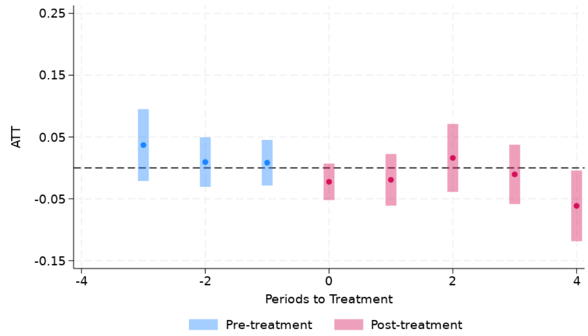
The entropy balancing specification satisfies the parallel trends assumption for most traits, as shown by the pre-trend test p-values in Table 12. We cannot reject the null hypothesis of parallel pre-trends for overall personality traits (p = 0.930), Openness

Figure 7: Staggered DID ATT. Year-level aggregation, Entropy Balance

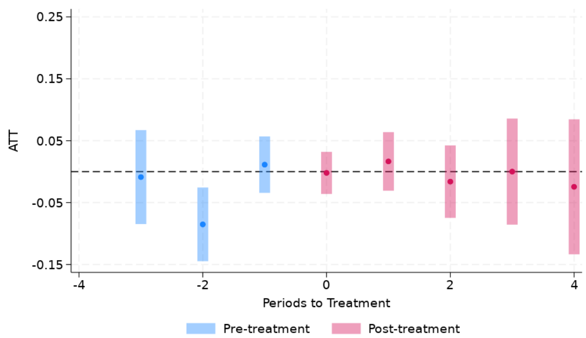
(a) All Personality Traits



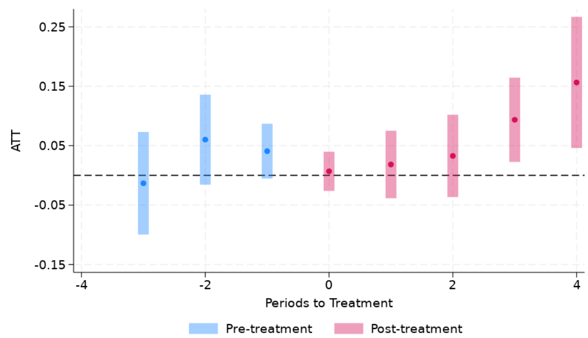
(b) Agreeableness



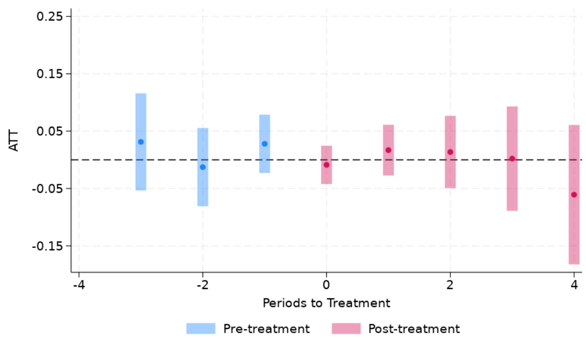
(c) Conscientiousness



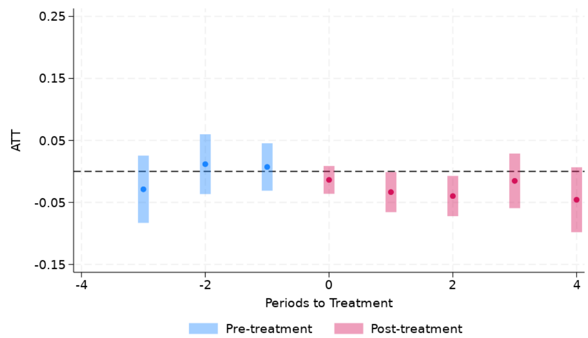
(d) Openness



(e) Extraversion



(f) Emotional Stability



Notes: Author's creation using Adzuna.

(p = 0.196), Emotional Stability (p = 0.331), and Extraversion (p = 0.716). However, the test suggests potential pre-trend differences for Conscientiousness (p = 0.022) and Agreeableness (p = 0.086).

Robustness checks using different temporal aggregations (half-year and quarter) are presented in Tables A.9 and A.10 and Figures A.16 and A.17 in Appendix A. The half-year entropy balancing analysis confirms the main findings, showing a significant positive effect on overall personality traits (4.1 percentage points, $p < 0.05$) with particularly strong effects for Openness (6.4 percentage points, $p < 0.01$). The quarterly analysis also shows positive effects using entropy balancing, with overall personality traits increasing by 3.1 percentage points ($p < 0.10$) and Openness by 4.7 percentage points ($p < 0.05$). However, the precision of estimates decreases at finer time aggregations, likely reflecting both the challenges of identifying effects when AI skills appear in less than 2 per cent of vacancies and the increased noise in measuring firm-level changes over shorter periods, when firms may anticipate changes in their worforce structure.

An important consideration is whether the observed effects reflect changes in AI-demanding positions specifically or broader changes in firms' overall hiring patterns. To address this, I conduct a robustness check where I exclude all AI-demanding vacancies from the analysis while maintaining the treatment timing based on when firms first post AI positions. This approach measures personality trait demands only in non-AI positions before and after firms adopt AI technologies. If the effects were driven solely by the composition of AI versus non-AI positions, we would expect the effects to disappear when excluding AI positions. Instead, Table A.11 in Appendix A shows that the results remain largely unchanged. The entropy balancing specification shows a positive effect on overall personality traits (2.5 percentage points, $p < 0.10$), marginally smaller than the 2.7 percentage points found in the full sample. For Openness, the effect is 3.0 percentage points ($p > 0.15$), compared to 3.6 percentage points in the full sample. The decline in Emotional Stability persists at 2.5 percentage points ($p < 0.05$), nearly identical to the full sample result. The similarity of results when excluding AI positions implies that AI adoption leads to changes in personality requirements across firms' entire workforce, not just in AI-intensive roles. This suggests broader organisational adaptation to AI technologies rather than simple compositional shifts.

The staggered DID analysis provides complementary evidence to the fixed effects results, with both approaches capturing different aspects of the AI-personality relationship. The consistency between the results, especially regarding Openness, improves our understanding of how AI affects labour markets through both immediate and dynamic channels. The positive effects on personality trait demands appear both in specific AI-intensive positions and more broadly across firms' hiring patterns following AI adoption. This suggests that the relationship between AI and personality demands reflects both targeted job-specific requirements and broader organisational adaptation to AI technologies. The stronger effects at more aggregated time periods likely reflect the gradual nature of these organisational changes, as firms adjust their hiring practices to complement their AI adoption. The significant negative effect on Emotional Stability suggests that AI adoption may reduce demand for traits associated with managing workplace stress and pressure.

8 Conclusions

This study provides comprehensive evidence on the demand for personality traits in the UK labour market and how this demand interacts with the increasing adoption of AI technologies. By analysing over 11.7 million job advertisements between 2017-2022, I identify several key patterns that improve our understanding of how personality traits are valued in online labour markets.

Main Findings

Addressing the first research question on the nature and extent of personality trait demands, I find that personality traits appear in 72 percent of job advertisements, more than traditional human capital measures like education (11 percent) and soft skills (62 percent). Extraversion is the most frequently demanded trait (44 percent), followed by Conscientiousness (34 percent), Openness (30 percent), Emotional Stability (14 percent), and Agreeableness (13 percent). The demand varies systematically across occupations, with customer-facing and administrative roles showing the highest requirements: Elementary Administration (88.6 per cent), Sales Assistants and Retail Cashiers (87.3 per cent), and Customer Service (85.3 per cent). In contrast, manual and construction-related occupations show much lower demands: Elementary Construction (20.2 per cent), Metal Forming and Welding Trades (33.1 per cent), and Building Finishing Trades (33.9 per cent). This pattern supports theoretical predictions about the importance of non-cognitive attributes in jobs requiring frequent interpersonal interaction (Deming, 2017).

There is strong evidence of assortative matching between personality trait demands and worker characteristics across occupations, particularly for Agreeableness ($\rho = 0.814$). This alignment between job requirements and worker self-reported traits supports theories of comparative advantage in job matching and validates our text-based approach to measuring personality demands. However, the exception of Emotional Stability highlights measurement challenges when comparing employer-stated requirements with worker self-assessments, particularly for traits that may be expressed differently in job advertisements versus personality surveys.

Although raw trait requirements have increased, most changes reflect shifts in occupational composition rather than within-occupation changes. After controlling for occupation and firm fixed effects, only two significant trends emerge during 2017-2022: a steady decline in Conscientiousness (-2.1 percentage points) and a modest increase in Extraversion (1.7 percentage points). This suggests that changes in personality requirements primarily reflect structural changes in the labour market rather than broad shifts in how firms value personality traits within occupations.

For the third research question, I use two complementary empirical strategies to examine how AI adoption affects personality trait demands. Jobs requiring AI skills are significantly more likely to demand Openness (7.2 percentage points) but show reduced demands for Extraversion (-2.7 percentage points), Emotional Stability (-2.2 percentage points), and Conscientiousness (-1.7 percentage points). This aligns with theoretical predictions that AI may complement creative and adaptive capabilities but potentially replace routine-oriented and interpersonal tasks.

The staggered difference-in-differences analysis provides causal evidence of how firms' personality demands change after their first AI adoption. Using entropy balancing to ensure comparable treated and control firms, I find significant effects on overall personality trait demands (2.7 percentage points, $p < 0.05$), with particularly strong effects for Openness (3.6 percentage points, $p < 0.10$) and a decline in Emotional Stability (2.6 percentage points, $p < 0.05$). The consistency of the Openness effect across both empirical approaches strengthens confidence in AI's role in increasing demand for creative and adaptive traits. The robustness of these findings to alternative time aggregations and to the exclusion of AI positions from the analysis further supports the causal interpretation of these effects, entailing that AI adoption influences personality requirements across firms' entire workforce rather than only in AI-intensive positions.

Mechanisms and Interpretation

This alignment between job-level effects and firm-wide adoption impacts suggests that AI adoption influences personality requirements through multiple channels. Although the strongest effects appear in AI-intensive positions, the positive impact on Openness extends more broadly across firms' hiring patterns following AI adoption. This indicates that as organisations integrate AI technologies, they increasingly value workers' capacity for innovation and flexible thinking, even in positions not directly involving AI skills.

These findings suggest that models of human capital and skill-biased technological change need to better incorporate personality traits as distinct factors in labour market outcomes. The consistent evidence that AI adoption increases demand for Openness, using both contemporaneous and dynamic analyses, indicates that technological change may affect personality requirements as systematically as it affects skill demands. This highlights the need for models that explicitly consider how automation complements or substitutes for different personality traits.

Policy Implications

For policy makers and educators, these results emphasise the importance of including personality development, particularly traits related to creativity and adaptability, in workforce preparation strategies. The finding that personality traits appear in 72 per cent of job advertisements, far exceeding formal education requirements, suggests that the traditional focus on academic qualifications may be insufficient. Furthermore, the strong complementarity between AI and Openness indicates that educational institutions should particularly emphasise the development of creative thinking and adaptability as AI adoption continues to expand across sectors.

For firms, the findings suggest the value of explicitly considering personality traits in hiring strategies, especially when adopting AI technologies. The systematic evidence of assortative matching between job requirements and worker characteristics indicates that clearly stating personality requirements can help achieve better worker-job fit. Moreover, the causal evidence that AI adoption leads to increased demand for Openness suggests that firms should proactively develop skills related to these traits in their workforce as they plan AI implementation.

Limitations and Future Research

Several important questions emerge for future research. First, although this study establishes causal evidence of AI's impact on personality demands, understanding the mechanisms behind these effects requires further investigation. The strong complementarity between AI and Openness suggests that AI may be changing how tasks are performed, but directly measuring these changes in work organisation would provide valuable insights. Second, the robust evidence of assortative matching between personality requirements and worker characteristics raises questions about efficiency and equity. Does better personality-job matching improve productivity and worker satisfaction, and how does this affect wage inequality? Finally, as AI technology continues to evolve, longer-term analysis will be crucial for understanding whether the identified patterns persist or evolve as firms gain more experience with AI implementation.

Contribution

In conclusion, this study shows that personality traits play a crucial role in the modern labour market, appearing in 72 per cent of job advertisements and showing systematic patterns across occupations. The evidence that AI adoption causally increases demand for Openness but potentially reduces requirements for other traits provides important insights into how technological change reshapes personality demands. Through both fixed effects and staggered difference-in-differences analyses, I find consistent evidence that AI complements creative and adaptive capabilities. These findings suggest that as AI adoption continues to expand, the ability to think creatively and adapt to change may become increasingly valuable in the labour market.

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9 Appendices

Appendix A - Figures and Tables

Table A.1: Occupation Characteristics in 2021 vs 2021 Census data

SOC	Name	Salary	Vacancies	Share	vs Census
111	Chief Executives and Senior Officials	32710	2172	0.1%	-67.0%
112	Production Managers and Directors	39471	30125	1.0%	-29.7%
113	Functional Managers and Directors	53967	31597	1.1%	-43.7%
115	Financial Institution Managers and Directors	42494	1572	0.1%	-86.9%
116	Managers and Directors in Transport and Logistics	32847	28909	1.0%	94.5%
117	Senior Officers in Protective Services	33109	429	0.0%	-90.8%
118	Health and Social Services Managers and Directors	36402	7820	0.3%	-10.8%
119	Managers and Directors in Retail and Wholesale	25263	5599	0.2%	-87.2%
121	Managers and Proprietors in Agriculture Related S.	33062	290	0.0%	-91.7%

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Table A.1 – continued from previous page

SOC	Name	Salary	Vacancies	Share	vs Census
122	Managers and Proprietors in Hospitality and Leisure S.	26514	25038	0.9%	-23.9%
124	Managers and Proprietors in Health and Care S.	36509	16373	0.6%	108.6%
125	Managers and Proprietors in Other Services	37251	20207	0.7%	-68.5%
211	Natural and Social Science Professionals	40216	6002	0.2%	-57.6%
212	Engineering Professionals	46820	38630	1.3%	7.8%
213	I.T. and Telecommunications Professionals	53345	174096	6.0%	187.2%
214	Conservation and Environment Professionals	37023	3692	0.1%	15.3%
215	Research and Development Managers	47057	3516	0.1%	9.0%
221	Health Professionals	49102	13124	0.5%	-64.9%
222	Therapy Professionals	36280	9741	0.3%	-2.7%
223	Nursing and Midwifery Professionals	37639	101933	3.5%	78.3%
231	Teaching and Educational Professionals	34845	38653	1.3%	-68.9%
241	Legal Professionals	55087	12525	0.4%	-29.5%
242	Business, Research and Administrative Professionals	50150	118196	4.1%	93.1%
243	Architects, Town Planners and Surveyors	48297	22169	0.8%	-3.2%
244	Welfare Professionals	34791	10862	0.4%	-22.5%
245	Librarians and Related Professionals	28842	254	0.0%	-91.4%
246	Quality and Regulatory Professionals	42531	22690	0.8%	206.7%
247	Media Professionals	36107	8310	0.3%	-41.1%
311	Science, Engineering and Production Technicians	30750	28458	1.0%	33.0%
312	Draughtspersons and Related Architectural Technicians	38480	3686	0.1%	-22.5%
313	Information Technology Technicians	31164	42571	1.5%	144.7%
321	Health Associate Professionals	33549	2808	0.1%	-74.2%
323	Welfare and Housing Associate Professionals	24577	46856	1.6%	80.1%
331	Protective Service Occupations	34952	3029	0.1%	-92.6%
341	Artistic, Literary and Media Occupations	34375	6381	0.2%	-80.1%
342	Design Occupations	45596	10375	0.4%	-25.1%
344	Sports and Fitness Occupations	29774	8470	0.3%	-31.0%
351	Transport Associate Professionals	35421	235	0.0%	-91.6%
352	Legal Associate Professionals	37626	6443	0.2%	11.7%
353	Business, Finance and Related Associate Prof.	41443	85773	3.0%	62.1%
354	Sales, Marketing and Related Associate Prof.	35470	150925	5.2%	88.6%
355	Conservation and Environmental Associate Prof.	25624	1127	0.0%	48.9%
356	Public Services and Other Associate Prof.	29428	98623	3.4%	132.6%
411	Admin. Occ.: Government and Related Organisations	31395	1812	0.1%	-96.3%
412	Admin. Occ.: Finance	28818	52018	1.8%	-24.7%
413	Admin. Occ.: Records	23728	27051	0.9%	-38.3%
415	Other Administrative Occupations	22249	44454	1.5%	-27.4%

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Table A.1 – continued from previous page

SOC	Name	Salary	Vacancies	Share	vs Census
416	Administrative Occupations: Office Managers and Sup.	28716	10931	0.4%	-42.5%
421	Secretarial and Related Occupations	28587	23336	0.8%	-72.6%
511	Agricultural and Related Trades	23400	3393	0.1%	-89.7%
521	Metal Forming, Welding and Related Trades	28009	4934	0.2%	-53.5%
522	Metal Machining, Fitting and Instrument Making Trades	32900	25082	0.9%	-18.3%
523	Vehicle Trades	30638	15090	0.5%	-48.9%
524	Electrical and Electronic Trades	41256	51441	1.8%	28.6%
525	Skilled Metal, Electrical and Electronic Trades Sup.	41915	1406	0.0%	-75.3%
531	Construction and Building Trades	40592	30457	1.1%	-64.9%
532	Building Finishing Trades	29613	3749	0.1%	-84.4%
533	Construction and Building Trades Sup.	37667	2878	0.1%	-37.1%
541	Textiles and Garments Trades	24473	393	0.0%	-91.7%
542	Printing Trades	24185	634	0.0%	-90.9%
543	Food Preparation and Hospitality Trades	24170	85146	3.0%	81.1%
544	Other Skilled Trades	28751	1090	0.0%	-89.1%
612	Childcare and Related Personal Services	22397	44325	1.5%	-42.6%
613	Animal Care and Control Services	23719	2133	0.1%	-71.2%
614	Caring Personal Services	20965	444155	15.4%	277.2%
621	Leisure and Travel Services	22782	8134	0.3%	-54.6%
622	Hairdressers and Related Services	23358	2221	0.1%	-92.4%
623	Housekeeping and Related Services	20995	7838	0.3%	-43.9%
624	Cleaning and Housekeeping Managers and Sup.	29088	25796	0.9%	256.8%
711	Sales Assistants and Retail Cashiers	20952	49762	1.7%	-71.4%
712	Sales Related Occupations	27191	12116	0.4%	-23.7%
713	Sales Supervisors	22404	5631	0.2%	-61.5%
721	Customer Service Occupations	22099	110675	3.8%	215.8%
722	Customer Service Managers and Sup.	28938	50708	1.8%	533.1%
811	Process Operatives	24503	1115	0.0%	-96.3%
812	Plant and Machine Operatives	23756	2563	0.1%	-88.9%
813	Assemblers and Routine Operatives	32306	6170	0.2%	-73.0%
814	Construction Operatives	27234	15322	0.5%	-24.7%
821	Road Transport Drivers	30771	123764	4.3%	38.7%
822	Mobile Machine Drivers and Operatives	24399	13550	0.5%	-3.6%
823	Other Drivers and Transport Operatives	28500	2512	0.1%	-64.7%
911	Elementary Agricultural Occupations	22736	1312	0.0%	-84.5%
912	Elementary Construction Occupations	24769	10550	0.4%	-40.8%
913	Elementary Process Plant Occupations	21575	7294	0.3%	-75.4%
921	Elementary Administration Occupations	21333	11370	0.4%	-53.5%
923	Elementary Cleaning Occupations	16478	76428	2.7%	-1.3%
924	Elementary Security Occupations	24552	44234	1.5%	33.4%

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Table A.1 – continued from previous page

SOC	Name	Salary	Vacancies	Share	vs Census
925	Elementary Sales Occupations	20926	564	0.0%	-95.4%
926	Elementary Storage Occupations	21762	62555	2.2%	33.9%
927	Other Elementary Services Occupations	20590	99993	3.5%	6.9%

Table A.2: Summary statistics

	Category	Mean	SD
Basic Statistics	Number of Ads	11662124	
	Mean length characters	2,297	1236
	Number of firms	128,559	
Baseline	No trait requirements	0.28	0.45
	No traits nor skills requirements	0.09	0.29
	Obs. with no requirements	89,620	
Traits	Any Personality Trait	0.72	0.45
	Conscientiousness	0.34	0.47
	Openness	0.30	0.46
	Emotional Stability	0.14	0.35
	Extraversion	0.44	0.50
	Agreeableness	0.13	0.34
Skills	Soft skills	0.62	0.48
	Hard skills	0.55	0.50
	AI skills	0.01	0.11
Seniority	High Seniority	0.01	0.08
	Middle Seniority	0.19	0.39
	Low Seniority	0.51	0.50
Education	No education specified	0.89	0.31
	GCSE	0.03	0.16
	A-level	0.04	0.19
	Bachelor's degree	0.03	0.17
	Master or Doctoral degree	0.02	0.12
Job schedule	Full time job	0.30	0.46
	Part time job	0.08	0.28
Job duration	Temporary job	0.13	0.34
	Permanent job	0.35	0.48
Experience	Experience requested	0.69	0.46
	No experience requested	0.01	0.09
Other job info	Remote Work	0.03	0.18
	Average Salary	31940	18690
	Negotiable salary	0.49	0.50
	Bonus offered	0.23	0.42

Notes: No trait requirements refers to the share of vacancies that do not mention words from Traits dictionaries. *No traits nor skills* refers to the share of vacancies that do not mention traits or Soft or Hard skills. *Obs. with no requirements* refers to the observations that did not match any of the job requirements in the text, hence the baseline sample for regression.

Table A.3: Personality Traits by 3-digit Occupation group

SOC	Name	P.T.	Agree.	Consc.	Emot.	Extra.	Open.
111	Chief Executives and Senior Officials	61.1%	11.0%	29.8%	10.6%	30.8%	24.4%
112	Production Managers and Directors	59.4%	4.2%	35.0%	7.8%	27.9%	23.0%
113	Functional Managers and Directors	68.7%	7.3%	33.6%	10.4%	34.6%	37.9%
115	Financial Institution Managers and Directors	63.7%	7.5%	35.5%	11.6%	33.0%	21.0%
116	Managers and Directors in Transport and Logistics	79.3%	5.9%	49.9%	10.2%	51.6%	26.1%
117	Senior Officers in Protective Services	68.2%	7.9%	30.2%	11.7%	40.4%	24.8%
118	Health and Social Services Managers and Directors	82.1%	19.2%	41.5%	16.8%	47.5%	35.0%
119	Managers and Directors in Retail and Wholesale	77.3%	6.0%	39.5%	15.7%	59.0%	33.0%
121	Managers and Proprietors in Agriculture Related S.	74.1%	10.3%	44.6%	8.3%	42.1%	29.1%
122	Managers and Proprietors in Hospitality and Leisure S.	81.5%	13.9%	40.8%	13.4%	64.0%	20.3%
124	Managers and Proprietors in Health and Care S.	75.2%	21.6%	36.3%	17.5%	40.6%	25.6%
125	Managers and Proprietors in Other Services	69.9%	9.8%	36.6%	12.7%	45.7%	24.7%
211	Natural and Social Science Professionals	71.5%	5.3%	26.7%	5.5%	37.6%	45.9%
212	Engineering Professionals	55.6%	3.2%	25.9%	6.3%	24.1%	29.4%
213	I.T. and Telecommunications Professionals	63.2%	4.0%	25.3%	5.7%	30.2%	39.4%
214	Conservation and Environment Professionals	74.7%	11.2%	35.6%	10.5%	49.8%	37.7%
215	Research and Development Managers	70.0%	8.9%	29.0%	5.9%	36.5%	48.1%
221	Health Professionals	69.7%	13.6%	23.3%	10.1%	42.7%	28.8%
222	Therapy Professionals	70.2%	10.2%	26.8%	9.6%	46.7%	21.1%
223	Nursing and Midwifery Professionals	75.1%	23.1%	39.3%	24.7%	41.1%	23.8%
231	Teaching and Educational Professionals	77.6%	11.1%	31.8%	13.2%	52.2%	32.5%
241	Legal Professionals	59.7%	10.4%	29.7%	6.4%	32.9%	18.9%
242	Business, Research and Administrative Professionals	64.5%	6.4%	32.9%	9.8%	31.8%	35.3%
243	Architects, Town Planners and Surveyors	51.3%	4.4%	28.7%	5.5%	24.4%	20.2%
244	Welfare Professionals	71.1%	15.1%	29.1%	17.2%	38.7%	37.7%
245	Librarians and Related Professionals	79.2%	12.9%	33.9%	14.0%	48.2%	46.2%
246	Quality and Regulatory Professionals	62.3%	5.1%	33.6%	8.5%	29.5%	29.5%
247	Media Professionals	82.9%	8.4%	31.9%	11.6%	50.2%	61.9%
311	Science, Engineering and Production Technicians	67.1%	4.9%	39.1%	10.6%	35.4%	26.5%
312	Draughtspersons and Related Architectural Technicians	57.7%	3.7%	27.3%	8.0%	27.2%	29.7%
313	Information Technology Technicians	69.5%	8.5%	34.1%	13.7%	41.4%	30.1%

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Table A.3 – continued from previous page

SOC	Name	P.T.	Agree.	Consc.	Emot.	Extra.	Open.
321	Health Associate Professionals	69.2%	9.4%	30.7%	7.2%	43.5%	19.6%
323	Welfare and Housing Associate Professionals	79.4%	18.0%	31.5%	24.4%	49.4%	39.3%
331	Protective Service Occupations	76.1%	11.2%	33.2%	26.4%	38.3%	31.8%
341	Artistic, Literary and Media Occupations	77.4%	6.2%	27.9%	10.2%	45.8%	51.8%
342	Design Occupations	84.7%	4.4%	25.0%	7.6%	48.0%	72.0%
344	Sports and Fitness Occupations	79.4%	16.2%	29.2%	5.5%	70.4%	24.4%
351	Transport Associate Professionals	50.9%	1.5%	31.6%	14.5%	26.4%	15.0%
352	Legal Associate Professionals	61.8%	8.2%	32.8%	10.7%	33.6%	20.6%
353	Business, Finance and Related Associate Prof.	65.3%	7.6%	35.2%	10.2%	34.2%	29.1%
354	Sales, Marketing and Related Associate Prof.	77.6%	7.8%	36.6%	11.5%	49.9%	39.7%
355	Conservation and Environmental Associate Prof.	79.8%	15.9%	32.3%	5.9%	59.1%	24.4%
356	Public Services and Other Associate Prof.	77.9%	9.8%	41.4%	15.8%	50.4%	32.0%
411	Admin. Occ.: Government and Related Organisations	61.5%	10.8%	24.8%	8.2%	38.9%	26.8%
412	Admin. Occ.: Finance	62.4%	6.2%	32.0%	10.7%	37.8%	19.9%
413	Admin. Occ.: Records	72.9%	7.2%	43.1%	15.2%	42.7%	23.7%
415	Other Administrative Occupations	76.8%	10.6%	44.7%	15.9%	47.8%	26.8%
416	Administrative Occupations: Office Managers and Sup.	73.8%	11.1%	43.7%	15.6%	50.0%	24.2%
421	Secretarial and Related Occupations	75.5%	17.5%	41.8%	18.3%	51.0%	24.9%
511	Agricultural and Related Trades	76.1%	9.1%	46.2%	4.2%	52.3%	27.3%
521	Metal Forming, Welding and Related Trades	33.2%	0.8%	20.6%	4.1%	11.0%	8.4%
522	Metal Machining, Fitting and Instrument Making Trades	49.7%	2.8%	29.2%	6.8%	22.0%	16.1%
523	Vehicle Trades	66.2%	5.8%	43.3%	12.6%	35.2%	16.0%
524	Electrical and Electronic Trades	53.4%	3.6%	27.5%	5.2%	23.1%	25.7%
525	Skilled Metal, Electrical and Electronic Trades Sup.	41.3%	3.0%	28.6%	5.9%	17.1%	10.0%
531	Construction and Building Trades	46.3%	7.6%	29.1%	3.1%	19.9%	12.9%
532	Building Finishing Trades	33.9%	3.6%	21.8%	3.0%	13.8%	8.7%
533	Construction and Building Trades Sup.	42.3%	2.6%	28.3%	4.2%	17.4%	12.1%
541	Textiles and Garments Trades	67.8%	8.1%	31.3%	8.5%	47.6%	25.3%
542	Printing Trades	59.4%	2.8%	28.0%	12.2%	27.9%	29.6%
543	Food Preparation and Hospitality Trades	81.2%	9.4%	41.6%	19.7%	58.7%	33.1%
544	Other Skilled Trades	65.8%	2.2%	41.4%	13.7%	33.9%	16.8%
612	Childcare and Related Personal Services	78.8%	17.5%	22.7%	18.4%	59.7%	34.4%
613	Animal Care and Control Services	81.2%	9.3%	28.6%	6.6%	61.6%	45.8%
614	Caring Personal Services	82.6%	39.1%	26.6%	27.4%	50.2%	29.3%

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Table A.3 – continued from previous page

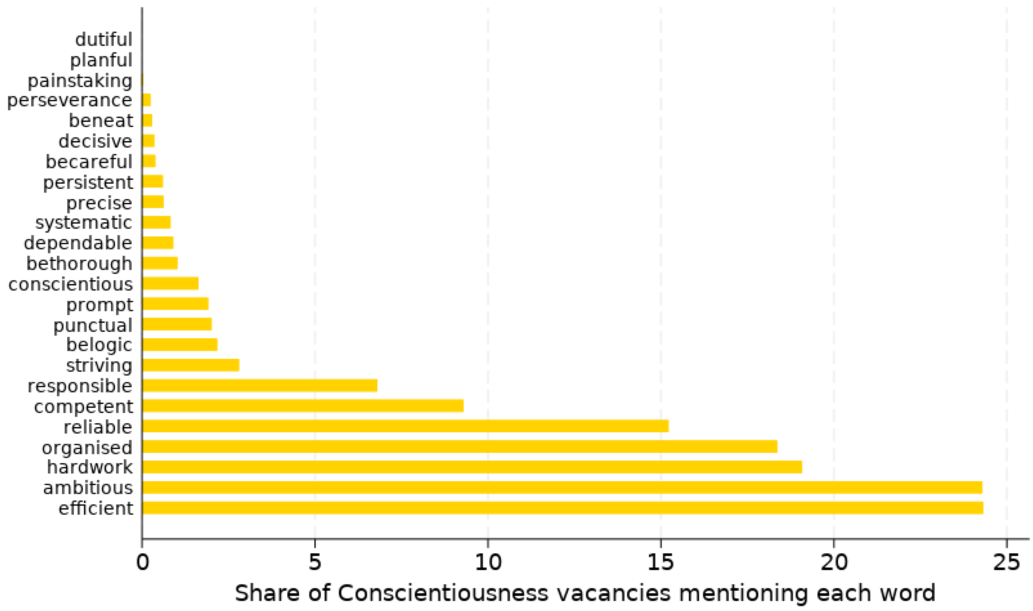
SOC	Name	P.T.	Agree.	Consc.	Emot.	Extra.	Open.
621	Leisure and Travel Services	83.6%	9.8%	51.7%	22.3%	67.6%	20.6%
622	Hairdressers and Related Services	78.8%	7.6%	33.1%	7.4%	61.8%	22.0%
623	Housekeeping and Related Services	72.2%	28.1%	33.8%	11.0%	37.9%	16.4%
624	Cleaning and Housekeeping Managers and Sup.	72.1%	20.5%	52.0%	15.4%	39.2%	15.8%
711	Sales Assistants and Retail Cashiers	87.3%	16.0%	42.8%	9.5%	76.4%	31.9%
712	Sales Related Occupations	82.1%	7.5%	35.2%	11.7%	49.3%	39.5%
713	Sales Supervisors	79.0%	13.0%	41.7%	4.7%	60.3%	43.8%
721	Customer Service Occupations	85.4%	17.8%	39.6%	17.7%	67.8%	30.3%
722	Customer Service Managers and Sup.	84.9%	13.0%	43.8%	20.9%	60.5%	30.1%
811	Process Operatives	49.5%	2.0%	29.6%	6.2%	21.4%	16.7%
812	Plant and Machine Operatives	49.2%	1.7%	29.8%	5.7%	24.5%	17.1%
813	Assemblers and Routine Operatives	52.0%	2.6%	29.3%	6.5%	26.5%	18.6%
814	Construction Operatives	62.6%	9.5%	39.7%	6.5%	31.6%	20.6%
821	Road Transport Drivers	52.6%	8.8%	33.5%	5.8%	27.9%	19.0%
822	Mobile Machine Drivers and Operatives	40.4%	5.2%	23.7%	4.0%	18.0%	10.9%
823	Other Drivers and Transport Operatives	61.9%	4.8%	45.3%	17.1%	30.8%	23.0%
911	Elementary Agricultural Occupations	66.9%	5.6%	38.3%	7.9%	32.4%	32.0%
912	Elementary Construction Occupations	20.2%	3.2%	13.9%	1.1%	6.6%	2.6%
913	Elementary Process Plant Occupations	55.6%	1.8%	29.8%	6.3%	29.2%	14.6%
921	Elementary Administration Occupations	88.6%	34.4%	48.5%	35.6%	42.4%	75.5%
923	Elementary Cleaning Occupations	63.9%	7.6%	39.4%	6.7%	33.5%	23.4%
924	Elementary Security Occupations	71.5%	9.4%	27.1%	11.0%	44.7%	34.0%
925	Elementary Sales Occupations	69.3%	10.8%	27.8%	4.6%	51.5%	17.1%
926	Elementary Storage Occupations	70.5%	6.3%	44.1%	6.2%	45.5%	19.5%
927	Other Elementary Services Occupations	82.6%	21.1%	38.5%	17.9%	67.0%	22.6%

Table A.4: Assortative matching: Personalities traits demand using UKHLS scores at the occupation level, no controls

	(1) P(Any P.T.)	(2) P(Agree.)	(3) P(Consc.)	(4) P(Emot.)	(5) P(Extra.)	(6) P(Open.)
Personalities score	0.023***					
	(0.000)					
Agreeableness score		0.089***				
		(0.000)				
Conscientiousness score			0.001***			
			(0.000)			
Emotional Stability score				−0.044***		
				(0.000)		
Extraversion score					0.089***	
					(0.000)	
Openness score						0.045***
						(0.000)
R^2	0.003	0.067	0.000	0.016	0.032	0.010

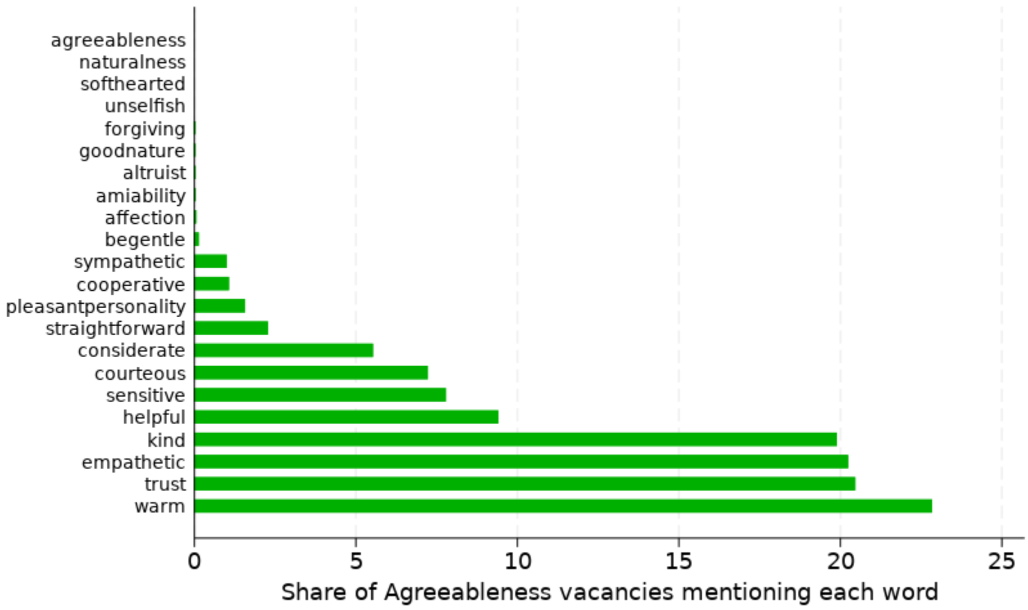
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ $N = 9888315$. "Any P.T." refers to Any Personality Trait, "Consc." to Conscientiousness, "Open." to Openness, "Agree." to Agreeableness, "Extra." to Extraversion, "Emot." to Emotional Stability. All variables refer to the occupation-level 2011-2017 UKHLS standardized value. Author's creation using Adzuna and UKHLS.

Figure A.1: Frequency of words in Conscientiousness



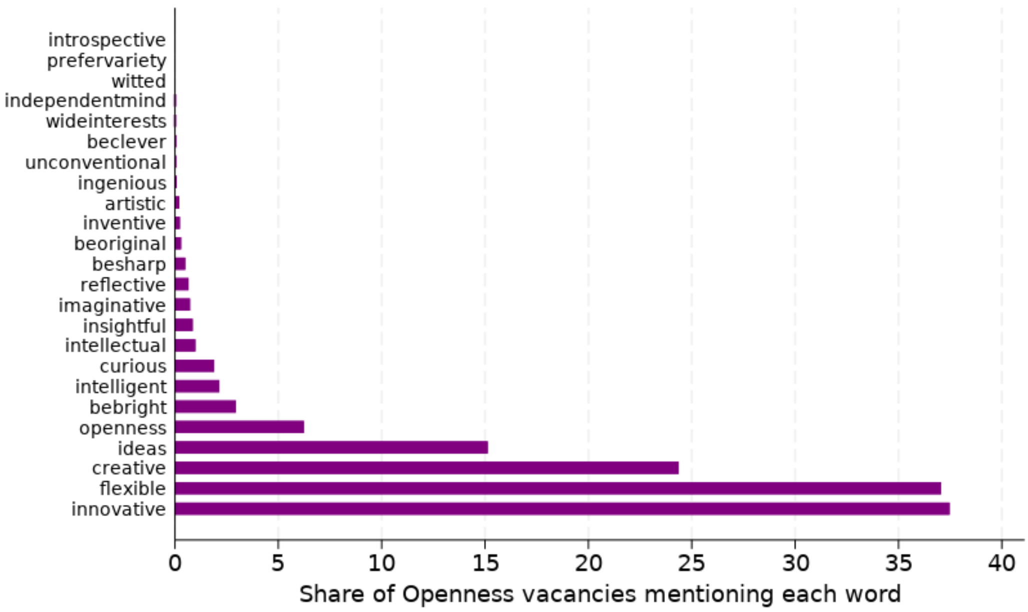
Notes: Author's creation using Adzuna.

Figure A.2: Frequency of words in Agreeableness



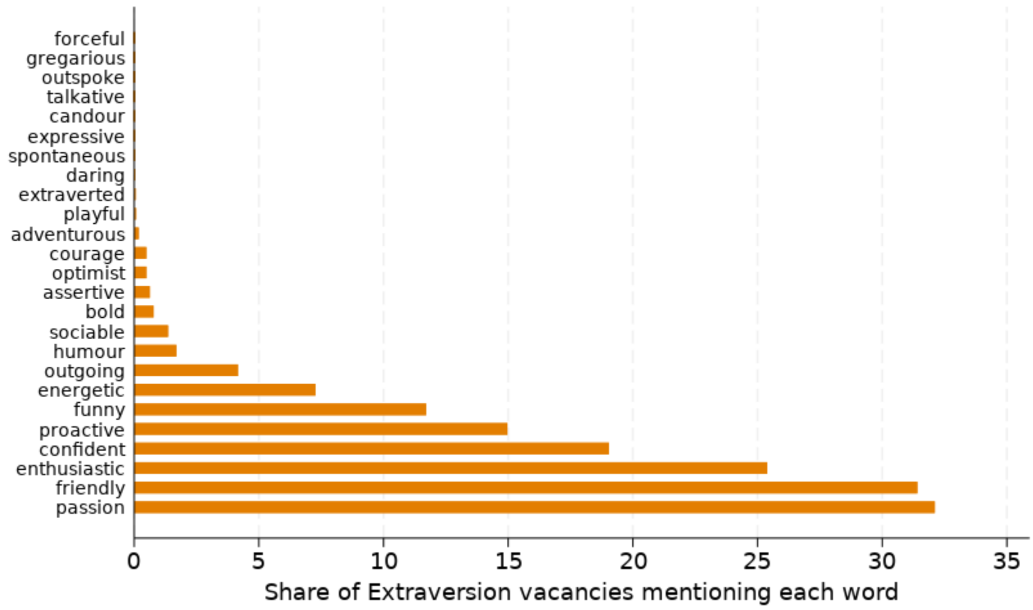
Notes: Author's creation using Adzuna.

Figure A.3: Frequency of words in Openness



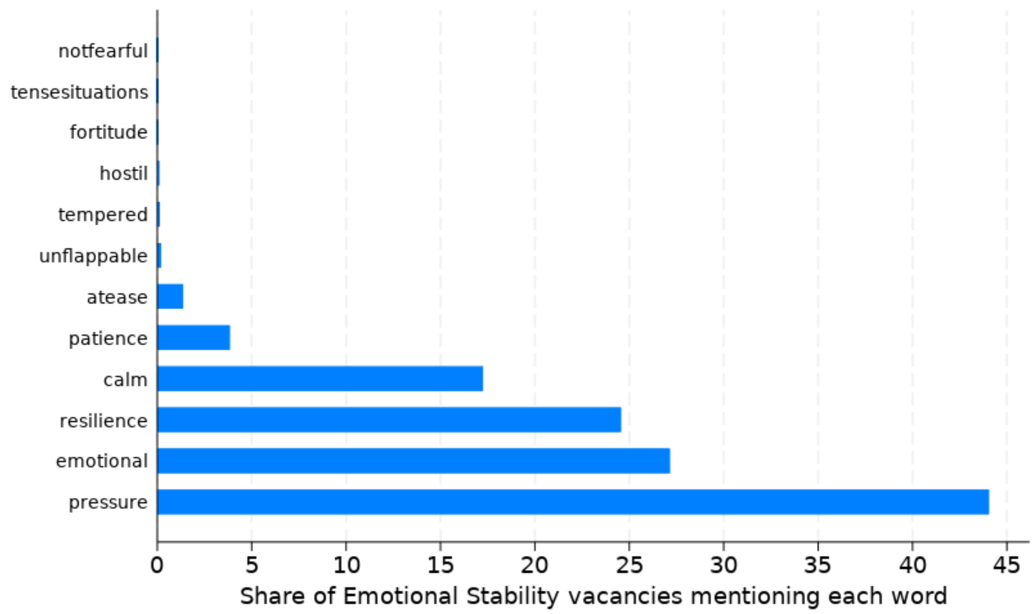
Notes: Author's creation using Adzuna.

Figure A.4: Frequency of words in Extraversion



Notes: Author's creation using Adzuna.

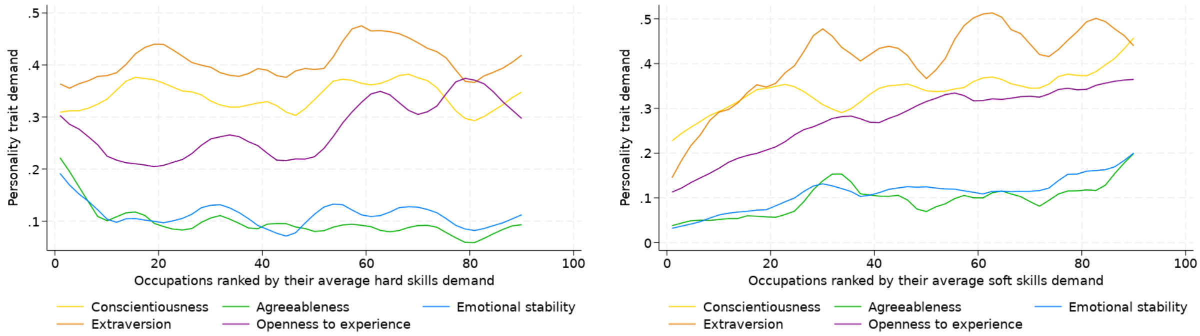
Figure A.5: Frequency of words in Emotional Stability



Notes: Author's creation using Adzuna.

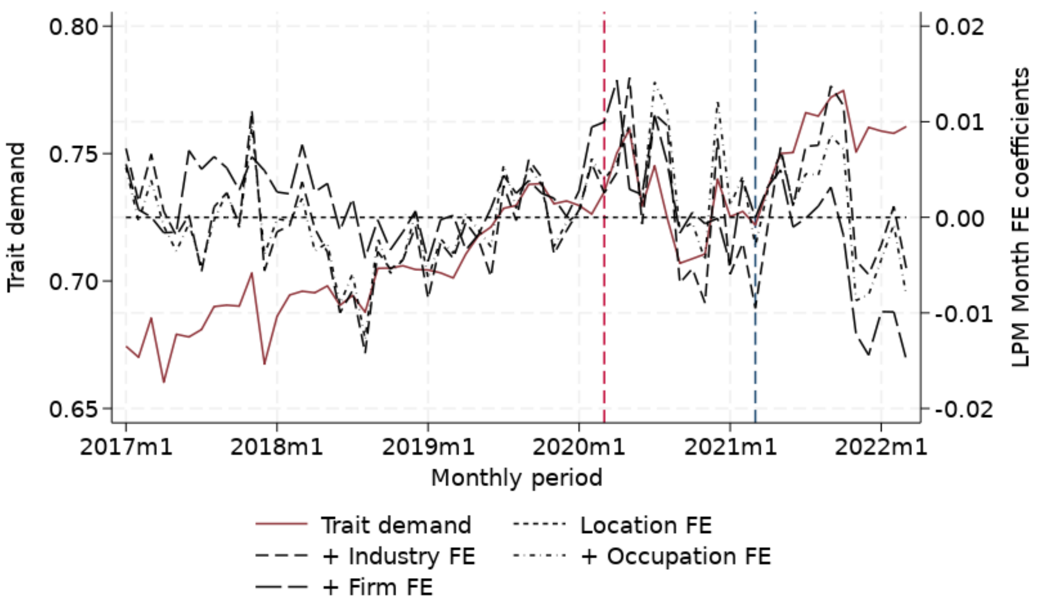
Figure A.6: Trait demand by hard and soft skill rank in Adzuna, at 3-digit SOC

(a) Demand by hard-skill ranking (b) Demand by soft-skill ranking



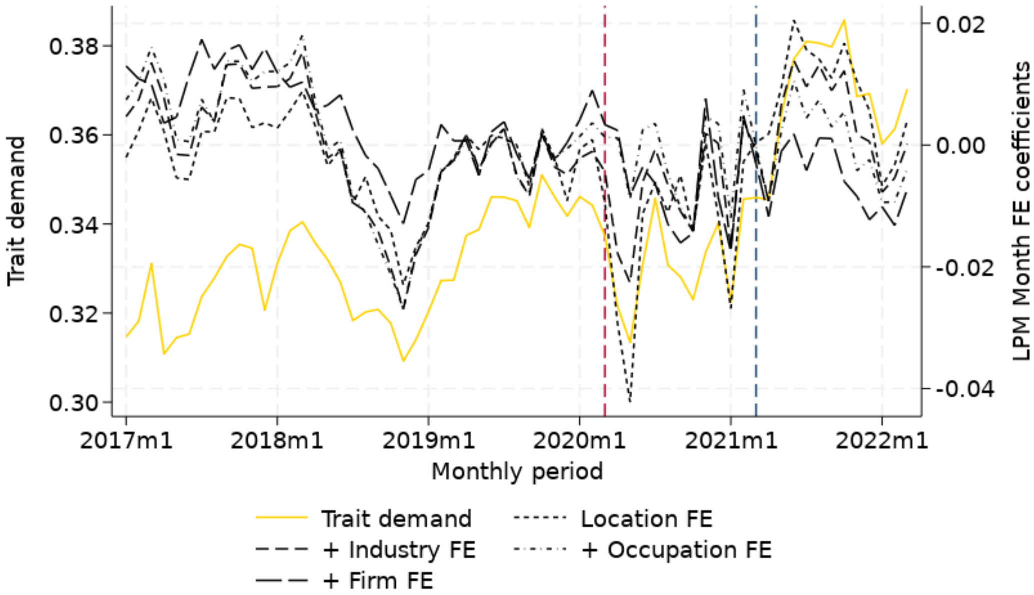
Notes: The figure plots a smoothed polynomial regression of the traits demand in each 3-digit SOC occupation against its rank in Adzuna demand of hard and soft skills by ranked occupations for 2017-2022. Author's creation using Adzuna.

Figure A.7: Month FE coefficients in all Personality Traits



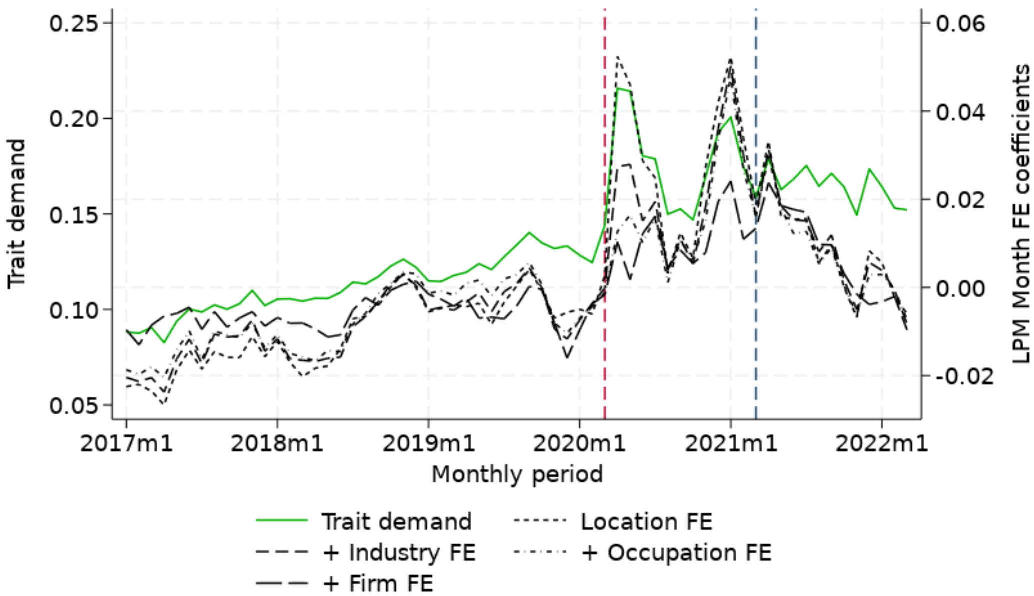
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.8: Month FE coefficients in Conscientiousness



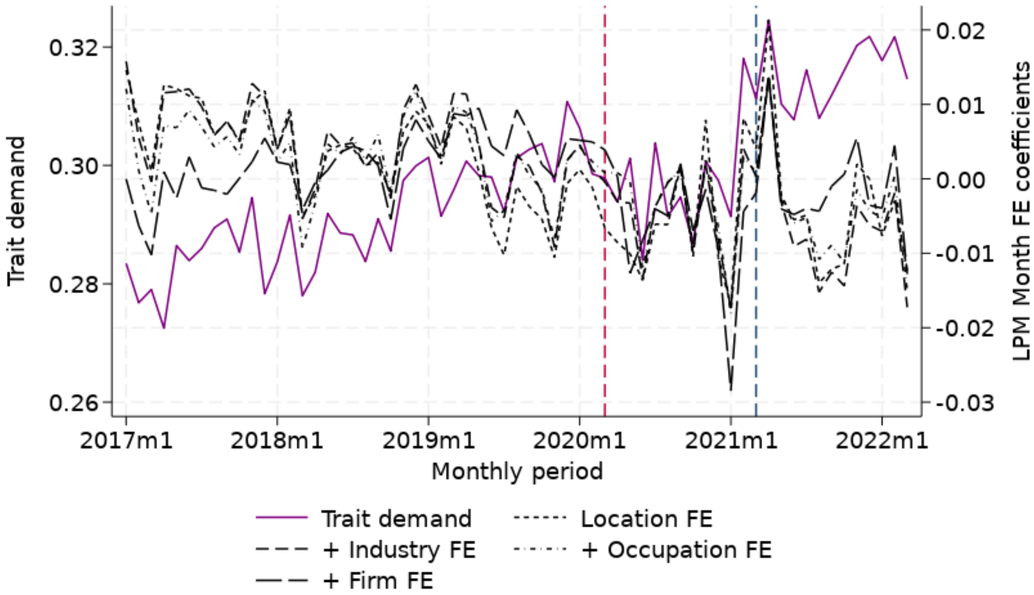
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.9: Month FE coefficients and trait demand for Agreeableness



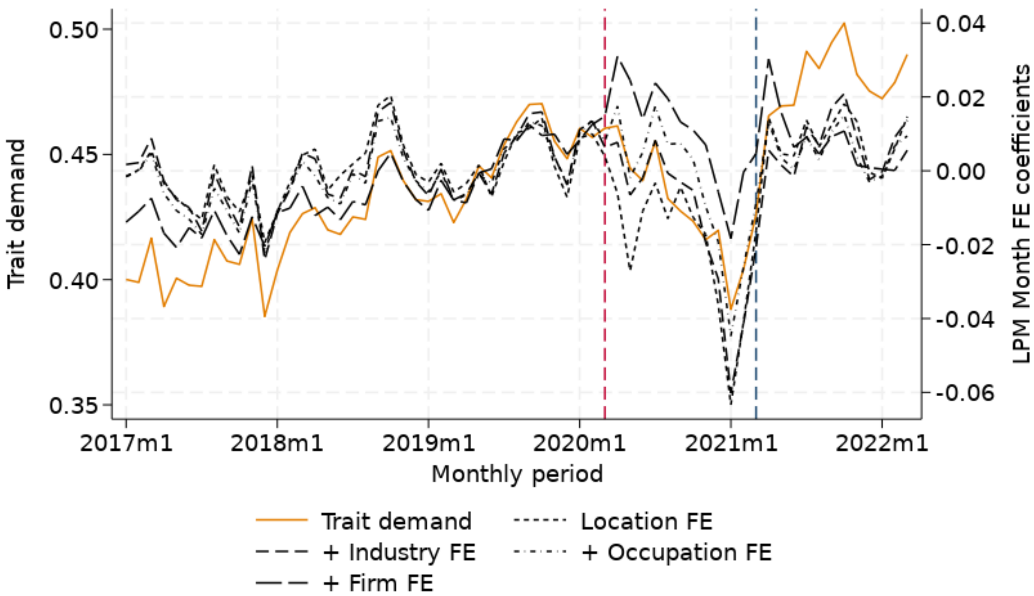
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.10: Month FE coefficients and trait demand for Openness



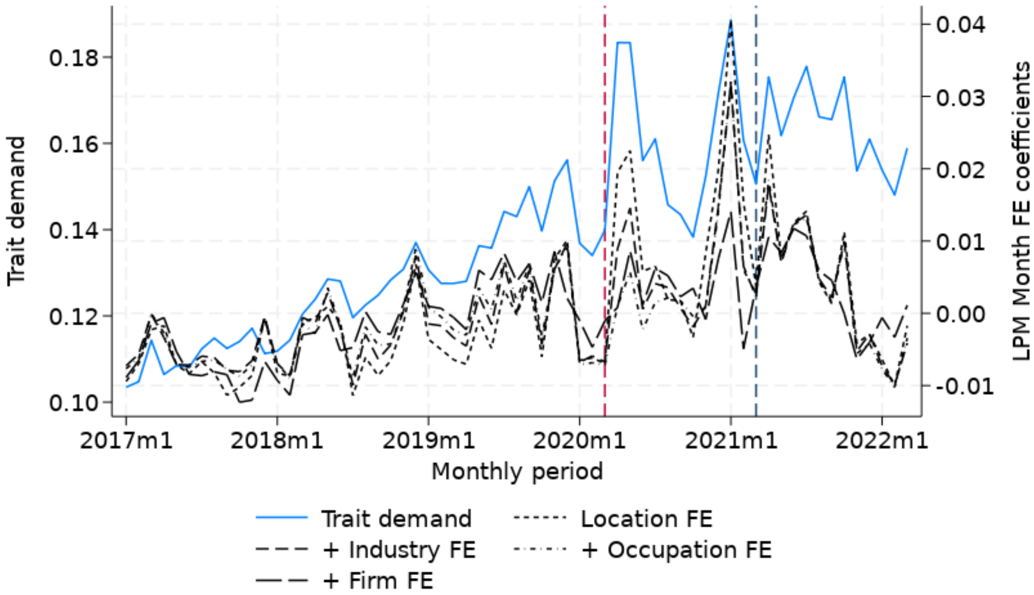
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.11: Month FE coefficients and trait demand for Extraversion



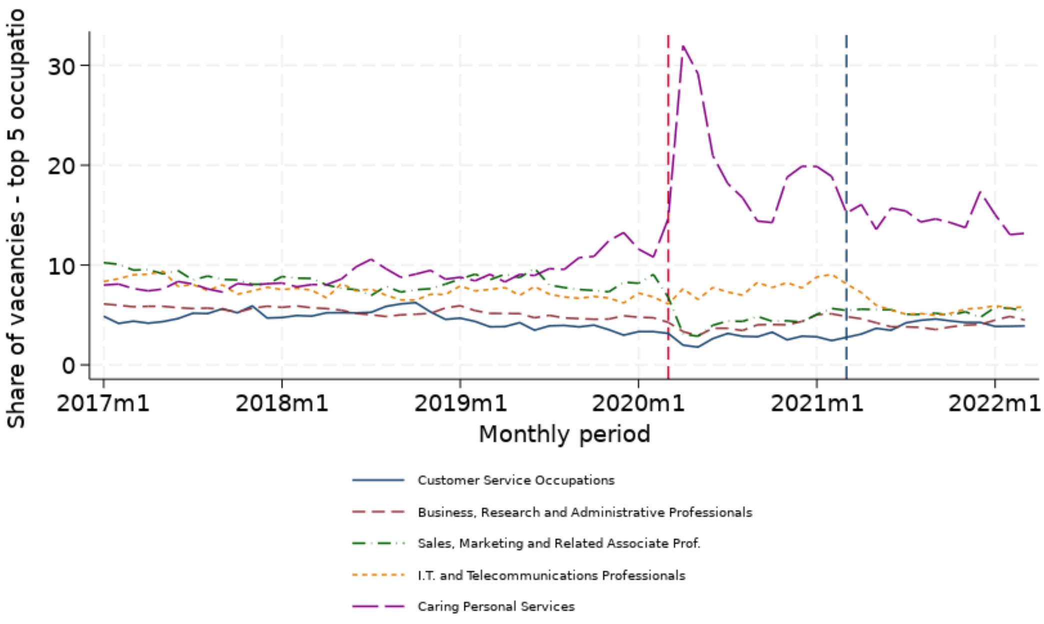
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.12: Month FE coefficients and trait demand for Emotional Stability



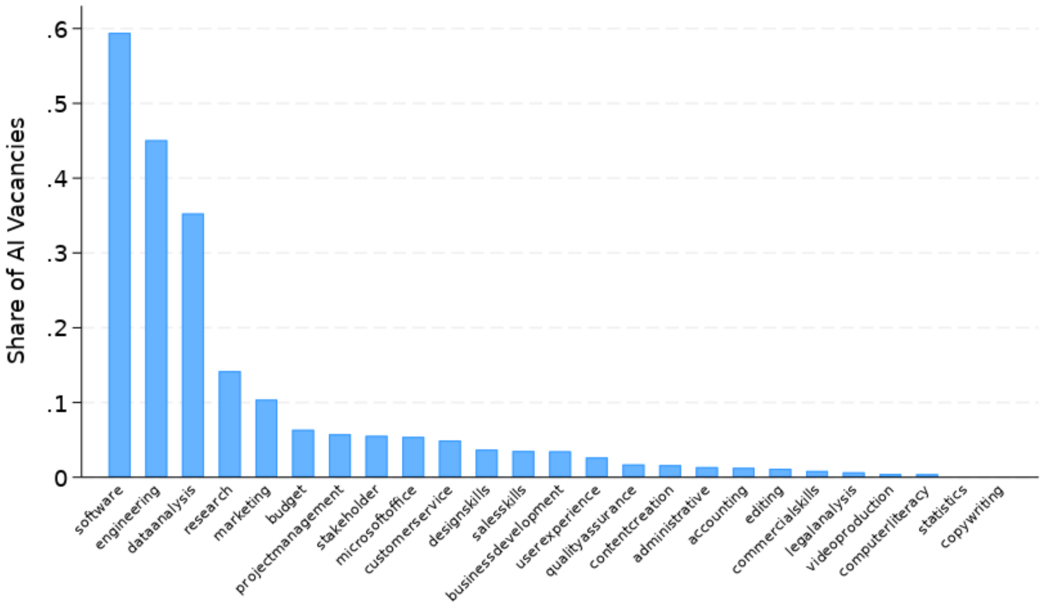
Notes: Dashed lines show the beginning (red) and end (blue) of Covid-19 restrictions. Author's creation using Adzuna.

Figure A.13: Change over time of top 5 occupations in Adzuna



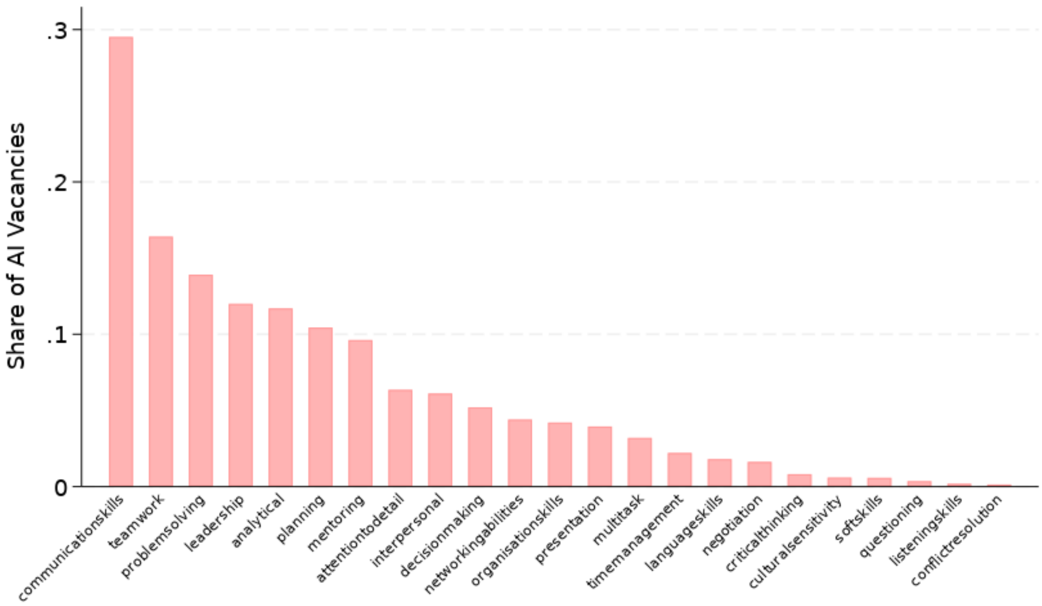
Notes: Author's creation using Adzuna.

Figure A.14: Hard Skills Demanded in AI Vacancies



Notes: Author's creation using Adzuna.

Figure A.15: Soft Skills Demanded in AI Vacancies



Notes: Author's creation using Adzuna.

Table A.5: Impact of AI on Personality Traits: Adding Controls Sequentially

	(1) Baseline	(2) +Controls	(3) +Time	(4) +Location	(5) +Firm	(6) +Occ	(7) All FE
Panel A: Overall Effect							
All Personality Traits	0.010***	-0.032***	-0.032***	-0.029***	0.012*	0.021***	0.016**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.005)	(0.007)
Panel B: Effects by Trait							
Agreeableness	-0.074***	-0.047***	-0.050***	-0.052***	-0.017***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.004)
Conscientiousness	-0.043***	-0.073***	-0.072***	-0.071***	-0.023***	-0.037***	-0.016**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.008)	(0.008)
EmotionalStability	-0.063***	-0.056***	-0.057***	-0.058***	-0.029***	-0.026***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.009)	(0.007)
Extraversion	-0.092***	-0.114***	-0.113***	-0.112***	-0.038***	-0.041***	-0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.007)
Openness	0.225***	0.171***	0.173***	0.172***	0.081***	0.120***	0.072***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.016)	(0.014)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No	Yes
Occupation FE	No	No	No	No	No	Yes	Yes
R-squared range	[0.000, 0.003]	[0.078, 0.119]	[0.080, 0.120]	[0.084, 0.121]	[0.273, 0.351]	[0.105, 0.169]	[0.281, 0.364]
N observations	11662124	11662124	11662124	9923701	9888315	9923701	9888315
N firms	128559	128559	128559	117229	81843	117229	81843

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a different specification with progressively added controls and fixed effects. The R-squared range shows the minimum and maximum values across the six trait regressions for each specification. All regressions with controls include traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Standard errors are clustered at the occupation and firm level in specifications (5)-(7).

Table A.6: Impact of Computer Skills on Personality Traits

	(1) Baseline	(2) +Controls	(3) +Time	(4) +Location	(5) +Firm	(6) +Occ	(7) All FE
Panel A: Overall Effect							
All Personality Traits	0.022***	-0.041***	-0.041***	-0.038***	0.003	0.001	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.005)	(0.004)
Panel B: Effects by Trait							
Agreeableness	-0.053***	-0.041***	-0.041***	-0.042***	-0.009**	-0.005	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.005)	(0.003)
Conscientiousness	0.028***	-0.020***	-0.019***	-0.018***	0.000	0.005	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)	(0.004)
EmotionalStability	-0.016***	-0.026***	-0.026***	-0.024***	-0.009**	-0.001	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.005)	(0.005)
Extraversion	-0.029***	-0.070***	-0.070***	-0.065***	-0.014***	-0.015*	-0.009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.009)	(0.006)
Openness	0.124***	0.070***	0.070***	0.068***	0.034***	0.037***	0.029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)	(0.005)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No	Yes
Occupation FE	No	No	No	No	No	Yes	Yes
R-squared range	[0.000, 0.010]	[0.080, 0.121]	[0.082, 0.122]	[0.084, 0.123]	[0.273, 0.351]	[0.105, 0.169]	[0.281, 0.364]
N observations	11662124	11662124	11662124	9923701	9888315	9923701	9888315
N firms	128559	128559	128559	117229	81843	117229	90

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a different specification with progressively added controls and fixed effects. The R-squared range shows the minimum and maximum values across the six trait regressions for each specification. All regressions with controls include traits and skills demand, remote work requirements, length of advertisement, contract type, work schedule, bonus offerings, education, and negotiable salary option. Standard errors are clustered at the occupation and firm level in specifications (5)-(7).

Table A.7: Comparing AI and Computer Skills Effects on Personality Traits

	(1) Baseline	(2) +Controls	(3) +Time	(4) +Location	(5) +Firm	(6) +Occ	(7) All FE
Panel A: Coefficient Differences (AI - Computer Skills)							
All Personality Traits	-0.012	0.009	0.009	0.009	0.009	0.020	0.013
Agree	-0.021	-0.006	-0.009	-0.010	-0.008	-0.007	-0.008
Consc	-0.071	-0.053	-0.053	-0.053	-0.023	-0.041	-0.020
Emot	-0.046	-0.030	-0.031	-0.033	-0.020	-0.025	-0.018
Extra	-0.063	-0.044	-0.043	-0.046	-0.023	-0.026	-0.017
Open	0.101	0.101	0.103	0.104	0.046	0.083	0.042
Panel B: T-Statistics							
All Personality Traits	-9.89	8.10	8.01	7.14	1.12	2.71	1.66
Agree	-31.15	-8.53	-10.01	-9.51	-1.48	-1.16	-1.57
Consc	-57.66	-45.01	-42.61	-37.01	-2.68	-4.06	-2.18
Emot	-62.00	-39.96	-33.88	-31.48	-3.21	-2.40	-2.06
Extra	-48.90	-34.98	-34.07	-31.77	-2.43	-2.04	-1.87
Open	75.53	80.89	87.37	77.17	5.12	4.71	2.86
Panel C: P-values							
All Personality Traits	0.000***	0.000***	0.000***	0.000***	0.264	0.007***	0.097*
Agree	0.000***	0.000***	0.000***	0.000***	0.138	0.247	0.116
Consc	0.000***	0.000***	0.000***	0.000***	0.007***	0.000***	0.029**
Emot	0.000***	0.000***	0.000***	0.000***	0.001***	0.016**	0.039**
Extra	0.000***	0.000***	0.000***	0.000***	0.015**	0.041**	0.061*
Open	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.004***
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No	Yes
Occupation FE	No	No	No	No	No	Yes	Yes

Notes: Panel A shows the difference between the effect of AI and Computer Skills when estimated separately. Panel B presents the z-statistics for these differences, calculated as $(\beta_{AI} - \beta_{CS})/\sqrt{SE(\beta_{AI})^2 + SE(\beta_{CS})^2}$. Panel C shows corresponding p-values, with stars indicating significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All comparisons use coefficients from separate regressions of each trait on AI and Computer Skills respectively.

Table A.8: Changes in AI Effects When Controlling for Computer Skills

	(1) Baseline	(2) +Controls	(3) +Time	(4) +Location	(5) +Firm	(6) +Occ	(7) All FE
Panel A: Coefficient Differences (AI only - AI with CS)							
All Personality Traits	0.013	-0.020	-0.020	-0.018	0.001	0.000	0.000
Agree	-0.029	-0.019	-0.019	-0.019	-0.002	-0.001	-0.001
Consc	0.018	-0.008	-0.008	-0.007	0.000	0.001	0.001
Emot	-0.008	-0.011	-0.011	-0.011	-0.002	-0.000	-0.001
Extra	-0.014	-0.031	-0.031	-0.029	-0.003	-0.003	-0.002
Open	0.066	0.030	0.030	0.029	0.008	0.009	0.005
Panel B: T-Statistics							
All Personality Traits	7.81	-13.38	-13.07	-10.54	0.06	0.00	0.05
Agree	-32.40	-21.04	-15.64	-13.52	-0.38	-0.28	-0.14
Consc	10.72	-4.87	-4.60	-3.70	0.02	0.12	0.06
Emot	-7.75	-11.66	-9.33	-7.37	-0.29	-0.00	-0.08
Extra	-7.95	-18.65	-18.16	-14.66	-0.27	-0.27	-0.16
Open	36.02	17.81	18.88	15.89	0.71	0.39	0.27
Panel C: P-values							
All Personality Traits	0.000***	0.000***	0.000***	0.000***	0.955	0.999	0.960
Agree	0.000***	0.000***	0.000***	0.000***	0.705	0.780	0.887
Consc	0.000***	0.000***	0.000***	0.000***	0.983	0.903	0.953
Emot	0.000***	0.000***	0.000***	0.000***	0.772	0.998	0.934
Extra	0.000***	0.000***	0.000***	0.000***	0.785	0.791	0.872
Open	0.000***	0.000***	0.000***	0.000***	0.481	0.693	0.786
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Location FE	No	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No	Yes
Occupation FE	No	No	No	No	No	Yes	Yes

Notes: Panel A shows the difference between AI coefficients estimated without and with computer skills controls. Panel B presents the z-statistics for these differences, calculated as $(\beta_{AI} - \beta_{AI|CS})/\sqrt{SE(\beta_{AI})^2 + SE(\beta_{AI|CS})^2}$. Panel C shows corresponding p-values, with stars indicating significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

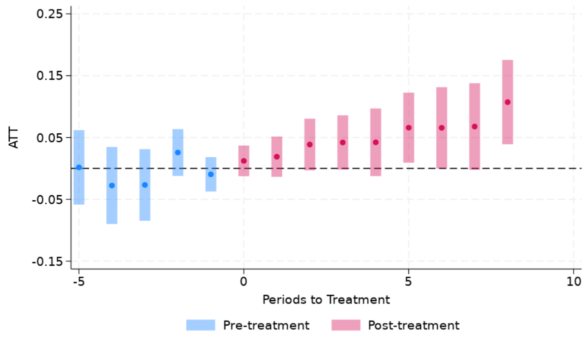
Table A.9: ATT Estimates: Half-year Aggregation

	Entropy Balance	Base	Controls
Panel A: Overall Effect			
All Personality Traits	0.041**	0.005	0.011
	(0.017)	(0.005)	(0.010)
Panel B: Effects by Trait			
Openness	0.064***	0.020***	0.045***
	(0.020)	(0.006)	(0.014)
Agreeableness	-0.007	-0.001	0.002
	(0.012)	(0.004)	(0.008)
Conscientiousness	0.027	0.006	0.001
	(0.021)	(0.006)	(0.012)
Emotional Stability	-0.010	-0.003	-0.017*
	(0.012)	(0.004)	(0.009)
Extraversion	0.025	-0.001	-0.004
	(0.021)	(0.006)	(0.014)
Pre-trend Test P-values			
All PT	0.060	0.067	0.090
Openness	0.000	0.846	0.001
Agreeableness	0.000	0.013	0.232
Conscientiousness	0.017	0.104	0.056
Emotional Stability	0.130	0.837	0.247
Extraversion	0.013	0.241	0.152
Number of Observations			
Observations	34,827	255,377	34,827

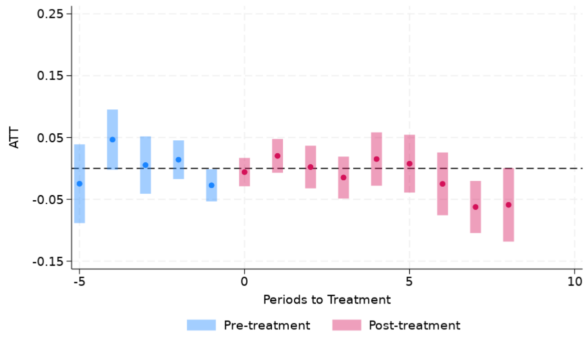
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table compares ATT estimates using three different estimators at half year level. Standard errors in parentheses, clustered at firm level. Pre-trend test p-values from chi-square test of joint significance of pre-treatment coefficients.

Figure A.16: Staggered DID ATT. half-year aggregation

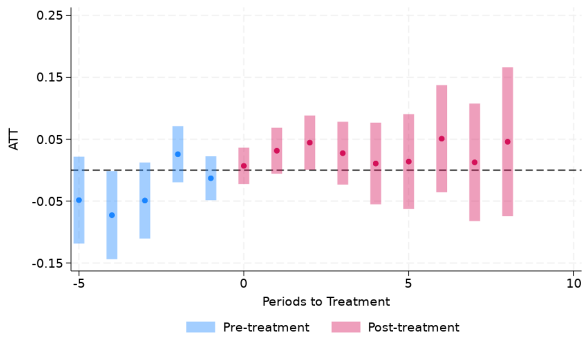
(a) All Personality Traits



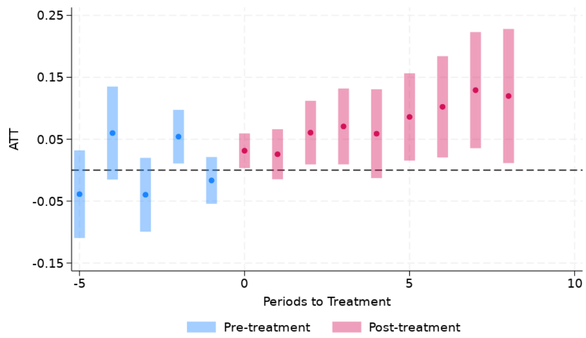
(b) Agreeableness



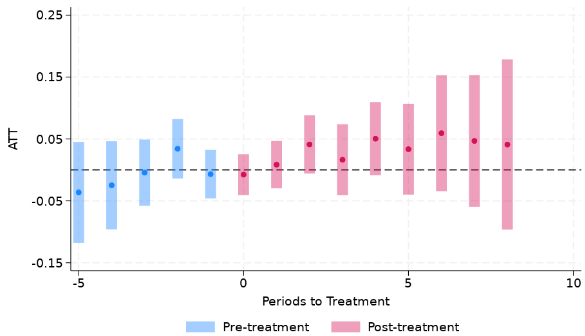
(c) Conscientiousness



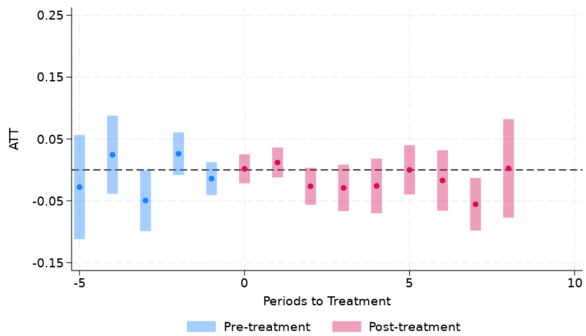
(d) Openness



(e) Extraversion



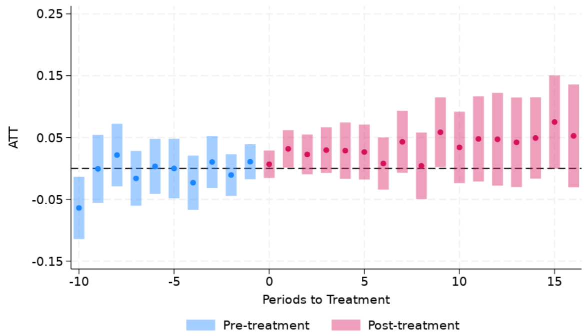
(f) Emotional Stability



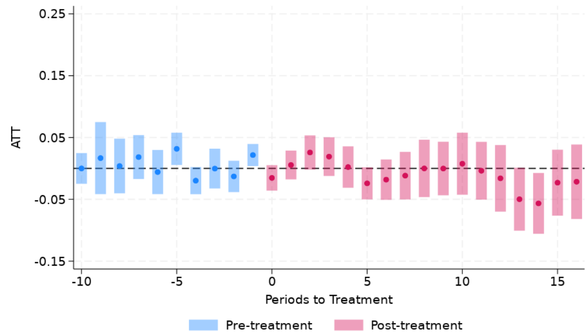
Notes: Author's creation using Adzuna.

Figure A.17: Staggered DID ATT. Quarter-level aggregation

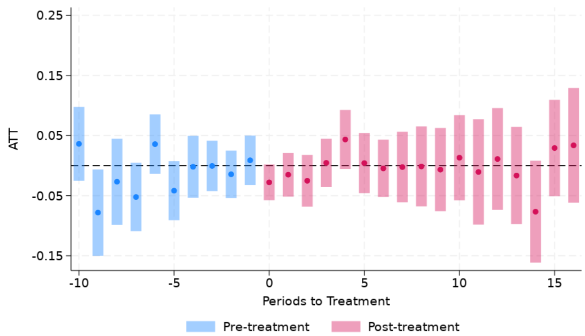
(a) All Personality Traits



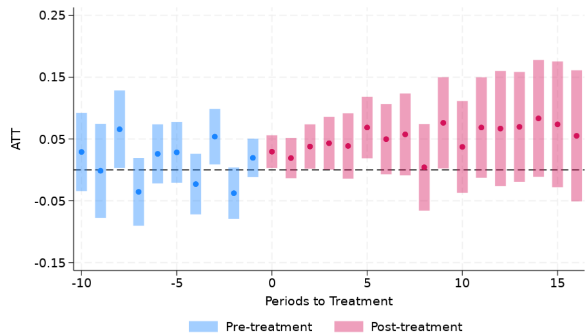
(b) Agreeableness



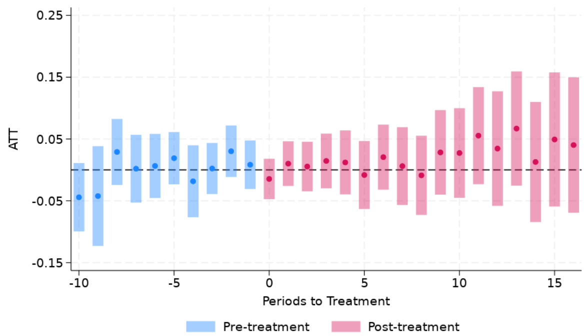
(c) Conscientiousness



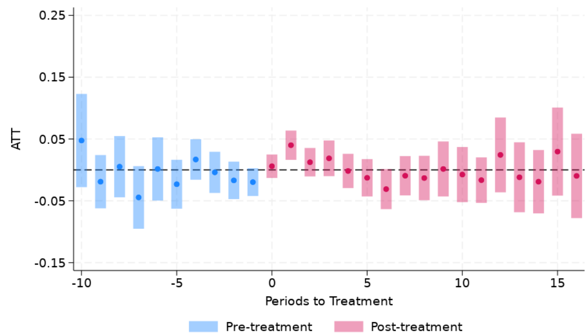
(d) Openness



(e) Extraversion



(f) Emotional Stability



Notes: Author's creation using Adzuna.

Table A.10: ATT Estimates: Quarter Aggregation

	Entropy Balance	Base	Controls
Panel A: Overall Effect			
All Personality Traits	0.031*	0.006	-0.007
	(0.016)	(0.005)	(0.010)
Panel B: Effects by Trait			
Openness	0.047**	0.019***	0.020
	(0.019)	(0.006)	(0.014)
Agreeableness	-0.007	-0.006	-0.008
	(0.012)	(0.004)	(0.009)
Conscientiousness	-0.003	0.001	-0.020
	(0.018)	(0.006)	(0.013)
Emotional Stability	0.004	0.004	-0.006
	(0.010)	(0.004)	(0.009)
Extraversion	0.013	0.005	-0.006
	(0.020)	(0.006)	(0.014)
Pre-trend Test P-values			
All PT	0.000	0.000	0.000
Openness	0.000	0.072	0.000
Agreeableness	0.000	0.005	0.000
Conscientiousness	0.000	0.000	0.000
Emotional Stability	0.000	0.022	0.000
Extraversion	0.000	0.003	0.000
Number of Observations			
Observations	52,626	361,993	52,626

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table compares ATT estimates using three different estimators at the quarterly-year level. Standard errors in parentheses, clustered at firm level. Pre-trend test p-values from chi-square test of joint significance of pre-treatment coefficients.

Table A.11: ATT Estimates for non-AI Positions: Year Aggregation

	Entropy Balance	Base	Controls
Panel A: Overall Effect			
All Personality Traits	0.025*	0.001	0.017*
	(0.014)	(0.006)	(0.009)
Panel B: Effects by Trait			
Openness	0.030	0.015**	0.043***
	(0.021)	(0.007)	(0.014)
Agreeableness	-0.014	-0.003	-0.003
	(0.017)	(0.005)	(0.009)
Conscientiousness	-0.002	0.001	0.007
	(0.019)	(0.007)	(0.012)
Emotional Stability	-0.025**	-0.004	-0.009
	(0.012)	(0.005)	(0.009)
Extraversion	0.003	0.002	-0.002
	(0.020)	(0.007)	(0.013)
Pre-trend Test P-values			
All PT	0.941	0.563	0.158
Openness	0.214	0.081	0.174
Agreeableness	0.081	0.325	0.125
Conscientiousness	0.024	0.826	0.451
Emotional Stability	0.365	0.446	0.395
Extraversion	0.775	0.584	0.349
Number of Observations			
Observations	22,009	174,250	22,009

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ATT estimates for Non-AI positions only. Treatment (AI adoption) based on first AI vacancy posted by firm. Standard errors in parentheses, clustered at firm level. Pre-trend test p-values from chi-square test of joint significance of pre-treatment coefficients.

Appendix B - Notes on the cleaning process

Other datasets used

Companies House:

Companies House is an executive agency of the UK government that provides information about registered and dissolved companies in the UK. Companies House includes 5,166,124 companies registered in the UK since 1885. It provides information for most companies' addresses, postcode of registered office, and a 4 to 6 digit Standard Industrial Code (SIC). After removing companies with the same name (hence impossible to differentiate), 4,832,015 unique companies remained. Since SIC codes are only provided for private companies, public institutions like the NHS, Universities, or Charities were not considered. Institutions and dormant companies whose SIC codes are generic (99999) were also not considered. The final Companies House dataset consists of 4,581,872 private companies.

FAME:

A financial database covering 3.4 million companies in the UK and the Republic of Ireland. The dataset contains information on company accounts, activities, ownership and management. I retrieved information on whether companies are publicly listed.

UK Household Labour Survey:

Also known as Understanding Society, the survey is a large-scale longitudinal study that aims to provide valuable insights into the social and economic aspects of individuals and households over time. Surveys a wide range of information from participants, including demographic data, employment status, income, health, and subjective well-being. Data were collected with the same methodology from 2009 until 2022.

In Wave C, performed during 2011 and 2012, the survey requested individuals to complete a short questionnaire on self-perceived attitudes, where the Big Five traits were inferred. The module presented three affirmations for each personality, and the individuals had to choose a number that best described how they saw themselves *as persons*, using a scale from 1 to 7, where 1 meant *does not apply to me at all* and 7 meant *applies to me perfectly*[19]. Then, an average score of the three responses for each trait was calculated.

- **Agreeableness:**
  - I see myself as someone who is sometimes rude to others.
  - I see myself as someone who has a forgiving nature.

[19] UKHLS creates a score for the *Neuroticism* trait. For comparison purposes with the demand side study, the values had been inverted (1/x) to infer *Emotional Stability*.

- I see myself as someone considerate and kind to almost everyone.

- **Conscientiousness:**
  - I see myself as someone who does a thorough job.
  - I see myself as someone who tends to be lazy.
  - I see myself as someone who does things efficiently.
- **Extraversion:**
  - I see myself as someone talkative.
  - I see myself as someone who is outgoing, sociable.
  - I see myself as someone who is reserved.
- **Neuroticism:**
  - I see myself as someone who worries a lot.
  - I see myself as someone who gets nervous easily.
  - I see myself as someone who is relaxed, handles stress well.
- **Openness:**
  - I see myself as someone who is original, comes up with new ideas.
  - I see myself as someone who values artistic, aesthetic experiences.
  - I see myself as someone who has an active imagination.

Cleaning of the dataset

The main purpose of the cleaning strategy was to standardise text entries, in particular the name of the company, location, and descriptive variable of the advertisement. To create an occupation variable, the Turrell et al. (2019) algorithm was used. The code requires as inputs advertisement text, job title, and industry. For the latter, companies variables were matched with Companies House. Cleaned text was later used as input to retrieve job requirements, wages, and location.

Since the entire dataset was too large for the cleaning process to be conducted in one attempt (646 GB), it was first divided into 272 weekly snapshots, and each snapshot was subdivided into 1 per cent samples using the last 2 digits of the vacancy identifier. Each of these 27,200 datasets contained around 10,000 observations.

Companies names cleaning process

Adzuna and Companies House companies lists were cleaned using the same code. The process, in STATA, involved the use of regular expressions to identify characters and words. The process intended to minimise the potential discrepancies between the same name in both datasets, therefore eliminating all non-relevant information to the name and homogenising formats. It included lowering the case; removing consecutive internal blank spaces, quotes, and special characters; changing symbol characters for their word counterpart (& for *and*), dropping endings such as "*.sol*" or "*.com*"; removing "*The*" at the beginning, and replacing text not encoded as American Standard Code for Information Interchange (ASCII) into ASCII.

In Adzuna, some companies' names identify the place where the job is located, such as *KPMG (Liverpool)*, or *Accenture (U.K.)*. This information is also available in the "location" variable, so its presence in the company name stops the algorithm from matching the company with Companies House. In consequence, the information inside the brackets at the end of a company was also removed. A considerable difference between Adzuna and Companies House is that the former frequently does not incorporate companies' categories, such as *Private Limited Company, Public Limited Company, Limited Liability Company* or its diverse acronyms and synonyms *(plc, llc, ltd, plc, lp, pcc, plc, scio, cio, cic, ukeig, limited, srl, inc, co, sp, group)*. These were removed if they appeared at the end of the company name.The cleaning process was repeated 3 times to ensure that companies with several inaccuracies in their names could be exhaustively cleaned ("*K.F.C (Liverpool) LTD++*" into "*kfc*").

Matching companies with Companies House

Since companies' names in Adzuna could have diverse variations, the cleaning process consisted of generating a dataset with all the existing entries of companies in Adzuna and applying a cleaning code. This *matching dataset* was then associated with the Companies House cleaned list of companies before removing public and dormant companies, merging into a unique data set both Adzuna's raw company name, the clean name common to Companies House, and all Company information matched from Companies House. Nearly half of the unique company entries in Adzuna (337,461) were matched. The remaining companies either present a fantasy name different from the legal name, which means they were not listed in Companies House or have missing company names. From the

Interestingly, out of the 4.5 million active and inactive companies listed in Companies House, less than 10 per cent were found in online job vacancies. This is explained by the high prevalence of Recruitment Agencies, whose growth since the global crisis in 2008 reshaped companies' strategy to recruit employees. Low barriers and increased digitalisation have benefited the industry over the past years. According to the Recruitment and Employment Confederation (REC), by 2021, more than 30,000 recruitment enterprises were operating across the UK. In the same year, nearly 550,000 permanent placements and 22.4 million temporary contracts were made by the recruitment industry (REC, 2022).

In addition, half of the companies in the Adzuna vacancy dataset could not be matched with a company in the CH data. The main reason is that companies do not necessarily publish their legal registration name when posting a job opening. These may appear with a shorter version, an acronym or a more known fantasy name. Even though the cleaning algorithm aims to unify criteria in terms of format and accessory wording, if a company publishes job advertisements using a highly different name than its legal name, then it is impossible to match it with Companies House. As an example, a company may appear in online postings as *The Berliner*, but their legal name in Companies House incorporates their complete identification *The Berliner Beer House*.

Finally, some companies may share a similar part of their legal name, (*The Berliner Services, The Berliner International, The Berliner Central*). When companies have an almost identical name, it is impossible to systematically identify which version of the name in Companies House corresponds to the clean name in Adzuna. To avoid false-positive matching, whenever a company's clean name was identical to another, none of them was incorporated.

Finally, those vacancies with company names not matched and therefore not identifiable were removed. Therefore, all the analysis done was on vacancy data which contained a matched firm name.

Recruitment agencies and companies not matched removal

In the Adzuna Database, 45 per cent of vacancies were posted by recruitment agencies, hence making it impossible to identify either the company behind the search nor the job's sector. It is possible that many enterprises, in particular small businesses, subcontract the human resource task and pay recruitment agencies to be in charge of the first recruiting stages. In addition, many existing enterprises may still not use online job boards to advertise their search, still relying on traditional means such as newspapers, word-of-mouth, or other types of referrals. Robustness checks on published wages show no significant differences between jobs posted through Recruitment agencies and those published by companies themselves.

Recruitment agencies were identified and removed following three strategies; firstly, company names containing words such as "*recruit*", "*employ,*", "*staffing*", "*personnel*", "*resourcing*", "*careers*", "*talent*" or "*placement*" were removed. These words were mostly associated with companies in SIC codes 62090 (other information technology service activities), 7810 (activities of employment placement agencies), 78200 (temporary employment agency activities), 78300 (human resources provision) and 82990 (other business support service activities), so all vacancies in these industries were removed as well. A manual inspection of companies that had a high rate of job advertisements led to the removal of another 33 recruitment agencies, including CV Library, Reed and Brook Street.

To identify companies' sectors, Standard Industrial Classification (SIC) is needed. Only private companies in the Companies House are assigned this information. Consequently, only vacancies with the company were found in both Adzuna and Companies House, and with no missing SIC, codes were kept. This led to a total of 64.6 million vacancies with associated company names and sectors not published by recruitment agencies.

Duplicates removal

Once companies' names were cleaned and matched with Companies House, and recruitment agencies were deleted, databases with the same 2 last digits of the ID variable were appended, to proceed with the removal of the duplicates.

One issue with vacancies aggregators is that an advertisement remaining open on a website does not necessarily reflect that the position has not been filled, nor vice-versa. While some companies have their advertisements posted for months or even years, constantly receiving applications, other companies may pay for a fixed advertisement time but fill the position before it ends, or not fill it at all. It becomes necessary then to deduplicate the database to only work with unique vacancies.

Using the ID variable provided by Adzuna, I kept the first observation of each vacancy that appears in the dataset. Two more rounds of duplicate removals were performed with other methods. First, by grouping variables with the same job title, company name, date created and source-id variable. In case some of the vacancies posted on different web pages were not initially captured by the Adzuna ID vacancy variable, a last duplication removal round was performed by deleting repeated observations with the same company, title, date of creation, description, and location. Since only a third of the total observations belong to unique vacancies, the number of vacancies was reduced to 20.7 million.

Cleaning text descriptions and generating new wage variables

The salary variable provided by Adzuna was coded from complementary information on web pages, and not necessarily from the text descriptions. Around 65 per cent of observations in the raw data had a non-missing salary. In comparison with other studies, Adzuna's wage variable is significantly high. For instance, wages are advertised in just 20 per cent of job advertisements in Marinescu and Wolthoff (2020) using CareerBuilder and 16.4 per cent of job advertisements in Kuhn et al. (2020) using a Chinese job portal. It is possible that, by only working with vacancies that have a posted wage, the sample becomes less representative of the general labour market. In particular, Brenčič (2012) shows that posted wages are more common in advertisements seeking less skilled workers.

When considering only the dataset with Companies House matching, recruitment agencies and duplicate removal, only 9.6 million vacancies had a non-missing wage. However, some of the entries in Adzuna's wage variable seemed to have errors or were coded in different time frames (daily/weekly/monthly rate instead of annual). I provide a robustness exercise of wage variable and revise Adzuna's entry, by retrieving salary information from the advertisement text. This entailed, first of all, cleaning job descriptions.

Similar, to the cleaning process for companies' names, the descriptions of the vacancies were cleaned using regular expressions. This process involved lowering the case, replacing HTML entities for known terms (*£* for *£* or *⋅* for "."), adding space to words besides special characters or numbers (changing *the salary will be:£35000.and the tasks will be* for *the salary will be: £ 35000 . and the task will be*) for easy identification of wages. Web pages, quotes, and special characters were removed. Finally, contractions such as "we're" or "you'd" were changed for "we are" and "you would". It followed a meticulous cleaning of the earnings text inside jobs' descriptions. Salaries in vacancies were posted in different formats. Table B.1 exemplifies the wide variety of arrangements found in job descriptions:

Table B.1: **Examples of wages differences in formats**

Differences	**Unique salaries**	**Range of salaries**
Punctuation and spaces	£35,000 £ 35000 £35, 000	£30,000-£40,000 £ 30.000 - £40000
The use of k for thousands or the lack of £ sign	£35k 35000 35k	£30k-£40,000 £ 30.000 - 40k 80 - 120000
Range separators		£30,000 to £40,000 £ 30000 - 40k £35. 000 and 40000
Monthly date	£1300 per month	
Weekly date	£500 per week	
Daily date	£80.5 per day	
Hourly date	£9 9 per hour	£8.46-10

Notes: Author's creation based on Adzuna.

The homogenising process involved replacing 2-digit annual wages for 5-digit numbers, adding pound signs when these were missing, removing empty spaces and characters in between large numbers, removing "k" when appearing after a number, and not considering numbers when referring to other items. A list of 25 common words that appear in text entries after 5-7 digit numbers were eliminated (for example, 30,000 *employees/organisations/passengers/people/clients, etc.*). An analogous cleaning exercise was done for monthly, weekly, daily and hourly information.

Once the text was cleaned, the wage was retrieved, both as unique payments and when it was offered between ranges. To construct a new earnings variable, wages which referred to annual payments were considered first. If this information was not found, then the mean of the lower and upper-range payment offers was considered. This strategy was also used by Chaturvedi et al. (2021) and Kruyen et al. (2020).

If this was not retrieved, then monthly, weekly, daily and hourly rates were considered following the same strategy and taking into account whether the job was part-time or full-time. Finally, if no information could be retrieved from the text, then Adzuna's salary variable was considered, after being revised so that all salaries were computed annually. The creation of the new salary variable out of the text entries increased the dataset by 2,446,300 observations.

A last cleaning on duplicate vacancies was performed, by dropping observations with the same source-id and by dropping observations with the same company, job title, date created, description, and location. The final dataset, with a non-cero new salary, includes 11,430,457 observations. The loss of vacancies history is described in Table B.5.

Creating NUTS location variable

Adzuna presented two location variables: *location_raw*, which could contain entries such as "Newcastle, Staffordshire" and *location_path*, containing long entries such as "UK ∼ North West England ∼ Greater Manchester ∼ Manchester ∼ The Trafford Centre". The first variable is the raw information extracted from the job vacancy, sometimes only incorporating the town where the job is located and, in a few cases, it also incorporates the postcode. The second is coded by Adzuna, but on some occasions, it does not incorporate the full path but only "UK", or "UK∼London". When it does follow the path, the information is always accurate. The approach followed was to first use *location_path*, then complement those observations with a missing detailed location variable with *location_raw*. Ultimately, they were complemented using the information from postcodes. Table B.2 is an example of *location_path* and the resulting subdivision[20]:

Table B.2: **Location example**

Loc. 1	Loc. 2	Loc. 3	Loc. 4	Loc. 5	Loc. 6
UK	North West England	Greater Manchester	Manchester	The Trafford Center	-

Notes: Author's creation based on Adzuna.

Similar to the process for matching the companies, the strategy was to match locations with a nomenclature that allows to use known location categories. Locations were mapped with the Nomenclature of Territorial Units for Statistics (NUTS). The NUTS identification at one digit (UK + letter) corresponds to 12 UK regions, as shown in Table B.3. A list containing the 3,102 unique locations found in Adzuna's location variable was created and assigned a NUTS code at 2 digits (UK+letter+number). Then, each job vacancy was

[20] All examples are illustrative and do not represent any actual vacancy information.

associated with this list, to obtain a matching as the one in Table B.4.

Table B.3: **Nuts 1**

NUTS	Code
North East	UKC
North West	UKD
Yorkshire and The Humber	UKE
East Midlands	UKF
West Midlands	UKG
East of England	UKH
London	UKI
South East	UKJ
South West	UKK
Wales	UKL
Scotland	UKM
Northern Ireland	UKN

Table B.4: **Nuts 2**

NUTS	Code
Belper	UKF1
Ely	UKH1
Mortlake	UKI7
Porthmadog	UKL1
Newton-Le-Willows	UKD7
Barnacle	UKG3
Sea Mills	UKK1
Cross Keys	UKL2
Ickenham	UKI7
Maghera	UKN0
Darlington	UKC1

Notes: Author's creation based on ONS.

A similar approach was taken for all the components of *location_raw*: they were split and matched with their corresponding NUTS codes at 2 digits. For those observations with missing information on Location 3 onwards, postcodes were used to retrieve the corresponding NUTS. These belong to four sources: first, Adzuna provided a variable with postcodes, although it had 70 per cent missing values. For those missing, postcodes in the location variable or the title of the job were retrieved. Finally, Companies House provides the location and postcode of the companies' headquarters. For those observations with job locations set in London, Companies House postcodes were used. Postcodes were ultimately matched with NUTS. In total, 96 per cent of observations have non-missing values of NUTS at 1 digit and 85 per cent at 2 digits.

Adding Standard Occupational Classification (SOC)

The major disadvantage of Adzuna's database is that it does not come with official classification labels. I implemented a Natural Language Processing (NLP) matching algorithm that maps the free-form text of job descriptions into UK Standard Occupational Classification (SOC) at three digits, following Turrell et al. (2019). Their algorithm has an accuracy rate of 76 per cent. Python codes are available on GitHub. This algorithm was also implemented by Bellatin and Galassi (2022), who group occupations according to their involvement in the production and use of digital technologies.

By identifying occupations SOC categories, it is possible to provide a granular analysis, identifying the change in personality trait demand within similar occupations. The algorithm requires as inputs a job title, a text description, and a sector identification.

Table B.5: Cleaning of the database

Process	**N vacancies**	**N no missing W***	**Mean W***	**SD W***	**Δ**
Adzuna raw database	276,325,386	178,229,590	31,120	18,524	-
Without recruitment agencies	150,918,209	83,727,680	29,882	18,558	-45%
Without missing companies match	66,833,773	32,647,950	28,365	18,392	-56%
Keep only Private companies with SIC	64,642,205	31,619,913	28,303	18,468	-3%
Remove duplicates vacancy-id, source-id, same description-location	20,783,111	10,490,006	28,342	18,830	-68%
Remove salaries missing	9,657,106	9,657,106	29,454	18,964	-54%
Incorporate new salaries from cleaned description	12,103,405	11,866,183	31,930	18,873	25%
Remove outliers in wages and text size	11,659,923	11,430,457	32,018	18,944	-4%

Notes: Author's creation based on Adzuna. $*W$ = Salary considered after trimming 1% tails.

For that, being able to match Adzuna's company's name with Companies House was fundamental.

Classification Algorithm of Turrell et al. (2019)

Authors' contribution uses the job title, description and sector for job postings from the recruitment website Reed.com. In addition, they build dictionaries using the information published by the Office for National Statistics (ONS), for the four-digit UK SOC job titles and job descriptions. Inspired in Bellatin and Galassi (2022) description, the algorithm follows these steps:

1. Cleans the job posting text data using standard text analysis tools.
2. Creates a vector space for the dictionary of UK SOC text data provided by the ONS, using the term frequency-inverse document frequency (IF-IDF).
3. Searches for exact matches between the job titles in the job postings and those in the UK SOC list.
4. Combines the job posting title, the description and the sector into one string and expresses this string as a vector in the IF-IDF matrix of the UK SOC data.
5. For jobs that were not matched, it calculates the cosine similarity between the string obtained in the previous step, and the information in the UK SOC dictionary, and selects the five categories in the UK SOC list with the highest cosine similarity.
6. If the job posting title is empty, it returns the job posting with the highest cosine similarity. Instead, if there is text in the job posting title, the fuzzy-wuzzy Python

package is used to identify the best fuzzy match out of the top five ONS categories, following Levenshtein distance calculations.

Creation of new variables for the analysis

I built dictionaries of job requirements that were later searched on job advertisements. The thesaurus of both personality traits and requirements was expanded with germane variations, including words containing spelling variations and errors. To identify potential false positives, I did manual checks in 8 rounds of 100 advertisements, for each dictionary. By looking at the 10 closed words in the proximity of the text retrieved, I ensure to be grasping sentences with the correct meaning. When the searched word retrieved a different connotation, I modified the false-positive retrieval. For instance, *flexible hours* were replace by *flx hours* to avoid it being retrieved under the *flexible* matching. Terms with multiple words, such as *machine learning*, were joint (*machinelearning*), and the code only matched these when surrounded by blank spaces, commas or stops. In total, 1702 word replacements were done.

For the Personality Traits dictionary, I followed the *Knowledge engineering* approach, where a set of explicit rules to classify text are manually defined. A job posting is identified as requiring personality traits as long as it lists at least one keyword in its text description. The strategy of identifying a requirement by pinpointing its appearance in the text description and job titles has been used by Deming and Kahn (2018), Acemoglu et al. (2022), Alekseeva et al. (2021), among others. To construct the traits dictionary, adjectives belonging to the Big Five Personality schemes were used. In comparison with previous papers using rather arbitrary *character-related* language, the dictionary was created strictly following trait-related words used in the seminal psychology and economics papers Goldberg (1990), Costa Jr and McCrae (1992), Goldberg (1992), McCrae and John (1992), John (1990), Saucier (1994) and Heckman and Kautz (2012).

For Education, I use ONS education descriptions complemented with UK qualification levels[21]. I built 8 categories, later reduced to 5 following Nandi and Nicoletti (2014). The variable was constructed to consider the lowest educational level that was made explicit in the job search. Hence, if the advertisement is looking for someone with 'a bachelor's degree in Social Science, but a master's is preferable', the observation is marked as requiring at least a bachelor's level. Interestingly, the great majority of the vacancies did not mention an educational requirement: only 12 per cent of vacancies mentioned an education requirement.

For remote work, I inspired in Draca et al. (2022) dictionary of words. According to the authors, the pandemic of Covid-19 accelerated the adoption of remote work practices.

[21] (https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels).

The appearance of remote-work-related words in job vacancies in the UK increased by 300 per cent since 2019. Figure B.1 shows the weekly share of occupations that mention Remote Work in Adzuna, before and After the Covid-19 outburst.

Figure B.1: Weekly share of occupations that mention Remote Work

Notes: Author's creation based on Adzuna.

For Seniority, I followed Nandi and Nicoletti (2014) Nyhus and Pons (2005), who claim that the relevance of a personality trait may differ according to the position. The structure of hierarchy in some occupations may be more sensitive to personality characteristics. For the same SOC code, individuals applying for senior or managerial positions, *ceteris paribus* the experience and education, have different traits than for junior placements. I follow hierarchy descriptions available in Blogs, such as Indeed.

Adzuna's raw database incorporated information from the advertisements that were not necessarily available in the text entry. This was the case for Part and Full-time indicators, and Temporary and Permanent schedules. I created dictionaries for the four categories and complemented Adzuna's variables whenever they were missing.

Finally, I incorporated a dictionary on Experience and Bonuses. For the first one, I identify whether advertisements require any type of experience or explicitly say that this is not required. For the latter, I explore different variations in the text that signal applicants that the position could have a bonus or pay-for-performance reward.

Dictionaries

The skills used by Acemoglu et al. (2022) are *machine learning, computer vision, machine vision, deep learning, virtual agents, image recognition, natural language processing, speech recognition, pattern recognition, object recognition, neural networks, ai chatbot, supervised learning, text mining, unsupervised learning, image processing, mahout, recommender* *systems, support vector machines, random forests, latent semantic analysis (lsa), sentiment analysis, opinion mining, latent dirichlet allocation (lda), predictive models, kernel methods, keras, gradient boosting, openCV, xgboost, libsvm, word2vec, machine translation, and sentiment classification.*

The skills used by Babina et al. (2024) that were not in Acemoglu et al. (2022) that were incorporated are *apache uima, artificial intelligence, autoencoders, bayesian networks/methods, caffe deep learning framework, classification algorithms, clustering algorithms, computational linguistics, convolutional neural network (cnn), dbscan (density-based spatial clustering), deeplearning4j, dimensionality reduction, dlib, expectation-maximization algorithm, hidden markov model, information extraction, jung framework, k-means, long short-term memory (lstm), matrix factorization, maximum entropy classifier, microsoft cognitive toolkit, mlpack, mxnet, naive bayes, natural language toolkit (nltk), nd4j, opennlp, pybrain, recurrent neural network (rnn), scikit-learn, semi-supervised learning, stochastic gradient descent (sgd), theano, unstructured information management architecture, vowpal, wabbit, weka.*

I expanded the list with the following terms: *a b testing, ai, bidirectional encoder (bert), chaid, cloud technology, cntk, cnns, convolutional, convolutional networks, cross domain learning, data augmentation, decision trees, deep embedding, discriminant analysis, dnn techniques, document embeddings, emotion detection, ensemble learning, ensemble methods, entity linking, fastai, feature engineering, federated learning, ffmpeg, gaussian processes, generative adversarial networks (gans), generative models, generative pre-trained transformer (gpt), hierarchical clustering, huggingface, hyperparameter tuning, image fusion, image segmentation, intelligent automation, k-nearest method, kalman filtering, knowledge distillation, kubernetes, mlflow, model compression, multi-task learning, named entity recognition, natural language generation (nlg), natural language understanding (nlu), object tracking, optical character recognition, pattern detection, pcl, predictive churn, predictive modelling, pytorch, quantum computing, recurrent network, reinforcement learning, resnets vaes, robotic process automation, rnns, sequence-to-sequence modelling, shot learning, siamese networks, similarity models, sound recognition, text classification, topic detection, topic modelling, tree based lerners, tree-based classifiers, t-sne, umap, uniform manifold, vision processing.*

Category	**Words searched**
Traits	
Agreeableness	affection, agreeableness, altruist, amiability, be gentle, considerate, co-operative, courteous, empathetic, forgiving, good nature, helpful, kind, naturalness, pleasant personality, sensitive, soft hearted, straightforward, sympathetic, trust, unselfish, warm

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Table B.6 – continued from previous page

Category	Words searched
Extraversion	adventurous, assertive, bold, candour, confident, courage, daring, energetic, enthusiastic, expressive, extraverted, forceful, friendly, funny, gregarious, humour, optimist, outgoing, outspoke, passion, playful, proactive, sociable, spontaneous, talkative
Conscientiousness	ambitious, be careful, competent, conscientious, decisive, dependable, dutiful, efficient, hard work, be logic, be neat, organised, painstaking, perseverance, persistent, planful, precise, prompt, punctual, reliable, responsible, striving, systematic, be thorough
Emotional Stability	at ease, calm, emotional, hostil, not fearful, tempered, fortitude, resilience, tense situations, unflappable, patience, pressure
Openness	artistic, be bright, be clever, creative, curious, flexible, ideas, imaginative, independent mind, ingenious, innovative, insightful, intellectual, intelligent, introspective, inventive, openness, be original, prefer variety, reflective, be sharp, unconventional, wide interests, witted
Skills	
Soft Skills	analytical, communication skills, critical thinking, cultural sensitivity, decision making, language skills, leadership, listening skills, mentoring, negotiation, networking abilities, presentation, problem solving, interpersonal, teamwork, time management, attention to detail, organisation skills, multitask, conflict resolution, soft skills, planning, questioning
Hard Skills	accounting, administrative, content creation, copywriting, data analysis, design skills, editing, engineering, legal analysis, marketing, microsoft office, project management, quality assurance, sales skills, software, statistics, user experience, video production, customer service, business development, computer literacy, commercial skills, budget, research, stakeholder

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Table B.6 – continued from previous page

Category	**Words searched**
AI Skills	machine learning, computer vision, machine vision, deep learning, virtual agents, image recognition, speech recognition, pattern recognition, object recognition, neural networks, supervised learning, text mining, support vector machines, unsupervised learning, image processing, image fusion, mahout, recommender systems, random forests, latent semantic analysis, sentiment analysis, opinion mining, latent dirichlet allocation, predictive models, kernel methods, keras, gradient boosting, gradient descent, opencv, xgboost, libsvm, word2vec, ai chatbot, machine translation, sentiment classification, generative adversarial networks, reinforcement learning, quantum computing, federated learning, natural language understanding, natural language processing, natural language generation, mlops, artificial intelligence, cloud technology, tensorflow, pytorch, scikit learn, natural language toolkit, bidirectional encoder, shot learning, ensemble methods, decision trees, k means clustering, autoencoders, robotic process automation, cnns, rnns, optical character recognition, named entity recognition, topic modelling, ab testing, dimensionality reduction, feature engineering, hyperparameter tuning, data augmentation, model compression, knowledge distillation, kalman filtering, kubernetes, azure ml, weka, clustering algorithms, classification algorithms, density based spatial clustering, caffe deep learning framework, generative pretrained transformer, expectation maximization, jung framework, theano, hugging face, ffmpeg, dlib, mxnet, vowpal wabbit, mlflow, bayesian methods, kubeflow, spark ml, discriminant analysis, long short term memory, hidden markov model, computational linguistics
Work Location	
Remote Work	conducted remote, fully remote, home based, homework, homeworking, job is remote, job is virtual, location is remote, location remote, position is remote, position remote, remote work, role will be remote, telecommuting, telework, virtual job, work from home, work home, work remote, working remote, flexible with office, remote position, role is remote, remote basis, hybrid work, hybrid remote
Seniority	
Level 1	chief, director, executive, vice president
Level 2 high	associate, coordinator, project lead, senior, supervisor, team lead, supervising a team, manager
Level 2 low	administrator, agent role, analyst, consultant, generalist, representative role, technician, secretary
Level 3	apprentice, assistant, clerk, internship, junior, receptionist, trainee, trial period, entry level
Education	

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Table B.6 – continued from previous page

Category	Words searched
No Formal Education	basic functional skills, basic skills qualification, entry level certificate, entry level functional skills, entry level qualifications, entry nqf level, essential skills wales, level 1 scqf, level 1 svq, level 2 scqf, level 2 svq, level 3 scqf, level 3 svq, no education requirements, no esol, no formal qualification, no previous experience or qualification, no previous qualification, no qualification, scottish national 1, scottish national 2, scottish national 3, scqf level 2, scqf level 3, skills for life, svq level 2, svq level 3, no formal education
GCSE Level	gcse, gnvq, btec award, btec first, btec level 1, certificate of secondary education, first certificate, foundation welsh baccalaureate, key skills level 1, level 1 award, level 1 certificate, level 1 diploma, level 1 esol, level 1 essential skills, level 1 functional skills, level 1 key skills, level 1 national vocational qualification, level 1 nvq, nqf level 1, nvq level 1, rqf level 1, scqf level 4, diploma level 1, esol 1, national level 1, qualification level 1, level 1 qualification, qcf level 1, level 1 qcf, functional skills level 1, essential skills level 1, level 1 apprenticeship, cipd level 1, level 1 cipd, level 4 scqf, level 4 svq, svq level 4
O-Level	o level, btec level 2, general certificate of education, intermediate apprenticeship, intermediate welsh baccalaureate, key skills level 2, level 2 award, level 2 certificate, level 2 diploma, level 2 esol, level 2 essential skill, level 2 functional skill, level 2 key skills, level 2 national, level 2 nvq, national level 2, nqf level 2, nvq level 2, rqf level 2, scqf level 5, secondary education, diploma level 2, award level 3, esol 2, qcf level 2, level 2 qcf, esol level 2, functional skills level 2, essential skills level 2, qualification level 2, level 2 qualification, level 2 apprenticeship, cipd level 2, level 2 cipd, level 5 scqf, level 5 svq, svq level 5, certificate of secondary education
A-Level	a level qualification, as level qualification, access to higher education diploma, advanced apprenticeship, advanced diploma, advanced extension, advanced welsh baccalaureate, baccalaureate, btec award level 3, btec certificate level 3, btec diploma level 3, btec level 3, btec national, diploma programme, extended certificate, extended diploma, key skills level 3, level 3 award, level 3 certificate, level 3 esol, level 3 national, level 3 nvq, national level 3, nqf level 3, nvq level 3, ocr national, progression diploma, rqf level 3, scottish advanced higher, scottish baccalaureate, scottish higher, scqf level 6, diploma level 3, award level 3, esol 3, nvqs level 3, qcf level 3, level 3 qcf, functional skills level 3, essential skills level 3, qualification level 3, level 3 qualification, level 3 apprenticeship, cipd level 3, level 3 cipd, level 6 scqf, level 6 svq, svq level 6

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Table B.6 – continued from previous page

Category	Words searched
Higher Certificate	hnc, certhe, certificate of higher education, higher apprenticeship, higher national certificate, level 4 award, level 4 certificate, level 4 diploma, level 4 national, level 4 nvq, national level 4, nqf level 4, nvq level 4, scqf level 7, diploma level 4, award level 4, nvqs level 4, qcf level 4, level 4 qcf, functional skills level 4, essential skills level 4, qualification level 4, level 4 qualification, level 4 apprenticeship, cipd level 4, level 4 cipd, level 7 scqf, level 7 svq, svq level 7
Higher Diploma	hnd, btec professional, diphe, diploma of further education, diploma of higher education, foundation degree, higher diploma, higher national diploma, level 5 award, level 5 certificate, level 5 diploma, level 5 national, level 5 nvq, national level 5, nqf level 5, nvq level 5, rqf level 4, scqf level 8, diploma level 5, award level 5, nvqs level 5, qcf level 5, level 5 qcf, qualification level 5, level 5 qualification, cipd level 5, level 5 cipd, level 8 scqf, level 5 apprenticeship, level 5 professional, level 8 svq, svq level 8
Bachelor's Degree	bachelor, bachelors degree, btec advanced professional, degree apprenticeship, first degree, grad cert, grad dip, bachelor certificate, bachelor diploma, level 6 award, level 6 certificate, level 6 diploma, level 6 national, level 6 nvq, national level 6, nqf level 6, nvq level 6, ordinary degree, oxbridge ma, rqf level 5, scottish ma, scqf level 10, scqf level 9, ugad, undergraduate, higher education, diploma level 6, award level 6, nvqs level 6, qcf level 6, level 6 qcf, qualification level 6, level 6 qualification, cipd level 6, level 6 cipd, level 9 scqf, level 10 scqf, level 6 apprenticeship, level 6 professional, level 10 svq, svq level 10, have a degree, bsc or masters, degree or master, bsc or msc, ba or ma, honours degree
Master's Degree	award level 7, ba and ma, cipd level 7, diploma level 7, have a master, have a masters, level 11 scqf, level 11 svq, level 7 apprenticeship, level 7 award, level 7 certificate, level 7 cipd, level 7 diploma, level 7 national, level 7 nvq, level 7 professional, level 7 qcf, master of arts, master of business administration, master of engineering, master of law, master of mathematics, master of pharmacy, master of philosophy, master of physics, master of professional studies, master of public health, master of research, master of science, master of social work, master of studies, masters, masters by research, masters degree, national level 7, nqf level 7, nvq level 7, nvqs level 7, postgrad, postgraduate certificate, postgraduate certificate in education, postgraduate diploma, professional masters, qcf level 7, rqf level 6, rqf level 7, scqf level 11, svq level 11
Doctorate	doctor of philosophy, doctoral degree, doctorate, doctors degree, level 8 award, level 8 certificate, level 8 diploma, level 8 national, level 8 nvq, national level 8, nqf level 8, nvq level 8, phd, rqf level 8, scqf level 12, diploma level 8, award level 8, nvqs level 8, qcf level 8, level 8 qcf, cipd level 8, level 8 cipd, level 12 scqf, level 8 apprenticeship, level 8 professional, svq level 12, level 12 svq
Schedule	

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Table B.6 – continued from previous page

Category	Words searched
Full-time	9 to 5, day shift, full time, standard hours, night shift
Part-time	4 hour, 6 hour, part time, 20 hour, 30 hour
Duration	
Temporary	apprenticeship, fixed term, freelance, interim, internship, project base, seasonal contract, self employed, short term contract, temporary, day to day contract, zero hours, casual contract
Permanent	long term, ongoing contract, permanent
Experience	
Required	3 to 5 years, experienced, can demonstrate, demonstrable, essential experience, experience a minimum, experience for, experience in, experience is also, experience needed, experience of, experience preferably, experience required, experience working, extensive experience, for experienced, has experience, have experience, have previous experience, have some knowledge, have worked, minimum experience, months experience, need experience, past experience, practical experience, previous, prior experience, proven, recent experience, relevant experience, right experience, solid experience, strong experience, suitable experience, three to five years, two to three years, with experience, work experience, worked in similar, years experience, years of experience, you got experience, required experience, experience essential, experience is preferred
Not Required	a novice, do not need any, do not need experience, don't need experience, don't need previous, experience is not, experience not, lots of experience, need any experience, no essential experience, no experience, no formal experience, no formal qualifications or experience, no past experience, no previous, no prior, no work experience, not essential, not necessary, not need previous, with no experience, without any experience, don't need experience, not needed
Other	
Bonus	bonus, commission, incentive, profit sharing, reward scheme, stock options, variable pay, performance related, rewards packages, pay for performance
Teaching	can teach, teaching
Negotiable	on experience, negotiable salary, salary negotiable, hour negotiable, salary is negotiable, salary up to
Communication	working directly with, reporting, report into, your team leader, working with, working closely, under the direction, speaking to, directly to, work alongside, required by, keeping your, work closely, reports, step to, shadowing, managing the, assistance to the, work with, managed by, approval of, communicate with, supporting

Dictionaries built following (1) Goldberg (1990); (2) Costa Jr and McCrae (1992); (3) Goldberg (1992); (4) McCrae and John (1992); (5) John (1990); (6) Saucier (1994); (7) Heckman and Kautz (2012) were scrutinised as not to retrieve false positive words. Each word's context was analysed by sampling the dataset in 8 rounds of 100 advertisements per word. When the word's context was not related to personality traits and a straightforward amendment of the word was not possible, this was removed from the dictionary. Words that did not retrieve any match were also not considered.

Before searching for words, modifications were made to some words to avoid false positives and account for different variations of words. The list of changes done to the text is the following:

Personality Traits language:

"altruistic" for "altruist ", "altruism" for "altruist ", "amiable" for "amiability ", "empathy" for "empathetic ", "empathic" for "empathetic ", "extraversion" for "extraverted ", "extrovert" for "extraverted", "extrovertion" for "extraverted", "emotion" for "emotional", "emotionally" for "emotional", "reslient" for "recilience, "extroversion" for "extraverted ", "extroverted" for "extraverted ", "optimism" for "optimist ", "optimistic" for "optimist ", "outspoken" for "outspoke ", "spontaneity" for "spontaneous ", "ambition" for "ambitious", "competence" for "competent", "efficiency" for "efficient", "persevere" for "perseverance", "persevering" for "perseverance", "persistence" for "persistent", "hostile" for "hostil ", "hostility" for "hostil ", "creativity" for "creative", "creatively" for "creative", "innovation" for "innovative", "innovations" for "innovative", "innovating" for "innovative", "innovator" for "innovative", "intellect" for "intellectual", "intellectually" for "intellectual", "unconvention" for "unconventional", "pro active" for "proactive", "compassion" for "comps", "compassionate" for "comps", "an executive" for "an exec", "analytics" for "analysis", "and executive" for "and exec", "sense of adventure" for "adventurous", "humor" for "humour", "anger" for "angry", "anxiety" for "anxious", "agreeable personality" for "agreeableness", "being on time" for "punctual", "co operative" for "cooperative", "comfortable using" for "confoble using", "appreciative of" for "appreciativeof", "at ease" for "atease", "curios" for "curious", "owned cooperative" for "owned cop", "your energy" for "energetic", "with energy" for "energetic", "and energy" for "energetic", "encourages" for "encorages", "encourage" for "encorage", "encouraged" for "encoraged", "encouragement" for "encoragement", "discourage" for "discorage", "encouraging" for "encoraging", "confidential" for "confidntial", "self confidence" for "self confident", "confident employer" for "employer", "confident in" for "good in", "confidentiality" for "confid", "confidentially" for "confid", "confident at" for "good at", "confidently" for "good at", "originally posted" for "posted", "original proof" for "proof", "daring and apply" for "apply", "darington" for "daryngton", "daring to" for "daryng to", "our daring" for "our", "calendaring" for "calendar", "expressive arts" for "arts", "boldon" for "bolon", "nwebold" for "newbld", "not fearful" for "notfearful", "never fearful" for "notfearful", "be fearful" for "notfearful", "being fearful" for "notfearful", "careful to select" for "to select", " careful " for " becareful ", "spontaneous holiday" for "holiday", "to spontaneous" for "to fast", "from spontaneous" for "from fast", "spontaneous monthly" for "monthly", "spontaneous moments" for "moments", "various spontaneous" for "various", "spontaneous events" for "events", "are clever" for "beclever", "be clever" for "beclever", ", clever" for " beclever", "clever," for "beclever ", "with clever" for "beclever","some clever" for "beclever", "clever and" for "beclever", "and clever" for "beclever", "flexible shift" for "flx shift", "flexible shifts" for "flx shifts", "flexible working" for "flx work", "flexible work" for "flx work", "flexible with" for "flx with", "flexible basis" for "flx basis", "flexible hours" for "flx hours", "flexible benefit" for "flx benefit", "flexible benefits" for "flx benefits", "flexible about" for "flx about", "hours are flexible" for "hours are flx", "flexible annual" for "flx annual", "flexible to" for "flx to", "flexible for" for "flx for", "is flexible" for "is flx", "flexible hour" for "flx hour", "fully flexible" for "fully flx", "flexible schedule" for "flx schedule", "flexible salary" for "flx salary", "to flexible" for "tp flx", "flexible new" for "flx new", "flexible holiday" for "flx holiday", "flexible way" for "flx way", "flexible ways" for "flx ways", "pay flexible" for "flx pay", "work flexible" for "flx work", "flexible contract" for "flx contract", "flexible opportunities" for "flx opportunities", "flexible options" for "flx options”, “flexible subcontract” for “flx subcontract”, “be flexible as” for “flx as”, “flexible between” for “flx between”, “flexible start” for “flx start”, “flexible rota” for “flx rota”, “weeks are flexible” for “flx week”, “flexible days” for “flx days”, “choose flexible” for “choose flx”, “entirely flexible” for “entirely flx”, “flexible within” for “flx within”, “for flexible” for “for flx”, “flexible additional” for “flx additional”, “flexible fixed” for “flx fixed”, “times flexible” for “times flx”, “location flexible” for “location flx”, “flexible on” for “flx on”, “flexible schedules” for “flx schedules”, “flexible reward” for “flx reward”, “flexible rewards” for “flx rewards”, “flexible 40” for “flx 40”, “flexible weekend” for “flx weekend”, “flexible vacancies” for “flx vacancies”, “scheme flexible” for “scheme flx”, “flexible in working” for “flx in working”, “flexible menu” for “flx menu”, “time flexible” for “time flx”, “flexible pm” for “flx pm”, “flexible saturdays” for “flx saturdays”, “flexible home” for “flx home”, “flexible team“ : “flx team”, “cleaner flexible“ : “cleaner flx”, “flexible and optional“ : “flx and optional”, “flexible self employed“ : “flx self employed”, “flexible in relation to“ : “flx in relation to”,“flexible and able to“ : “flx and able to”, “flexible, full“ : “flx, full”, “flexible full“ : “flx full”, “flexible pattern“ : “flx pattern”, “hours of work can be flexible“ : “flx hours”, “flexible approach to remote working“ : “flx remote working”, “flexible work” for “flx work”, “flexible and guaranteed hours“ : “flx hours”, “flexible networks“ : “flx networks”, “flexible job“ : “flx job”, “benefits flexible“ : “flx benefits”, “weekdays flexible“ : “flx weekdays”, “flexible guaranteed hours“ : “flx hours”, “freelance and flexible“ : “freelance and flx”, “flexible with office“ : “flx with office”, “options flexible“ : “options flx”, “flexible core“ : “flx core”, “flexiblejob“ : “flx job”, “workflexible“ : “work flx”, “flexbile interview“ : “flx interview”, “flexible temporary“ : “flx temporary”, “flexible, part“ : “flx, part”, “flexible part“ : “flx part”, “flexible and home“ : “flx and home”, “days are flexible“ : “days are flx”, “flexible employment“ : “flx employment”, “that flexible“ : “that flx”, “flexible location“ : “flx location”, “flexible rotas“ : “flx rotas”, “flexible and remote“ : “flx and remote”, “flexible pension“ : “flx pension”, “esteemed” for “estemed”, “be bright ” for “bebright ”, “ bright and” for “ bebright”, “and bright” for “bebright”, ”, bright ” for “ bebright ”, “ bright, ” for “ bebright ”, “ a bright ” for “ bebright ”, “brightest” for “bebright”, “bright welcoming” for “welcoming”, “bright future” for “future”, “bright sunny” for “sunny”, “be helpful” for “be help”, “is helpful” for “is help”, “experience helpful” for “experience help”, “independent minded” for “independentmind”, “independent mind” for “independentmind”, “prefer variety” for “prefervariety”, “straight forward” for “straightforward”, “straightforward for you” for “forward for you”, “straight forward for you” for “forward for you”, “straightforward questionnaire” for “questionnaire”, “very straightforward” for “very”, “provides straight forward” for “provides”, “straightforward design” for “design”, “is straight forward” for “is”, “friendly policies” for “frend policies”, “family friendly” for “family frend”, “friendliness” for “friendly”, “user friendly” for “user friend”, “friendly local” for “local”, “dogfriendly” for “dog”, “ecofriendly” for “eco”, “ gentle ” for “ begentle ”, “solver” for “solving”, “wide interest” for “wideinterests”, “wider interest” for “wideinterests”, “otherwise” for “other”, “likewise” for “like”, “connectwise” for “connect”, “deliberateness” for “deliberate”, “beneath” for “beneth”, “ neat ” for “ beneat ”, “ be neat ” for “ beneat ”, “helpful tool” for “tool”, “effective communication” for “communication skill”, “optimisation” for “optimization”, “optimisations” for “optimizations”, “optimising” for “optimizing”, “optimise” for “optimize”, “optimised” for “optimized”, “optimises” for “optimizes”, “optimiser” for “optimizer”, “empathy” for “empathetic”, “enthusiasm” for “enthusiastic”, “open, ” for “openness ”, “open and” for “openness ”,“and open ” for “openness ”,“openmind” for “openness”, “open mind” for “openness ”,“open minded” for “openness ”, “openness close ” for “close”, “open and close” for “close”, “open source” for “source”, “openness source” for “source”, “enthusiast” for “enthusiastic”, “fun ” for “fun ”, “fun day” for “fus day”, “fun park” for “fus park”, “fun ” for “funny ”, “fun,” for “funny ”, “fun.” for “funny ”, “grounded in” for “in”, “be grounded in ” for “in”, “grounded established” for “established”, “a grounded” for “ a ”,“grounded knowledge” for “knowledge”, “grounded programming” for “programming”,“grounded perspective” for “perspective”,“grounded reflected” for “reflected”,“grounded solutions” for “solutions”, “grounded and” for “begrounded”, “and grounded” for “begrounded”, ”, grounded” for “

begrounded”, “grounded,” for “begrounded ”, “be grounded” for “begrounded”, “grounded analysis” for “analysis”, “well grounded” for “well”, “ a grounded,” for “ a ”, ”, grounded in” for “ in”, “begrounded in” for “ in”, ”, grounded in ” for “in ”, “hard working” for “hardwork”, “sociable hours” for “hours”, “sociable working hours” for “working hours”, “hard work” for “hardwork”, “hardworker” for “hardwork”, “hardworking” for “hardwork”, “logic apps” for “apps”, “ logic ” for “ belogic ”,“ logical ” for “ belogic ”, “thorough knowledge” for “knowledge”, “bethorough knowledge” for “knowledge”, “and thorough” for “bethorough”, ”,thorough” for “bethorough”, “thorough and” for “bethorough”,“be thorough” for “bethorough”, “home working” for “homeworking”, “sensitive information” for “information”, “sensitive or contentious information” for “contentious information”, “sensitive and restricted information” for “restricted information”, “sensitive data” for “data”, “sensitive company” for “company”, “intellectual property” for “property”, “intellectual dis” for “dis”, “track record” for “experienced”, “background” for “experienced”, “outgoing mail” for “mail”, “outgoing call” for “call”, “pleasant attitude” for “pleasantpersonality”, “pleasant personality” for “pleasantpersonality”, “pleasant manner” for “pleasantpersonality”, “be pleasant” for “pleasantpersonality”, “pleasant and” for “pleasantpersonality”, “kind of” for “jind of”, “kinds of” for “jinds of”, “kindly” for “jindly”, “kind to” for “jind to”, “tender minded” for “tendermind”, “ tender mind” for “tendermind”, “good nature” for “goodnature”, “tense situations“:“tensesituations”, “under control“:“undercontrol”, “competencies” for “skills”, “competence in” for “skilled in”, “competence with” for “skilled with”, “soft heart” for “warm heart”, “soft hearted” for “warm hearted”, “competency” for “skilled”, “competently” for “skilled”, “organized” for “organised”,“show consideration” for “considerate”, “temperance” for “tempered”, “temperament” for “tempered”, “original solutions” for “beoriginal”, “original thinking” for “beoriginal”, “original ideas” for “beoriginal”, “original research” for “beoriginal”, “be original” for “beoriginal ”, “original, ” for “beoriginal”, “original writing” for “beoriginal”, “original content” for “beoriginal”, “is original” for “beoriginal”, “think originally” for “beoriginal”, ”, original” for “ beoriginal”, “original thought” for “beoriginal”, “original choice” for “beoriginal”, “originality” for “beoriginal”, “creating original” for “beoriginal”, “national trust” for “nationaltr”, “trusts” for “trus”, “trustee” for “trusee”,“trustees” for “trusees”, “cooperative trust” for “coperative”, “nhs trust” for “nhs”, “trust us” for “trus us”, “trusted” for “trused”, “ our trust” for “ our trus”, “local trust” for “local”, “trust are” for “are”, “academy trust” for “academy”, “trust schools” for “schools”, “the trust” for “the trus”, “trust is” for “is”, “foundation trust” for “foundation”, “at trust” for “at trus”, “entrusted” for “enrusted”, “wildlife trust” for “wildlife”, “castle trust” for “castle”, “trust scheme” for “scheme”, “trust duties” for “duties”, “education trust” for “education”, “adventure trust” for “adventure”, “disabilities trust” for “disabilities”, “affinity trust” for “affinity”, “academies trust” for “academies”, “whole trust” for “whole”, “trust offers” for “offers”, “trust within” for “within”, “trust and corporate” for “corporate”, “trust duties” for “duties”, “trust and grants” for “grants”, “leisure trust” for “leisure”, “we trust” for “we”, “trust manages” for “manages”, “enterprise trust” for “enterprise”, “trust keith” for “keith”, “trust flagship” for “flagship”, “woodland trust” for “woodland”, “trust and fundraising” for “fundraising”, “care trust” for “care”, “health trust” for “health”, “rivers trust” for “rivers”, “transform trust” for “transform”, “transformation trust” for “transformation”, “are a trust ” for “are ”, “trust qvd” for “qvd”, “educational trust” for “educational”, “trust exposure” for “exposure”, “trust has” for “has”, “dean trust” for “dean”, “trust delivers” for “delivers”, “as a trust ” for “ ”, “london trust” for “london”, “trustpilot” for “ ”, “trust pilot” for “ ”, “trust education” for “education”, “trust we believe” for “we believe”, “northern trust” for “northern”, “trust website” for “website”, “trust. org” for “.org”, “trust . org” for “.org”, “trust.org” for “.org”, “trust org” for “org”, “persist” for “persistent”, “prompt response” for “prom response”, “as prompt” for “as prom”, “prompting” for “promting”, “precisely what” for “what”, “as prompt” for “as prom”, “warm welcome” for “welcome”, “warm you” for “you”, “reliable vehicle” for “rel veh”, “representative of” for “represent of”, “responsible to” for “res to”, “responsible of” for “res of”, “responsible in” for “res in”, “responsible for” for “res for”, “reflective of” for “ref of”, “a reflective” for “a ref”, “ sharp ” for “

besharp ", "socially responsible" for "socially res", "unsociable" for "unsoci", "are striving" for "are str", "sympathetically converted" for "converted", "sympathetically restored" for "restored", "sympathetic refurbishment" for "refurbishment", "sympathetic donors" for "donors".

Soft skills language:
"communication skills" for "communicationskills", "critical thinking" for "criticalthinking", "cultural sensitivity" for "culturalsensitivity", "decision making" for "decisionmaking", "language skills" for "languageskills", "listening skills" for "listeningskills", "problem solving" for "problemsolving", "time management" for "timemanagement", "attention to detail" for "attentiontodetail", "organisation skills" for "organisationskills", "conflict resolution" for "conflictresolution", "soft skills" for "softskills","maintain relationships" for "networkingabilities", "network abilities" for "networkingabilities", "working relationships" for "networkingabilities", "network ability" for "networkingabilities", "relationship building" for "networkingabilities", "headhunting" for "networkingabilities", "networking events" for "networkingabilities", "maintain contacts" for "networkingabilities", "external relationships" for "networkingabilities", "strong relationships" for "networkingabilities", "personal network" for "networkingabilities", "ability to network" for "networkingabilities", "attend events" for "networkingabilities", "business relationships" for "networkingabilities", "positive relationships" for "networkingabilities", "good listening" for "listening skills", "good listener" for "listening skills", "active listening" for "listening skills", "ability to listen" for "listening skills", "resolve issues" for "problemsolving", "problem solver" for "problemsolving", "fluency" for "fluent", "representation" for "reprsentation", "representations" for "reprsentation", "making decisions" for "decisionmaking", "make decisions" for "decisionmaking", "best decisions" for "decisionmaking", "good decisions" for "decisionmaking", "take decisions" for "decisionmaking","informed decisions" for "decisionmaking", "difficult decisions" for "decisionmaking", "appropriate decisions" for "decisionmaking", "resolving the complex problems" for "problemsolving", "resolving complex problems" for "problemsolving", "negotiating" for "negotiation", "negotiator" for "negotiation", "good spoken" for "communicationskills", "transparent communication" for "communicationskills", "good communication" for "communicationskills", "strong communication" for "communicationskills", "excellent communication" for "communicationskills", "written and verbal" for "communicationskills", "written and oral" for "communicationskills", "oral and written" for "communicationskills", "communication abilities" for "communicationskills", "great communication" for "communicationskills", "oral" for "communicationskills", "verbal, written" for "communicationskills", "technical writting" for "communicationskills", "verbal and written" for "communicationskills", "written" for "communicationskills", "verbal" for "communicationskills", "oral" for "communicationskills", "ability to communicate" for "communicationskills", "strong communicator" for "communicationskills", "excellent communicator" for "communicationskills", "good communicator" for "communicationskills", "communicator" for "communicationskills", "able to communicate" for "communicationskills", "transparent communication" for "communicationskills", "great communication" for "communicationskills", "can lead" for "leadership", "people management" for "leadership", "able to lead" for "leadership", "team leadership" for "supervisingateam", "team leadership" for "leading a team", "team management" for "leading a team", "cultural awareness" for "culturalsensitivity", "crosscultural" for "culturalsensitivity", "multicultural" for "culturalsensitivity", "multi cultural" for "culturalsensitivity", "culturally diverse" for "culturalsensitivity", "culturally aware" for "culturalsensitivity", "cultural diversity" for "culturalsensitivity", "asking questions" for "questioning", "european language" for "languageskills", "fluent in chinese" for "languageskills", "fluent in german" for "languageskills", "fluent in french" for "languageskills", "fluent in english" for "languageskills", "fluent in mandarin" for "languageskills", "fluent in spanish" for "languageskills", "fluent in portuguese" for "languageskills","fluent in polish" for "languageskills", "fluent speaking" for "languageskills", "fluent in dutch" for "languageskills", "fluent in russian" for "languageskills", "two languages" for "languageskills", "fluent in both" for "languageskills", "fluent in hebrew" for "languageskills", "fluent in speaking" for "languageskills", "fluent in italian" for "languageskills", "fluent in welsh" for "languageskills",

"fluent in japanese" for "languageskills", "fluent in danish" for "languageskills", "fluent in english and" for "languageskills", "communicating in two langauges" for "languageskills", "fluent both english and" for "languageskills", "fluent in english as well as" for "languageskills", "fluent in another" for "languageskills", "fluent in the german" for "languageskills", "number of languages" for "languageskills", "fluent in turkish" for "languageskills", "coaching" for "mentoring", "provide guidance" for "mentoring", "multiple projects" for "multitask", "multiple tasks" for "multitask", "training and mentoring" for "training", "mentoring and training" for "training", "multi projects" for "multitask", "multitasker" for "multitask", "multitasking" for "multitask", "ability to motivate" for "mentoring","able to motivate" for "mentoring", "couching" for "mentoring", "problem resolution" for "problemsolving", "complex problems" for "problemsolving", "other languages" for "languageskills", "additional languages" for "languageskills", "multilingual" for "languageskills", "office skills" for "microsoftoffice", "excel skills" for "microsoftoffice", "ms packages" for "microsoftoffice", "ms package" for "microsoftoffice", "organisational skills" for "organisationskills", "organizational skills" for "organisationskills", "organisational capacity" for "organisationskills", "organisational abilities" for "organisationskills", "organisational ability" for "organisationskills", "excellent organisation" for "organisationskills", "organisation, coordination" for "organisationskills", "organisational and managements skills" for "organisationskills", "excellent organisational" for "organisationskills", "good organisational" for "organisationskills", "strong organisational" for "organisationskills", "organisational, " for "organisationskills ", "organisational and " for "organisationskills ", "strong managements skills" for "organisationskills", "excellent managements skills" for "organisationskills", "competent managements skills" for "organisationskills", "strong organisational" for "organisationskills", "prioritisation" for "organisationskills", "able to prioritise" for "organisationskills", "excellent organisation" for "organisationskills", "mentoring of the junior" for "mentoring", "mentoring junior" for "mentoring", "able to mentor the more junior members" for "mentoring", "mentoring our junior" for "mentoring", "mentoring our more junior" for "mentoring", "able to mentor junior" for "mentoring", "especially junior" for "mentoring", "mentor junior" for "mentoring", "mentoring and training of more junior" for "mentoring", "mentoring to junior" for "mentoring", "mentoring of junior" for "mentoring", "mentoring and coaching junior" for "mentoring", "mentor more junior" for "mentoring", "training of junior" for "mentoring", "eye for detail" for "attentiontodetail", "detail oriented" for "attentiontodetail", "detailed approach" for "attentiontodetail", "mentoring more junior" for "mentoring", "support junior" for "mentoring", "managing junior" for "mentoring", "developing junior" for "mentoring", "developing more junior" for "mentoring", "support to more junior" for "mentoring", "support more junior" for "mentoring", "development of junior" for "mentoring", "work of junior" for "mentoring", "coaching more junior" for "mentoring", "coaching of junior" for "mentoring", "training junior" for "mentoring", "supervising junior" for "mentoring", "work as a team" for "teamwork", "work in a team" for "teamwork ", "work in teams" for "teamwork", "work well in a team" for "teamwork", "within a team" for "teamwork", " intern " for " internship ", "team work" for "teamwork", "team working" for "teamwork", "team environment" for "teamwork", "able to relate" for "teamwork", "team player" for "teamwork", "collaborative work" for "teamwork".

Hard skills language:

"content creation" for "contentcreation", "design skills" for "designskills", "data analysis" for "dataanalysis", "legal analysis" for "legalanalysis", "microsoft office" for "microsoftoffice", "project management" for "projectmanagement", "quality assurance" for "qualityassurance", "sales skills" for "salesskills", "user experience" for "userexperience", "video production" for "videoproduction", "customer service" for "customerservice", "business development" for "businessdevelopment", "computer literacy" for "computerliteracy", "commercial skills" for "commercialskills", "business opportunities" for "businessdevelopment", "database management" for "dataanalysis", "data analytics" for "dataanalysis", "commercial abilities" for "commercialskills", "commercially aware" for "commercialskills", "commercially awareness" for "commercialskills", "focus on commercial" for "commercialskills", "commercially astute" for "commercialskills", “timekeeper” for “timemanagement”, “time keeping” for “timemanagement”, “commercially minded” for “commercialskills”, “commercially focused” for “commercialskills”, “commercially astute” for “commercialskills”, “commercially driven” for “commercialskills“ , “commercially focussed” for “commercialskills”, “word outlook” for “microsoftoffice”, “excel and outlook” for “microsoftoffice”, “microsoft outlook” for “microsoftoffice”, “profficient in word” for “microsoftoffice”,“microsoft word” for “microsoftoffice”, “proficient in excel” for “microsoftoffice”, “microsoft excel” for “microsoftoffice”, “power point” for “microsoftoffice”, “powerpoint” for “microsoftoffice”, “competent in microsoft” for “microsoftoffice”, “microsoft packages” for “microsoftoffice”, “office 365” for “microsoftoffice”, “ms excel” for “microsoftoffice”, “command of microsoft” for “microsoftoffice”, “within budget” for “within budg”, “word excel” for “microsoftoffice”, “word and excel” for “microsoftoffice”, “excel and word” for “microsoftoffice”, “word, excel” for “microsoftoffice”, “excel, word” for “microsoftoffice”, “outlook and” for “microsoftoffice”, “and outlook” for “microsoftoffice”, “using outlook” for “microsoftoffice”, “ms office” for “microsoftoffice”, “microsoft teams” for “call”, “microsoft programmes” for “microsoftoffice”, “positive outlook” for “positive”, “working with team” for “teamwork”, “statistical” for “statistics”, “pc literate” for “computerliteracy”, “computer literate” for “computerliteracy”, “using a computer” for “computerliteracy”, “computer skills” for “computerliteracy”, “pc skills” for “computerliteracy”, “analytics” for “analysis”, “investigative skills” for “analytical skills”, “research” for “research skills”, “cancer research” for “cancer”,“cancer research” for “cancer”, “research organisations” for “organisations”, “researching” for “research skills”, “research organisation” for “organisations”, “research programmes” for “programmes”, “researcher” for “research”, “good numeracy” for “analytical skills”, “numeracy skills” for “analytical skills”, “numeracy litarate” for “analytical skills”, “conflict management” for “conflictresolution”, “collaborative working” for “teamwork”, “supervising a” for “supervisingateam”, “managing a team” for “supervisingateam”, “team management” for “supervisingateam”, “part of a team” for “teamwork”, “sunrise senior” for “sunrise”, “seniors” for “old”, “associated” for “asociated”, “associates” for “asociates”, “their representatives” for “their clients”, “client representatives” for “client”, “sales representative” for “representativerole salesskills”, “sales representatives” for “representativerole salesskills”, “customerservice” for “representativerole customerservice”, “customer” for “representativerole customer”, “marketing representative” for “marketing representativerole”, “representative role” for “representativerole”, “our consultants” for “our consult”, “a consultant” for “a consult”, “consultants available” for “consult available”, “our qualified consultants” for “our consult”, “agent role” for “agentrole”, “sales agent” for “agentrole”, “support agent” for “agentrole”, “customerservice agent” for “agentrole”, “customerservice agent” for “agentrole”, “service agent” for “agentrole”, “accountant” for “accounting”, “directory” for “directo”, “directorate” for “directo”, “sales experience” for “salesskills experienced”, “sales person” for “salesskills”, “experience in sales” for “salesskills experienced”, “identify key sales” for “salesskills”, “sales oriented” for “salesskills”, “sales culture” for “salesskills”, “sales representative” for “sales representative salesskills”, “of sales” for “salesskills”, “sales plan” for “salesskills”, “sales plans” for “salesskills”, “sales associate” for “salesskills”, “sales role” for “salesskills”, “sales team” for “salesskills team”, “sales manager” for “salesskills manager”, “sales job” for “salesskills”, “sales target” for “salesskills”, “direct sales” for “salesskills”, “success in sales” for “salesskills”, “success as sales” for “salesskills”, “develop sales” for “salesskills”, “sales strategies” for “salesskills”, “sales targets” for “salesskills”, “target driven sales” for “salesskills”, “digital design” for “designskills”, “design engineer” for “designskills”, “graphic design” for “designskills”, “motion design” for “designskills”, “design tools” for “designskills”, “photoshop” for “designskills”, “motion graphics” for “designskills”, “digital art” for “designskills”, “adobe” for “designskills”, “design management” for “designskills”, “technical designs” for “designskills”, “photo shop” for “designskills”, “creating content” for “contentcreation”, “generate content” for “contentcreation”, “content generation” for “contentcreation”, “management of content” for “contentcreation”, “illustrator” for “designskills”, “content strategy” for “contentcreation”, “content development” for “contentcreation”, “content management” for “contentcreation”, “content creators” for “contentcreation”, “social content” for “contentcreation”, “managing content” for “contentcreation”, “website content” for “contentcreation”, “content writer” for “contentcreation”, “editorial management” for “editing”, “editorial skills” for “editing”, “editorial tasks” for “editing”, “editorial role” for “editing”, “editorial roles” for “editing”, “publishing skills” for “editing”, “editorial judgment” for “editing”, “editorial experience” for “editing experienced”, “editorial style” for “editing”, “editorial work” for “editing”, “proofreading” for “editing”, “proof reading” for “editing”, “drafting” for “editing”, “copy writing” for “editing”, “copywriting” for “editing”, “copywriter” for “editing”, “copywrite” for “editing”, “good editorial” for “editing”, “excellent editorial” for “editing”, “editorial assistant” for “editing assistant”, “editorial ability” for “editing”, “editorial judgment” for “editing”, “creating engaging content” for “contentcreation”, “develop content” for “contentcreation”, “developing content” for “contentcreation”, “writing, editorial” for “editing”, “legal text” for “legalanalysis”, “legal role” for “legalanalysis”, “legal abilities” for “legalanalysis”, “paralegal” for “legalanalysis”, “legal background” for “legalanalysis”, “legal qualifications” for “legalanalysis”, “legal qualification” for “legalanalysis”, “legal excecutive” for “legal excecutive legalanalysis”, “lawyer” for “lawyer legalanalysis”, “reading leases” for “legalanalysis”, “lawyers” for “lawyers legalanalysis”, “reading leases” for “legalanalysis”, “legal clerk” for “legalanalysis”, “provide legal” for “legalanalysis”, “legal billing” for “legalanalysis”, “ engineer ” for “ engineering ”, “legal documentation” for “legalanalysis”, “legal approach” for “legalanalysis”, “caseload” for “legalanalysis”, “understand our customers” for “customerservice”, “customer focused” for “customerservice”, “customer focus” for “customerservice”, “identify customer needs” for “customerservice”, “understanding the customers” for “customerservice”, “needs of the customers” for “customerservice”, “manage customer” for “customerservice”, “customer orders” for “customerservice”, “interact with customers” for “customerservice”, “quality checking” for “qualityassurance”, “quality checks” for “qualityassurance”, “quality check” for “qualityassurance”, “ensuring quality” for “qualityassurance”, “search engine” for “software”, “sem ” for “software”, “seo ” for “software ”, “web development” for “software”, “programming” for “software”, “mobile app development” for “software”, “coding” for “software”, “web design” for “software”, “cybersecurity” for “software”, “data mining” for “dataanalysis”, “data visualization” for “dataanalysis”, “database skills” for “dataanalysis”, “data to” for “dataanalysis”, “quantitative analysis” for “dataanalysis ”, “data modelling” for “dataanalysis”, “datasets” for “dataanalysis”, “interpret data” for “dataanalysis”, “data reporting” for “dataanalysis”, “it skills” for “dataanalysis”, “it literate” for “dataanalysis”, “it literacy” for “dataanalysis”, “variety of data” for “dataanalysis”, “data skills” for “dataanalysis”, “data models” for “dataanalysis”, “data sets” for “dataanalysis”, “data analyst” for “dataanalysis analyst”, “data monitoring” for “dataanalysis”, “data scientist” for “dataanalysis”, “data skill” for “dataanalysis”, “handling data” for “dataanalysis”, “complex data” for “dataanalysis”, “big data” for “dataanalysis”, “data science” for “dataanalysis”, “data engineer” for “dataanalysis”, “collate data” for “dataanalysis”, “data interpretation” for “dataanalysis”, “interpretation of data” for “dataanalysis”, “creation of data” for “dataanalysis”, “relational databases” for “dataanalysis”, “database management” for “dataanalysis”, “database utilisation” for “dataanalysis”, “data management” for “dataanalysis”, “database administration” for “dataanalysis”, “comparative data” for “dataanalysis”, “process data” for “dataanalysis”, “raw data” for “dataanalysis”, “data insight” for “dataanalysis”, “customer data” for “dataanalysis”, “customer databases” for “dataanalysis”, “company databases” for “dataanalysis”, “accurate databases” for “dataanalysis”, “accurate data” for “dataanalysis”, “data driven” for “dataanalysis”, “data entry” for “dataanalysis”, “data reviews” for “dataanalysis”, “review data” for “dataanalysis”, “project coordination” for “projectmanagement”, “project planning ” for “projectmanagement”, “contract drafting” for “projectmanagement”, “producing video” for “videoproduction”, “photography” for “videoproduction”, “video editing” for “videoproduction”, “video creation” for “videoproduction”, “videographer” for “videoproduction”, “film maker” for “videoproduction”, “creating videos” for “videoproduction”, “video experience” for “videoproduction experienced”, “filming” for “videoproduction”, “social interaction” for “interpersonal”, “social skills” for “interpersonal”, “people skills” for “interpersonal”, “people person” for “interpersonal”, “clerical” for “administrative”,“ ux ” for “userexperience”, “ ux, ” for “userexperience”, “ ux.” for “userexperience”, “statistics” for “statistical”, “stake holder” for “stakeholder”, “client management” for “stakeholder management”, “supply chain management” for “product management“.

AI language:
“ ai ” for “ artificialintelligence ”, “ xai ” for “ artificialintelligence ”, “ ai,” for “ artificialintelligence ”, ”, ai ” for “ artificialintelligence ”, “artificial intelligence” for “ artificialintelligence ”, “ gpt ” for “generativepretrainedtransformer”, “generative models” for “generativepretrainedtransformer”, “generative pretrained” for “generativepretrainedtransformer”, “generative pre” for “generativepretrainedtransformer”, “ai chatbox” for “aichatbox”, “artificialintelligence chatbox” for “aichatbox”, “machine learning” for “machinelearning”, “ ml ” for “ machinelearning ”, ”, ml ” for “ machinelearning ”, “ ml,” for “ machinelearning ”, “cross domain learning” for “machinelearning”, “cross - domain learning” for “machinelearning”, “reinforcement learning” for “machinelearning”, “mlpack” for “machinelearning”, “federated learning” for “machinelearning”, “pybrain” for “machinelearning”, “shot learning” for “machinelearning”, “hugging face” for “huggingface”, “multi task learning” for “machinelearning”, “multi - task learning” for “machinelearning”, “residual learning” for “machinelearning”, “mediapipe” for “machinelearning”, “media pipe” for “machinelearning”, “computer vision” for “computervision”, “image segmentation” for “computervision”, “vision processing” for “computervision”, “robotic process automation” for “roboticprocessautomation”, “ rpa ” for “ roboticprocessautomation ”, “autonomous robotics” for “roboticprocessautomation”, “intelligent automation” for “roboticprocessautomation”, “machine vision” for “machinevision”, “ bert ” for “bidirectionalencoder”, “bidirectional encoder” for “bidirectionalencoder”, ”, bert” for “ bidirectionalencoder”, “ bert,” for “ bidirectionalencoder”, “deep learning” for “deeplearning”, “residual network” for “deeplearning”, “ resnet ” for “deeplearning”, “fastai” for “deeplearning”, “nd4j” for “deeplearning”, “microsoft cognitive toolkit” for “deeplearning”, “ cntk ” for “deeplearning”, “deep embeddings” for “deeplearning”, “deep embedding” for “deeplearning”, “kalman filtering” for “kalmanfiltering”, “kalman filter” for “kalmanfiltering”, “virtual agents” for “virtualagents”, “support vector machines” for “supportvectormachines”, “ svm ” for “ supportvectormachines ”, “ svm,” for “ supportvectormachines ”, ”, svm ” for “ supportvectormachines ”, “image recognition” for “imagerecognition”, “point cloud library” for “imagerecognition”, “image fusion” for “imagefusion”, “natural language toolkit“ : “naturallanguagetoolkit”, “nltk“ : “naturallanguagetoolkit”, “ maximum entropy ” for “ naturallanguageprocessing ”, “ nlp ” for “naturallanguageprocessing”, ”, nlp ” for “ naturallanguageprocessing ”, “ nlp, ” for “ naturallanguageprocessing ”, “ corenlp” for “ naturallanguageprocessing ”, “ opennlp” for “ naturallanguageprocessing ”,“ apache uima” for “ naturallanguageprocessing ”, “natural language processing” for “naturallanguageprocessing”, “ gensim ” for “ naturallanguageprocessing ”, “document embeddings” for “naturallanguageprocessing”, “doc2vec” for “naturallanguageprocessing”, “speech recognition” for “speechrecognition”, “sound recognition” for “speechrecognition”, “scikit learn” for “scikitlearn”, “scikit - learn” for “scikitlearn”, “pattern recognition” for “patternrecognition”, “pattern detection” for “patternrecognition”,“discriminant” for “discriminantanalysis”, “object recognition” for “objectrecognition”, “object tracking” for “objectrecognition”, “neural networks” for “neuralnetworks”, “convolutional” for “neuralnetworks”, “ lstm ” for “longshorttermmemory”, “ lstms ” for “longshorttermmemory”, “ , lstm ” for “longshorttermmemory”, “ , lstms ” for “longshorttermmemory”, “ lstm, ” for “longshorttermmemory”, “ lstms, ” for “longshorttermmemory”, “recurrent network” for “neuralnetworks”, “recurrent networks” for “neuralnetworks”, “siamese networks” for “neuralnetworks”, “ rnn ” for “ rnns ”, “dnn techniques” for “neuralnetworks”, “supervised learning” for “supervisedlearning”, “gaussian processes” for “supervisedlearning”, “text mining” for “textmining”, “information extraction” for “textmining”, “unstructured information management” for “textmining”, “support vector machines” for “supportvectormachines”, “unsupervised learning” for “unsupervisedlearning”, “image processing” for “imageprocessing”,“jung framework” for “jungframework”,

"recommender systems" for "recommendersystems", "random forests" for "randomforests", "random forest" for "randomforests", "latent semantic analysis" for "latentsemanticanalysis", "sentiment analysis" for "sentimentanalysis", "emotion detection" for "sentimentanalysis", "tensor flow" for "tensorflow", "opinion mining" for "opinionmining", "hidden markov model":"hiddenmarkovmodel", "latent dirichlet allocation" for "latentdirichletallocation", " lda " for " latentdirichletallocation ", " lda," for " latentdirichletallocation ", ", lda" for " latentdirichletallocation ", "predictive models" for "predictivemodels", "predictive modelling" for "predictivemodels", "kernel methods" for "kernelmethods", "kernel method" for "kernelmethods", "gradient descent" for "gradientdescent", " sgd " for "gradientdescent", "gradient boosting" for "gradientboosting", "gradient boost" for "gradientboosting", "gradient boosted" for "gradientboosting", "machine translation" for "machinetranslation", "seq2seq" for "machinetranslation", "sequence - to - sequence" for "machinetranslation", "sequence to sequence" for "machinetranslation", "sentiment classification" for "classificationalgorithms", "classification algorithms" for "classificationalgorithms", "classification algorithm" for "classificationalgorithms", " gans " for "generativeadversarialnetworks", ", gans " for "generativeadversarialnetworks", " gans, " for "generativeadversarialnetworks", " generative adversarial networks" for "generativeadversarialnetworks", "quantum computing" for "quantumcomputing", " nlu " for "naturallanguageunderstanding", ", nlu " for " naturallanguageunderstanding ", " nlu, " for " naturallanguageunderstanding ", "natural language understanding" for "naturallanguageunderstanding", " nlg " for "naturallanguagegeneration", ", nlg " for " naturallanguagegeneration ", " nlg, " for " naturallanguagegeneration ", " natural language generation " for "naturallanguagegeneration", "nlg health " for "health", "nlg are" for "are", "cloud technology" for "cloudtechnology", "cloud technologies" for "cloudtechnology", "ensemble methods" for "ensemblemethods", "ensemble learning" for "ensemblemethods", "decision trees" for "decisiontrees", " chaid" for "decisiontrees", "tree based lerners" for "decisiontrees", "tree - based lerners" for "decisiontrees", "tree - based classifiers" for "decisiontrees", "tree based classifiers" for "decisiontrees", "k means clustering" for "clusteringalgorithms", "hierarchical clustering" for "clusteringalgorithms", "k - means clustering" for "clusteringalgorithms", "clustering algorithms" for "clusteringalgorithms", "optical character recognition" for "opticalcharacterrecognition", "optical flow" for "opticalcharacterrecognition", "named entity recognition" for "namedentityrecognition", "entity linking" for " naturallanguageprocessing ", "topic modeling" for "topicmodelling", "topic modelling" for "topicmodelling","topic detection" for "topicmodelling", "text classification" for "classificationalgorithms", "similarity models" for "topicmodelling", "a b testing" for "abtesting", "a . b testing" for "abtesting", "dimensionality reduction" for "dimensionalityreduction", " umap " for "dimensionalityreduction", "uniform manifold" for "dimensionalityreduction", "dimension reduction" for "dimensionalityreduction", " tsne " for "dimensionalityreduction", "t - sne" for "dimensionalityreduction", " t sne " for "dimensionalityreduction", "feature engineering" for "featureengineering", "hyperparameter tuning" for "hyperparametertuning", "hyper parameter tuning" for "hyperparametertuning", "data augmentation" for "dataaugmentation", "model compression" for "modelcompression", "naive bayes" for "bayesianmethods", "naïve bayes" for "bayesianmethods", "naï ve bayes" for "bayesianmethods", "bayesian" for "bayesianmethods", "knowledge distillation" for "knowledgedistillation", "density based spatial clustering" for "densitybasedspatialclustering","density - based spatial clustering" for "densitybasedspatialclustering", " dbscan " for "densitybasedspatialclustering", "computational linguistics" : "computationallinguistics", "expectation maximization" : "expectationmaximization", "caffe deep learning framework":"caffedeeplearningframework".

Contract language:

"conducted remote" for "conductedremote", "fully remote" for "fullyremote", "home based" for "homebased", "home work" for "homework", "job is virtual" for "jobisvirtual", "location is remote" for "locationisremote", "location remote" for "locationremote", "position is remote" for "positionisremote", "position remote" for "positionremote", "remote work" for "remotework", "role will be remote" for "rolewillberemote”, “virtual job” for “virtualjob”, “work from home” for “workfromhome”, “work home” for “workhome”, “work remote” for “workremote”, “working remote” for “workingremote”, “flx with office” for “flxwithoffice”, “remote position” for “remoteposition”, “role is remote” for “roleisremote”, “remote basis” for “remotebasis”, “hybrid work” for “hybridwork”, “hybrid remote” for “hybridremote”, “vice president” for “vicepresident”, “project lead” for “projectlead”, “team lead” for “teamlead”, “supervising a team” for “supervisingateam”, “trial period” for “trialperiod”, “entry level” for “entrylevel”, “tele commuting” for “telecommuting”, “tele work” for “telework ”, “no telecommuting” for “no”, “does not offer teleworker” for “no”, “no taking work home” for “no”, “take work home” for “no”, “teaching assistant” for “academic assistant”, “secure position” for “permanent position”, “temporary to permanent” for “temporary”, “not permanent” for “temporary”, “lead to permanent” for “temporary”, “not temporary” for “permanent”, “getting a permanent” for “temporary”, “seasonal contract” for “seasonal contract”, “seasonal hours” for “seasonal contract”, “decommissions” for “decom”, “commissioning” for “comis”, “rewards and benefits” for “rewards packages”, “pay - for - performance” for “pay for performance”, “share options” for “stock options”,“based on performance” for “pay for performance”, “short term, long term” for “short term contract, long term contract”, “short term , long term” for “short term contract, long term contract”, “short term and long term” for “short term contract and long term contract”, “short term basis” for “short term contract”,“short term or long term” for “short term contract or long term contract”, “contract is short term” for “short term contract”, “or short term” for “or short term contract”, “ temp ” for “ temporary ”, “long term conditions” for “conditions”, “long term condition” for “condition”, “long term strategy” for “strategy”, “long term strategic” for “strategic”, “long term satisfaction” for “satisfaction”, “long term residential” for “residential”, “long term financial” for “financial”, “long term happiness” for “happiness”, “long term need” for “need”, “long term health” for “health”, “temporary ongoing” for “temporary contract”, “ongoing contract subject” for “temporary contract”, “ perm ” for “ permanent ”, “ perm, ” for “ permanent ”, “ ,perm ” for “ permanent ”, “ temp, ” for “ temporary ”, “ ,temp ” for “ temporary ”, “experience is needed” for “experience needed”, “years of experience” for “years experience”, “ yrs ” for “ years ”, “don“ t need experience” for “dont need experience”, “don’ t need previous” for “dont need experience“ , “experience is essential” for “experience essential”, “not essential” for “no essential”, “not essential” for “no essential”, “no formal qualifications” for “no formal qualification”, “casual work” for “casual contract”, “casual basis” for “casual contract”, “casual work” for “casual contract”, “casual hours” for “part time”, “casual shifts” for “casual contract”, “40 hours” for “full time”, “40 hour” for “full time”, “38.5 hour” for “full time”, “38.5 hours” for “full time”,“38 hours” for “full time”, “38 hour” for “full time”,“37 hours” for “full time”, “37 hour” for “full time”, “9 to 17” for “9 to 5”, “9 17” for “9 to 5”, “9 . 17” for “9 to 5”, “profit sharing” for “profitsharing”, “reward scheme” for “rewardscheme”, “stock options” for “stockoptions”, “variable pay” for “variablepay”, “performance related” for “performancerelated”, “rewards packages” for “rewardspackages”, “pay for performance” for “payforperformance”, “fixed term” for “fixedterm”, “short term contract” for “shorttermcontract”, “day to day contract” for “daytodaycontract”, “zero hours” for “zerohours”, “casual contract” for “casualcontract”, “long term” for “longterm”, “ongoing contract” for “ongoingcontract”, “4 hour” for “4hour”, “4 hours” for “4hour”,“6 hour” for “6hour”, “6 hours” for “6hour”,“20 hour” for “20hour”, “20 hours” for “20hour”,“30 hour” for “30hour”, “9 to 5” for “9to5”, “full time” for “fulltime”, “standard hours” for “standardhours”, “day shift” for “dayshift”, “night shift” for “nightshift”, “3 to 5 years” for “3to5years”, “experience a minimum” for “experienceaminimum”, “experience for” for “experiencefor”, “experience in” for “experiencein”, “experience is also” for “experienceisalso”, “experience needed” for “experienceneeded”, “experience of” for “experienceof”, “experience preferably” for “experiencepreferably”, “experience required” for “experiencerequired”, “experience working” for “experienceworking”, “extensive experience” for “extensiveexperience”, “have experience” for “haveexperience”, “have previous experience” for “havepreviousexperience”, “have some knowledge” for “havesomeknowledge”, “have worked” for “haveworked”, “can teach” for “canteach”, “minimum experience” for “minimumexperience”, “months experience” for “monthsexperience”, “need experience” for “needexperience”, “past experience” for “pastexperience”, “practical experience” for “practicalexperience”, “prior experience” for “priorexperience”, “recent experience” for “recentexperience”, “relevant experience” for “relevantexperience”, “right experience” for “rightexperience”, “solid experience” for “solidexperience”, “strong experience” for “strongexperience”, “suitable experience” for “suitableexperience”, “three to five years” for “threetoFiveyears”, “two to three years” for “twotothreeyears”, “work experience” for “workexperience”, “worked in similar” for “workedinsimilar”, “required experience” for “requiredexperience”, “experience essential” for “experienceessential”, “experience is preferred” for “experienceispreferred”, “do not need any” for “donotneedany”, “do not need experience” for “donotneedexperience”, “experience is not” for “experienceisnot”, “no essential experience” for “noessentialexperience”, “no formal experience” for “noformalexperience”, “no formal qualifications or experience” for “noformalqualificationsorexperience”, “no past experience” for “nopastexperience”, “no work experience” for “noworkexperience”, “with no experience” for “withnoexperience”, “without any experience” for “withoutanyexperience”, “working directly with” for “workingdirectly”, “don t need experience” for “dontneedexperience”, “not needed” for “notneeded”, “working directly with” for “workingdirectlywith”, “report into” for “reportinto”, “your team leader” for “yourteamleader”, “working with” for “workingwith”, “working closely” for “workingclosely”, “under the direction” for “underthedirection”, “speaking to” for “speakingto”, “directly to” for “directlyto”, “work alongside” for “workalongside”, “required by” for “requiredby”, “keeping your” for “keepingyour”, “work closely” for “workclosely”, “step up to” for “stepto”, “managing the” for “managingthe”, “assistance to the” for “assistancetothe”, “work with” for “workwith”, “managed by” for “managedby”, “approval of” for “approvalof”, “communicate with” for “communicatewith”, “on experience” for “onexperience”, “negotiable salary” for “negotiablesalary”, “salary negotiable” for “salarynegotiable”, “hour negotiable” for “hournegotiable”, “salary is negotiable” for “salaryisnegotiable”, “salary up to” for “salaryupto“.

Education language:
“at level” for “level”, “at either level” for “level”, “ masters of ” for “ masterof ”,“ master in ” for “ masterof ”, “ masters in ” for “ masterof ”, “hour ” for “hours”, “skill ” for “skills ”, “cipd qualified” for “cipd”, “qualified to level” for “level”, “qualifications” for “qualification”, “mcipd” for “cipd”, “scqf level 1 ” for “scqflevel2 ”, “svq level 1 ” for “svqlevel2 ”, “ elc ” for “entrylevelcertificate”, “ cse “:“ certificateofsecondaryeducation ”, “a levels” for “alevelqualification”, “as levels” for “aslevelqualification”, “a level science” for “alevelqualification”, “a level in math” for “alevelqualification”, “a level in english” for “alevelqualification”, “as level in math” for “aslevelqualification”, “as level in english” for “aslevelqualification”, “as level in science” for “aslevelqualification”, “ certhe ” for “ certificateofhighereducation ”, “post graduate” for “postgraduate”, “ graduate ” for “ bachelor ”, “ bsc ” for “ bachelor ”, “ b . ed ” for “ bachelor ”, “ b. ed ” for “ bachelor ”, “ ba hons ” for “ bachelor ”, “ b eng ” for “ bachelor ”, “ b. eng ” for “ bachelorofengineering ”, “ beng ” for “ bachelorofengineering”, “ mba ” for “ masterofbusinessadministration ”, “ ll. b ” for “ bacheloroflaws”, “ meng ” for “ mastersofengineering ”, “ mmath ” for “ mastersofmathematics ”, “ mphil ” for “masterofphilosophy ”, “ mpsych ” for “ masterofphysics ”, “ mprof ” for “ masterofprofessionalstudies ”, “ mres ” for “ masterofresearch ”, “ msc ” for “ masterofscience ”, “ msc, ” for “ masterofscience ”, “ msci ” for “ masterofscience ”, “ msci, ” for “ masterofscience ”, “ mst ” for “ masterofstudies ”, “ m. sc ” for “ masterofscience ”, “ m . sc ” for “ masterofscience ”, “ llm ” for “ masteroflaw ”, “ ll . m ” for “ masteroflaw ”, “ mpharm ” for “ mastersofpharmacy ”, “ mchem ” for “ masterofchemistry ”, “ ms ” for “ masterofscience ”, “ msw ” for “ masterofsocialwork ”, “ pcge ” for “ postgraduatecertificateineducation ”, “ pcg ” for “ postgraduatecertificate ”, “ pgd ” for “ postgraduatediploma ”, “ pgcert ” for “ postgraduatecertificate ”, “ pg cert ” for “ postgraduatecertificate ”, “ph. d” for “ phd ”, “ph d” for “ phd ”, “ ma programme ” for “ masterofart ”, “ ma programme ” for “ masterofart ”, “ ma in english ” for “ masterofart ”, “hold an ma ” for “ masterofart ”, “ ma degree ” for “ masterofart ”, “honors degree” for “honoursdegree”, “self employed” for “selfemployed”, “self employment” for “selfemployed”,

"seasonal contract" for "seasonalcontract", "basic functional skills" for "basicfunctionalskills", "basic skills qualification" for "basicskillsqualification", "entry level certificate" for "entrylevelcertificate", "entry level functional skills" for "entrylevelfunctionalskills", "entry level qualifications" for "entrylevelqualifications", "entry nqf level" for "entrynqflevel", "essential skills wales" for "essentialskillswales", "level 1 scqf" for "level1scqf", "level 1 svq" for "level1svq", "level 2 scqf" for "level2scqf", "level 2 svq" for "level2svq", "level 3 scqf" for "level3scqf", "level 3 svq" for "level3svq", "no education requirements" for "noeducationrequirements", "no formal qualification" for "noformalqualification", "no previous experience or qualification" for "nopreviousexperienceorqualification", "no previous qualification" for "nopreviousqualification", "no qualification" for "noqualification", "scottish national 1" for "scottishnational1", "scottish national 2" for "scottishnational2", "scottish national 3" for "scottishnational3", "scqf level 2" for "scqflevel2", "scqf level 3" for "scqflevel3", "skills for life" for "skillsforlife", "svq level 2" for "svqlevel2", "svq level 3" for "svqlevel3", "no formal education" for "noformaleducation", "btec award" for "btecaward", "btec first" for "btecfirst", "btec level 1" for "bteclevel1", "certificate of secondary education" for "certificateofsecondaryeducation", "first certificate" for "firstcertificate", "foundation welsh baccalaureate" for "foundationwelshbaccalaureate", "key skills level 1" for "keyskillslevel1", "level 1 award" for "level1award", "level 1 certificate" for "level1certificate", "level 1 diploma" for "level1diploma", "level 1 esol" for "level1esol", "level 1 essential skills" for "level1essentialskills", "level 1 functional skills" for "level1functionalskills", "level 1 key skills" for "level1keyskills", "level 1 national vocational qualification" for "level1nationalvocationalqualification", "level 1 nvq" for "level1nvq", "nqf level 1" for "nqflevel1", "nvq level 1" for "nvqlevel1", "rqf level 1" for "rqflevel1", "scqf level 4" for "scqflevel4", "diploma level 1" for "diplomalevel1", "national level 1" for "nationallevel1", "qualification level 1" for "qualificationlevel1", "level 1 qualification" for "level1qualification", "level 1 qcf" for "level1qcf", "functional skills level 1" for "functionalskillslevel1", "essential skills level 1" for "essentialskillslevel1", "level 1 apprenticeship" for "level1apprenticeship", "cipd level 1" for "cipdlevel1", "level 1 cipd" for "level1cipd", "level 4 scqf" for "level4scqf", "level 4 svq" for "level4svq", "svq level 4" for "svqlevel4", "btec level 2" for "bteclevel2", "general certificate of education" for "generalcertificateofeducation", "intermediate apprenticeship" for "intermediateapprenticeship", "intermediate welsh baccalaureate" for "intermediatewelshbaccalaureate", "key skills level 2" for "keyskillslevel2", "level 2 award" for "level2award", "level 2 certificate" for "level2certificate", "level 2 diploma" for "level2diploma", "level 2 esol" for "level2esol", "level 2 essential skill" for "level2essentialskill", "level 2 functional skill" for "level2functionalskill", "level 2 key skills" for "level2keyskills", "level 2 national" for "level2national", "level 2 nvq" for "level2nvq", "national level 2" for "nationallevel2", "nqf level 2" for "nqflevel2", "nvq level 2" for "nvqlevel2", "rqf level 2" for "rqflevel2", "scqf level 5" for "scqflevel5", "secondary education" for "secondaryeducation", "diploma level 2" for "diplomalevel2", "award level 3" for "awardlevel3", "esol level 2" for "esollevel2", "functional skills level 2" for "functionalskillslevel2", "essential skills level 2" for "essentialskillslevel2", "qualification level 2" for "qualificationlevel2", "level 2 qualification" for "level2qualification", "level 2 apprenticeship" for "level2apprenticeship", "cipd level 2" for "cipdlevel2", "level 2 cipd" for "level2cipd", "level 5 scqf" for "level5scqf", "level 5 svq" for "level5svq", "svq level 5" for "svqlevel5", "certificate of secondary education" for "certificateofsecondaryeducation", "a level qualification" for "alevelqualification", "as level qualification" for "aslevelqualification", "access to higher education diploma" for "accesstohighereducationdiploma", "advanced apprenticeship" for "advancedapprenticeship", "advanced diploma" for "advanceddiploma", "advanced extension" for "advancedextension", "advanced welsh baccalaureate" for "advancedwelshbaccalaureate", "btec award level 3" for "btecawardlevel3", "btec certificate level 3" for "bteccertificatelevel3", "btec diploma level 3" for "btecdiplomalevel3", "btec level 3" for "bteclevel3", "btec national" for "btecnational", "diploma programme" for "diplomaprogramme", "extended certificate" for "extendedcertificate", "extended diploma" for "extendeddiploma", "key skills level 3" for "keyskillslevel3", "level 3 award" for "level3award", "level 3 certificate" for "level3certificate", "level 3 esol" for "level3esol", "level 3 national" for "level3national", "level 3 nvq" for "level3nvq", "national level 3” for “nationallevel3”, “nqf level 3” for “nqflevel3”, “nvq level 3” for “nvqlevel3”, “ocr national” for “ocrnational”, “progression diploma” for “progressiondiploma”, “rqf level 3” for “rqflevel3”, “scottish advanced higher” for “scottishadvancedhigher”, “scottish baccalaureate” for “scottishbaccalaureate”, “scottish higher” for “scottishhigher”, “scqf level 6” for “scqflevel6”, “diploma level 3” for “diplomalevel3”, “award level 3” for “awardlevel3”, “functional skills level 3” for “functionalskillslevel3”, “essential skills level 3” for “essentialskillslevel3”, “qualification level 3” for “qualificationlevel3”, “level 3 qualification” for “level3qualification”, “level 3 apprenticeship” for “level3apprenticeship”, “cipd level 3” for “cipdlevel3”, “level 3 cipd” for “level3cipd”, “level 6 scqf” for “level6scqf”, “level 6 svq” for “level6svq”, “svq level 6” for “svqlevel6”, “certificate of higher education” for “certificateofhighereducation”, “higher apprenticeship” for “higherapprenticeship”, “higher national certificate” for “highernationalcertificate”, “level 4 award” for “level4award”, “level 4 certificate” for “level4certificate”, “level 4 diploma” for “level4diploma”, “level 4 national” for “level4national”, “level 4 nvq” for “level4nvq”, “national level 4” for “nationallevel4”, “nqf level 4” for “nqflevel4”, “nvq level 4” for “nvqlevel4”, “scqf level 7” for “scqflevel7”, “diploma level 4” for “diplomalevel4”, “award level 4” for “awardlevel4”, “functional skills level 4” for “functionalskillslevel4”, “essential skills level 4” for “essentialskillslevel4”, “qualification level 4” for “qualificationlevel4”, “level 4 qualification” for “level4qualification”, “level 4 apprenticeship” for “level4apprenticeship”, “cipd level 4” for “cipdlevel4”, “level 4 cipd” for “level4cipd”, “level 7 scqf” for “level7scqf”, “level 7 svq” for “level7svq”, “svq level 7” for “svqlevel7”, “btec professional” for “btecprofessional”, “diploma of further education” for “diplomaoffurthereducation”, “diploma of higher education” for “diplomaofhighereducation”, “foundation degree” for “foundationdegree”, “higher diploma” for “higherdiploma”, “higher national diploma” for “highernationaldiploma”, “level 5 award” for “level5award”, “level 5 certificate” for “level5certificate”, “level 5 diploma” for “level5diploma”, “level 5 national” for “level5national”, “level 5 nvq” for “level5nvq”, “national level 5” for “nationallevel5”, “nqf level 5” for “nqflevel5”, “nvq level 5” for “nvqlevel5”, “scqf level 8” for “scqflevel8”, “diploma level 5” for “diplomalevel5”, “award level 5” for “awardlevel5”, “qualification level 5” for “qualificationlevel5”, “level 5 qualification” for “level5qualification”, “cipd level 5” for “cipdlevel5”, “level 5 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for “masterofstudies”, “masters by research” for “mastersbyresearch”, “masters degree” for “mastersdegree”, “national level 7” for “nationallevel7”, “nqf level 7” for “nqflevel7”, “nvq level 7” for “nvqlevel7”, “postgraduate certificate” for “postgraduatecertificate”, “postgraduate certificate in education” for “postgraduatecertificateineducation”, “postgraduate diploma” for “postgraduatediploma”, “professional masters” for “professionalmasters”, “scqf level 11” for “scqflevel11”, “svq level 11” for “svqlevel11”, “doctor of philosophy” for “doctorofphilosophy”, “doctoral degree” for “doctoraldegree”, “doctors degree” for “doctorsdegree”, “level 8 award” for “level8award”, “level 8 certificate” for “level8certificate”, “level 8 diploma” for “level8diploma”, “level 8 national” for “level8national”, “level 8 nvq” for “level8nvq”, “national level 8” for “nationallevel8”, “nqf level 8” for “nqflevel8”, “nvq level 8” for “nvqlevel8”, “rqf level 8” for “rqflevel8”, “scqf level 12” for 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