# Demand for skills associated with Higher Technical Education in England

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This thesis is submitted for the degree of
**Doctor of Philosophy**

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## *Preface*

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Cambridge. The research described herein was conducted under the supervision of Professor Anna Vignoles in the Department of Education, University of Cambridge, between October 2018 and January 2021 and Sonia Ilie, Assistant Professor in the Department of Education, University of Cambridge, from January 2021 to September 2022.

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text. It is not substantially the same as any work that has already been submitted before for any degree or other qualification except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee (80000).

This research was conducted with the support of Gatsby Charitable Foundation, which provided funding and defined the topic of this research. The terms of this sponsorship, including rights and duties of the parties involved, were defined in an agreement signed by the University of Cambridge, the Foundation and myself. At no time did the Foundation seek to influence the way the research was conducted or its findings.

Part of the research for Chapter 4 *"What do job vacancies tell us about skills associated by employers with HTE qualifications?"* was carried out in collaboration with Elodie Andrieu, PhD student in Economics at King's College London. The collaborative work involved analysis of raw text of job ads that culminated in the creation of an educational variable. Other data related work presented in Chapter 4, such as evaluation of the representativeness and analysis of the data, interpretation and discussion of the findings are the result of my own work.

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## *Abstract*

Over past decades enrolment in bachelor's degree programmes has risen steeply. During the same period participation in Higher Technical Education (HTE, level 4/5 technical qualifications) has stagnated at best. There are different, overlapping, but also partly competing explanations for this pattern. There could have been an expansion in jobs requiring the high-level skills associated with degrees (but not HTE) and an increasing complexity of the job content. This changing mix of jobs and tasks performed in the workplace could, in turn, be triggered by recent technologies and management methods that drive up the demand for high level skills. It may also be that an increasing supply of highly educated workers contributes to job upskilling, so that, for example, when graduates (here meaning those qualified at level 6) take an administrative job, they find ways of using their higher-level skills, gradually changing the nature of the job and the expectations that surround it.

To shed light on the relative decline of HTE, this research study explores the labour market performance of HTE-qualified workers over the last twenty years in the context of a rapidly rising supply of degree holders and the spread of new technologies in workplaces, across and within occupations. In particular, it explores the interplay between qualifications, the tasks performed on the job and the skills necessary to undertake those tasks, and labour market outcomes.

Labour market outcomes are examined using the indicators of employment opportunities and wages, whereby wages are treated as an expression of individual productivity. The Mincerian wage function, explaining wages through a combination of educational attainment and work experience, provides a theoretical framework for this investigation. The research also looks at job tasks and the skills required to perform those tasks to evaluate the complexity of jobs.

The analysis draws on three datasets that provide information on occupational skills and labour market outcomes in the UK over time. They include: the UK Skills Employment Survey (SES), Labour Force Survey (LFS), Burning Glass Technology (BGT) data on job vacancies advertised online. The SES and LFS provide consistent worker-level data in different time periods, while the BGT contains information on millions of online job vacancies.

The findings point to a worsening labour market performance, on average, of the HTE-qualified over the last twenty years. They show how the HTE-qualified have been gradually displaced from many skilled occupations in response to an influx of degree holders onto the labour market. The research also describes how the growth of employment in more skilled occupations is associated with an increase in the number of graduates in the labour market. The research demonstrates that while on average, the level of tasks performed by the HTE-qualified has been relatively high, they have suffered from a downgrade in terms of skills applied on-the-job. In this respect the position of HTE holders as compared to other groups, and in particular graduates, has weakened over time in some occupations. This trend is observed in skilled professional and technical occupations (SOC major groups 2-3), occupations that have often been

prepared for through HTE programmes. One possibility is that in these occupations, the relative productivity of individuals with HTE qualifications and therefore the relative demand for these qualifications fell over time. (This refers to the relative productivity and relative demand in relation to the HTE-qualified as a group with a changing composition, rather than to the changing productivity of individuals over their working lives). The research shows that HTE-qualified workers were particularly likely to have been displaced in skilled jobs by degree holders. Conversely, the share of HTE-qualified increased in semi-skilled trade occupations, in which their comparative advantage was the highest. The share of HTE holders also grew in quickly expanding service sector jobs, in which their comparative advantage was low.

The labour market performance of the HTE-qualified varies according to the area of specialisation. Specialisations in teaching and health saw a sharp drop in earnings, and experienced worsening employment prospects over the last two decades which may be related to the introduction of a degree requirement for entry into the teaching and nursing professions. Those with engineering and manufacturing HTE specialisations show the strongest employment outcomes. A case study of the engineering sector revealed that employers in this sector associate more productive tasks with degrees, but under some circumstances they are open to employing the HTE-qualified.

While the declining labour market performance of the HTE qualified, relative to those with degrees, is one of the findings of this study, the causal relationships involved are not entirely clear. Drawing on the findings from the analysis of on-line job vacancy data presented in this research, further analysis might usefully include an examination of the factors which encourage employers to prefer HTE qualifications, such as firm characteristics, company geographical location and proximity to universities.

The research sought to differentiate between demand for specific types of skill and certain qualifications, recognising that qualifications seek to package skills in certain ways, while individual occupations also require packages of skills. In principle, employers will be interested in skills rather than qualifications, but they use qualifications as signals of the skills which their recruits are likely to possess. This research study has highlighted the potential use of online vacancy data, (alongside other datasets), to capture the subtleties of employer demand in relation to both skills and qualifications. Regularly analysed data of this type would provide, in real time, an important guide for those developing and reviewing programmes and qualifications. More analytical research should allow for an exploration of the extent to which the skills demand of a fast-changing economy can be best met through packaged qualifications, as opposed to targeted training exercises concentrating on individual skills.

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# 1 Introduction

In recent years in England, extensive policy attention has been given to midlevel technical qualifications at levels 4 and 5 (higher technical education or HTE). This reflects the relative weakness of this sector relative to the past, and relative to other countries (Field, 2019). The government now anticipates strengthening this sector, through the Institutes of Technical Education and other policy initiatives designed to concentrate funding on a relatively small number of technical qualifications at this level (Department for Education, 2020) . One key question that arises is the evidence of labour market demand for this type of qualification, and this research is designed to address this question.

Over past decades England has experienced an unprecedented increase in enrolment in higher education (HE) (which in this report will be used to refer to level 6 degrees and above, recognising that the expression is sometimes used to cover level 5 as well). The Institute for Fiscal Studies forecasts that the number of HE students in England will rise by 13% between the 2019/20 and the 2025/26 (Waltmann, et al., 2021). To fund the expansion of HE tuition fees have increased, resulting in a higher level of student debt. Since student loans are guaranteed by the government, the cost of loan default is absorbed by tax-payers. The government previously estimated that only one quarter of students who started their undergraduate studies in 2000-2021 will repay their loans in full (GOV.UK, 2022). In response to these challenges the government announced changes in post-secondary and HE funding arrangements. It envisages increasing a proportion of loans that will be paid off by the students, toughening entry requirements to HE for prospective students and expanding HTE provision (Department for Education, 2022).

For those wishing to study at post-secondary level there is a choice between three-year bachelor's programmes, and shorter one or two-year programmes leading to qualifications at level 4 and 5. One policy question is how much effort should the government devote to support HTE programmes, which are shorter and thus less costly both for individuals and the government. This partly depends on how effective these programmes are in matching skills in demand on the labour market and preparing individuals for successful careers. This research study aims to illuminate this question by examining labour market demand for HTE qualifications and the associated skills.

This study will therefore analyse changes in the labour market experience of the HTE-qualified. It will look at the comparative returns to HTE and other qualifications including level 6 qualifications – the most natural level of comparison, in different time periods. It will go beyond previous research by exploring changes in the content of jobs performed by the HTE-qualified, and the skills necessary to undertake those jobs. To achieve this type of fine-grained analysis, this study will make use of three datasets, including online job vacancy data as well as more traditional survey datasets. Use of the three different datasets provides a powerful triangulation tool, both to reinforce, and potentially challenge, provisional findings from the different data sources.

This introductory chapter provides a definition of Higher Technical Education (HTE) in England, describes the quantitative approach drawing on analysis of three different datasets. It then introduces the research questions that are addressed by this research, reviews relevant literature, and presents the theoretical foundations of the analysis that follows in the body of the thesis. Finally, it addresses some ethical issues associated with secondary data.

The literature review and the theoretical model presented in this introductory chapter underpin analysis carried out by the three substantive chapters (Chapters 2-4) of this thesis. The analysis discussed in the chapters aims to illuminate how the demand for HTE-qualified labour has changed over time, the main topic of the thesis. Each of the substantive chapters addresses the main issue of interest from a slightly different perspective as the chapters draw on three different datasets. Depending on the data characteristics each chapter discusses in more depth relevant research evidence and may provide additional specifications to the theoretical model.

## 1.1. Background, research aims and questions

### *1.1.1. Vocational qualifications as identified in the English qualification framework*

In England, vocational and technical qualifications are provided at different levels and in different fields. Depending on their level and type, vocational and technical qualifications are associated with very different outcomes (McIntosh & Morris, 2016).This research focuses on ‘higher technical’ programmes, following the now standard nomenclature in which this means technical programmes at level 4 and 5.  This includes for example Higher National Certificates (HNCs), Higher National Diplomas (HNDs), Foundation Degrees, and apprenticeships at levels 4 and 5. According to the Sainsbury Review these technical programmes should lead to skilled employment, and equip individuals with substantial technical knowledge and skills valued by industry (The Independent Panel on Technical Education, 2016)).  Higher technical programmes typically last 1-2 years (full-time equivalents). HTE therefore normally leads to jobs requiring some post-secondary education but not necessarily a full bachelor’s degree. Depending on the analysed datasets, the coverage of HTE may slightly differ. Each of the empirical chapters of this research (chapters 2-4) clarifies the coverage.

### *1.1.2. Situating the project’s research aims and questions*

Initially, some higher technical programmes (HND and HNC) were established to provide skilled labour for engineering jobs. In early discussions about the role of higher technical education following the end of the Second World War the government-appointed Percy Committee divided engineering jobs into 5 categories: 1. senior administrators; 2. engineer scientists and development engineers; 3. engineer managers (design, manufacture, operations and sales); 4. technical assistants and designer draughtsmen, 5. draughtsmen, foremen and craftsmen. The Committee envisaged that higher technical programmes would provide skills for the 4th category, and for the 3rd category alongside the universities (Field 2019). In practice, the difference between higher technical and graduate jobs may be hard to identify. Field (2019) in his historical review of level 4 and 5 qualifications observes that over the last half century many professions have increasingly expected employees to obtain a bachelor's degree rather than a lesser qualification. This was partly due to the impact of the Robbins report, which prioritised the expansion of full-time bachelor's degrees (Field, 2019). Recently, there has been a renewal of interest in vocational and technical education in the UK. The Augar review, looking at the funding of the post-18 education landscape, argues for expansion of level 4/5 provision and a better match between programmes on offer and labour market needs. This is echoed in a recent government reform plans of Higher Education (HE) and level 4/5 qualifications (Department for Education, 2022). This shift towards degrees was partly due to education policy providing stronger incentives to institutions and students to invest in a degree rather than level 4 and 5 programmes. Government spending per learner in post-18 programmes is much below that in HE and 16-18 (Augar, 2019). The Augar report shows that the enrolment in level 4 and 5 courses plummeted between 2009/10 and 2016/17 resulting in a persistent shortage of skilled technicians with level 4 and 5 qualifications (Augar, 2019). It also shows that within the current level 4/5 sector provision may not fully match labour market needs as only a small minority of learners study in STEM related areas in which the demand for qualified labour is high (Augar, 2019). Against that background, there are some indications of shortages of the technical competences associated with level 4/5 qualifications. A recent survey of employers in the UK points to shortages of technical competencies on the labour market, which may suggest that there is in fact a latent demand for HTE qualifications (Winterbotham, et al., 2020). Although the implication could also be that employers are looking for technical skills in addition to a strong academic background or for lower level technical skills.  This research aims to shed more light on this issue by looking at the demand for HTE qualifications and the associated skills as compared to the demand for other qualifications.

The vocational education and training (VET) sector, both at upper-secondary and post-secondary level, is relatively small in England as compared to VET systems in some other countries (such as Austria, Finland, Germany, and Switzerland). The proportion of HE graduates[1] in the adult UK population has been steadily rising in the last two decades. In the UK the share of degree holders (bachelor's degree and above) jumped from 13% for the 1960-64 birth cohort to 37% for the 1980-85 cohort (Blundell, Green and Jin, 2016). In 2016 more than half of 25–34-year-olds were educated to tertiary level (UK level 4/5 qualifications and above2), one of the highest rates among OECD countries (OECD, 2017, p. A1.2). During the same period, the share of the population with level 4 and 5 qualifications, the vast majority of which are vocationally oriented, remained relatively stable, but enrolment of new students sharply declined. In line with the Augar

[1] Meaning those with qualifications at level 6 and above.

[2] UK level 4 qualifications are classified internationally at level 5 in ISCED 2011, which is tertiary education.

report, Espinoza and Speckesser (2019) show that only 1.5% of the cohort who completed secondary education in 2002/03 acquired level 4/5 qualifications as their highest educational attainment by 2015. Given the growing dominance of qualifications at level 6 and above, which are very often general and academic, the authors conclude that "education in England emphasises general and academic education" (Espinoza & Speckesser, 2019, p. 15)

One explanation for the changing mix of qualifications in the labour force could be changing relative demand – an increase in the demand for degrees at level 6 and above relative to lower-level qualifications. The relatively low take up of vocational and technical qualifications, at levels 4 and 5 and below, could be related to the low demand for these qualifications from employers that could in turn be explained by changing job requirements. Changing job requirements might involve:

- Jobs mix: an expansion of jobs requiring high level skills associated with degrees,
- Jobs upgrading: whereby jobs previously requiring HTE qualifications have become more skilled over time, e.g. the job of a nurse may now involve more technical and scientific knowledge, and might for that reason necessitate level 6 education and training.

Changing job requirements could be related to new technologies and management methods that drive the demand for high level skills. It may also be that an inflow of highly educated labour contributes to job upskilling, so that, for example, when many graduates take an administrative job, they find ways of using their higher level skills, gradually changing the nature of the job and the expectations that surround it.

Lower relative take up of level 4/5 qualifications can also be related to other factors. It may be that the rising supply of graduates supress the demand for HTE qualifications, even though job requirements remain unchanged. In this scenario, employers would have preferences for highly qualified labour independently of the job tasks, so that, other things being equal, a graduate would be preferred to an HTE-qualified person in any job. This would be consistent with hypothesis advanced by researchers related to the Centre on Skills, Knowledge & Organisational Performance (SKOPE) in Oxford (Holmes & Mayhew, 2012; Keep & Mayhew, 2004). Keep and Mayhew (2004) question premises of higher education expansion advocated for many years by the British government and resulting in a massive growth of university attainment. The authors argue that the increase in the supply of graduates is not justified by a growth in employment requiring graduate skills. Consequently, many graduates end up in jobs for which they are overqualified and that traditionally required a lesser qualification. Flooding of graduates on the job market means that those with lower level qualifications have to compete for jobs with degree holders and are likely to be pushed down to unqualified jobs with poor training and progression prospects. According to the authors this situation is highly inefficient and reinforces polarisation of labour market opportunities. Keep (2015) argues that any attempt to reform vocational provision in the UK has to consider the weakness on the demand side, for poor returns to vocational qualifications reflect, in many respects, the jobs they prepare for. According to the author, in England vocational programmes tend to prepare for jobs situated at the lower end of the distribution of skills utilisation. Holmes and Mayhew (2012) express similar concern over an expectation that rapidly growing supply of graduates would drive job upskilling. They argue that the increase in the supply of gradates cannot be explained by a growth in employment relying on graduate skills.

Frequent changes in programmes may also lower interest in HTE qualifications from students and employers, as they can be confusing and decrease students and employers' knowledge of programmes on offer (Dickerson & Vignoles, 2007).

There are also institutional factors: bachelor's level education is expected in many professions, and historically in professions like nursing and engineering, bachelor's level education has over time become accepted and institutionalised as the norm (Field, 2019).

One further possible reason for the decline in higher technical qualifications is that, although there is a potentially important role for skills at this level in the economy, the programmes and qualifications on offer are of poor quality, reducing their attractiveness to both students and employers relative to degrees. So poor returns to higher technical qualifications could mask latent demand for better quality programmes at this level.

The mix of reasons behind the decline in the relative share of level 4/5 qualifications on the labour market has significant policy implications. Evidence of high returns to level 4/5 qualifications would suggest inadequate supply, calling for a policy response in the form of interventions to encourage provision at this level. Low returns might imply the opposite. However, heterogeneity in returns, which is often what we observe, calls for a more targeted approach designed to improve quality and support provision in sectors where returns are highest – for example in STEM-related areas. When allocating scarce resources, policy makers should, in principle, prioritise those education and training programmes with the largest economic returns to individuals and society.

To test alternative hypotheses (which are not mutually exclusive) that might explain the relative decline in the take up of level 4/5 qualifications, this research looks at changes in the labour market experience among HTE-qualified workers and labour with different qualifications, across and within occupations, and changes in the content of jobs carried out by the HTE-qualified.

With the increase in the supply of graduates, it is possible that those with HTE qualifications who might have been doing higher level technical jobs have been displaced by graduates and forced to take less skilled employment. If this phenomenon is widespread, we should observe HTE holders increasingly undertaking more low-level job tasks, negatively associated with wages.

Our research will not attempt to estimate individual returns to specific qualifications at one point of time, which is well addressed in the literature (see the literature review below) but would rather add to existing evidence by estimating the wage premia to HTE across cohorts over time between and within occupations. This approach should capture changes in wage premia over time. Our analysis will be conducted with repeated cross-sections, and an estimation of the wage premium would be carried out for each time period individually[3]. A similar analysis will be performed for different subject areas to identify variations in returns within HTE qualifications. By analysing wages by qualifications this research will attempt to compare the efficiency of various channels in preparing for jobs; e.g. are employees with degrees in jobs traditionally associated with level 4/5 qualifications more productive than those with HTE qualifications as proxied with wages?

The research will also explore whether, and to what extent, changing job requirements may explain some of the observed shift in the HTE wage premium. This approach is novel. The study will explore trends in the demand for specific skills over time and relate those trends to the labour market outcomes of individuals with postsecondary and HE qualifications (level 4/5 and 6 respectively). It will therefore address questions such as whether we observe an increase in more complex tasks in occupations where the share of graduates has been increasing, and how tasks performed on the job by the HTE-qualified change over time.

Finally, this research explores labour demand at a high level of granularity with online job vacancies data. It looks at the relative demand for different education levels within occupations, sectors and by geographical areas. This approach will allow an examination of whether areas with a high demand for graduates also record a high demand for HTE qualifications? Exploiting the very detailed information on job tasks available in the Burning Glass Technologies online job vacancy data, we aim to identify if there are any differences in nominally similar jobs depending on the level of education required. This will explore whether the mix of skills within specific occupations differs between ads asking for a degree and ads seeking HTE qualifications, and therefore if employers tend to allocate different responsibilities to graduates and individuals with HTE qualifications. We explore if employers see graduates as more productive than workers with HTE qualifications, with wages being a proxy for productivity.

To illustrate how job vacancy data can be used to analyse job tasks and employers' expectations towards the HTE-qualified within occupations, and how these data may be used to inform policy makers, providers and students, we undertake a case study of engineering jobs.

Whenever feasible the analysis is restricted to England. When such a breakdown is not possible, we report the results for the UK, recognising that the UK results in most cases reflect an approximation to the results that would have been obtained for England.

This research aims, therefore, to identify and describe relationships between specific phenomena, according to a prior hypothesis about how these phenomena interact with each other. The aims of the research are discussed in full below. Our methodological approach is quantitative, which means that we draw on large data sets to test hypotheses and establish how different elements of education and the labour market are interconnected.

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[3] Pooling data across time points, with a year dummy accounting for the year effect, represents an alternative approach. However, given the objective of our research – observe changes over time, this approach is not fully satisfactory as it assumes a constant effect of qualifications on wages across all time periods.

Inevitably, the quantitative approach used here has its limitations. Data describe only a part of a complex social reality, which is often impacted by other difficult-to-quantify factors. This implies the need for caution in reaching conclusions. Qualitative research approaches could complement this research. For example, our quantitative research on the demand for level 4/5 qualifications could be enriched with a set of interviews with employers trying to understand employer's motivation and criteria applied in the recruitment process, and with students to shed more light on their school experience, family history and criteria guiding them in the choice of their careers.

This research aims to provide a detailed description of labour market performance of individuals with HTE as compared to those with other qualifications over time and discusses how the observed changes can be related to job content. Conclusions regarding any causal relationship between HTE qualifications and labour market outcomes will need to be drawn cautiously. We can observe the wage premium associated with HTE qualifications or degrees in different time periods but we cannot claim that the observed difference is fully explained by the qualifications. We identify and take account of various factors that are correlated with education and wages and can be described with the data but not all of them due to data limitations. Changes in cohort characteristics and in ability distributions over time across individuals with different educational attainments are one of such factors. In this research we therefore advance plausible explanations of observed differences in outcomes between HTE-qualified and those with other qualifications drawing on available information without asserting their validity.

A series of three large data sets have been used to address the above aims, as described in what follows.

### *1.1.3. The data sets*

This research draws on three data sets that provide information on occupational skills and labour market outcomes in the UK over time. They include: the UK Skills Employment Survey (SES), the Labour Force Survey (LFS), Burning Glass Technology (BGT) data on job vacancies. Data analysis is performed with the R software.

The SES has been conducted since 1986 every 4-5 years in the UK. To keep a sufficiently large number of observations we perform analysis on the 12 UK regions data (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scottish Lowlands). SES provides information on skills, tasks performed on the job and other job characteristics, as reported by individuals in employment. Information on individual characteristics, such as age, gender, educational attainment, can also be extracted from the SES. However, SES data do not allow for the establishment of a causal relationship between changing skills and labour market outcomes. This is due to the cross-section character of the data, small sample sizes and few time points. The sample size of the SES data also makes it impossible to study changes in skills at a more granular level, e.g. by narrowly defined occupations.

The Labour Force Survey (LFS) managed by the UK Office for National Statistics is a nationally representative household survey, conducted quarterly since 1992. The LFS data is a convenient tool to estimate the labour market benefits of education, either in terms of a wage premium or employment opportunities, as it combines information on the education and employment of a person. The longitudinal nature of LFS data provides an opportunity to capture the seasonal variation in employment. However the period over which individuals are followed (five quarters) is too short to observe changes in the demand for the HTE-qualified. For these reasons we privilege an analysis of cross-sections over time. In comparison to the SES data the LFS includes a larger number of observations and represents a convenient tool to observe changes within occupations and by qualifications over time.

Analysis of the LFS data is also (like the SES) carried out on UK-wide data as the information on the geographical location (within the UK) where the person participating in the survey obtained her qualifications is not available, and more importantly to keep the number of observations as large as possible. We assume that findings from the analysis of the UK data are more representative of the education system and labour market in England than of other parts of the UK, given that England represents 84% of the UK population.

'Burning Glass Technologies' (BGT) data, derived from online vacancies, represent a new source of information on occupational requirements. The major difference between BGT and the two survey data sources is that BGT data represent the employer's perspective on 'ideal' candidates for the job whereas SES and LFS collect information from individuals in the labour force. BGT collects real time information on job openings in a range of countries including the UK. These include rich information on job characteristics, such as on skills required on the job, the geographical location where the ad was posted, wages and occupations (data for the UK were matched with the SOC classification). We analyse the raw text of job vacancies posted in England to identify qualification requirements as defined by employers and construct an educational variable on that basis.

Despite offering a new employer perspective, BGT data have some potential biases. Some jobs, such as in low skilled employment, are underrepresented as they are less likely to be posted online (e.g., jobs of babysitters, cleaning personnel are often filled through informal channels such as a recommendation of a friend). Exploring vacancy data to evaluate demand for skills may also risk overestimating the demand for jobs with a high turnover as the same vacancy can be posted many times.

The use of these three data sets to address the key research aims outlined above is partly driven by the existing empirical evidence and academic literature around HTE. While each substantive chapter (chapters 2-4) will provide a targeted literature review, the broad set of literature underpinning the project is addressed in what follows. This chapter subsequently discusses the theoretical foundations of the work, as well as the ethical implications of secondary data analysis in this context.

## 1.2. Review of relevant literature

This review of literature takes stock of existing evidence on labour market performance of HTE holders. Some articles referenced in this chapter are discussed in more depth in individual chapters if they are particularly pertinent to issues addressed there.

### *1.2.1. Setting the scene – overview of international evidence*

We start the discussion of relevant literature with cross-country evidence on vocational education and training (VET) to set the scene for the discussion of outcomes from vocational qualifications in the UK. Most of the international evidence concerns upper secondary vocational education and training, with much less comparative evidence at the higher technical level. Vocational education and training are provided in the majority of developed countries. Research studies evaluating labour market outcomes associated with VET identify positive short term but less clear long-term effects. There is some evidence that those who complete upper-secondary vocational and training programmes (equivalent to level 3 qualifications in England), and in particular those who have experienced a lot of training with employers, have stronger labour market outcomes, in terms of duration of job search, unemployment spells and wages, than those who choose more academic types of upper-secondary education (van der Klaauw, et al., 2004). Overall, countries with a high share of youth in VET with long spells of training with employers (apprenticeship)[4] have lower proportions of disconnected youth and youth experiencing a difficult transition to employment (Quintini & Manfredi, 2009).

Typically, students in vocational programmes spend less time studying academic subjects than their counterparts in academic programmes, and more time in occupation-specific training. Some research studies such as Hanushek et al. (2016) and Brunello and Rocco (2017) argue that occupation-specific skills provided by vocational programmes may be difficult to transfer across occupations and sectors, and someone with vocational credentials but a weaker academic background may therefore adapt less well in the long-run to new work requirements than an individual with similar level academic qualifications. A German study on the basis of worker self-assessment, suggests that human capital for vocational upper-secondary completers depreciates faster than for university graduates and the gap tends to increase over time (Ludwig & Pfeiffer, 2005). Accelerating human capital depreciation is explained by rapid organizational and technological change in workplaces.

A study by Hanushek et al. (2011) using data from the International Adult Literacy Survey (administered between 1994 and 1998), observe some short-term benefits to upper-secondary VET qualifications associated with a smooth transition from school to the labour market. But they argue that those completing vocational studies are more likely to lose their jobs after the age of 50 than those from academic pathways. They associate this disadvantage with the lack of the strong basic skills necessary to quickly adapt to

[4] In apprenticeships students spend at least 50% of their study time in training with employers.

changing work requirements triggered by technological change. Forster, Bol and van de Werfhorst (2016) performed a similar analysis using data from the Survey of Adult Skills carried out in 2012.They confirm that VET is associated with early career benefits, with the benefits being the largest in countries with strong apprenticeship systems. They also confirm that in some countries, the early career advantage associated with VET turns into a disadvantage later on. However, the negative effect of VET in late career is apparent in countries with no or limited apprenticeships, while in countries with strong apprenticeship systems (such as Germany, Austria), there is no clear evidence of a negative effect. Benefits associated with vocational education and training therefore depend on the content and organisation of the programme. The two studies mentioned above suggesting poorer long-term outcomes for those with VET qualifications have many limitations. They draw conclusions based on an analysis of cross-sectional data, which means that they are unable to separate the age, period, and cohort effects that all influence career trajectories.

A longitudinal study by Prada (2014) is one of few studies addressing this methodological challenge by accounting for previous performance of individuals. It estimates an impact of vocational, cognitive and non-cognitive skills on labour market outcomes and school choices in the United States, and found that individuals with strong vocational skills but low levels of cognitive and non-cognitive ability were better off not going to college (as measured by wages). The opposite was found for those with strong cognitive skills. It is not clear though to what extent the results of this study could apply to other vocational systems.

Those topping up VET qualifications with a degree can also expect different outcomes than graduates with an academic background. For example, in Italy HE graduates who, prior to entering degree programmes, completed VET were less likely to be employed and earn less than those with upper-secondary academic background (Agarwal, et al., 2019). A study exploring labour market outcomes of HE graduates with a VET background versus those coming from academic upper-secondary programmes in Switzerland finds different results (Oswald-Egg & Renold, 2021). The authors demonstrate the graduates with VET background earn significantly more one year after graduation and have to search for their first job for less time than those with academic background. However, these positive effects fade away with time. Oswald-Egg and Renold (2021) attribute discrepancy in outcomes in Italy and Switzerland to large differences in the design of VET and notably longer training spells with employers for VET upper-secondary students in Switzerland.

The international evidence, mostly on returns to upper-secondary education, provides limited guidance on the returns which may be expected from higher technical education in England, but it does provide evidence of the substantial variations in country experience, and demonstrates that labour market outcome from VET programmes depends on their design.

### 1.2.2. Labour market returns from education

Studies looking at the impact of education on labour market outcomes typically measure education in years of education and estimate the marginal effect of an additional year spent in education on earnings (or other measures of labour market performance). See for example (Card, 1999; Harmon, et al., 2020) for literature reviews). This approach works well in countries such as the US where years of education correspond to a specific educational attainment. In the UK and other countries where students at each level can chose between various educational options, using years of education may provide less precise results. For example, after GCSEs, students typically need 2 years to complete A levels (academic level 3 qualification). Some NVQ level 3 may require the same time for completion as A levels. Consequently, if outcomes to education were measured with years of education, it would be impossible to distinguish the effect of the NVQ from that of A levels, if the two qualifications have the same completion time.

Focusing on specific qualifications instead of years of education allows researchers to distinguish vocational qualifications from academic ones and to look at the returns to specific vocational qualifications. To estimate a wage premium to a qualification, wages associated with the highest qualification obtained by an individual are compared to the wages of those with lesser (and sometimes no) qualifications. This analysis thus aims to identify the incremental gain in wages by obtaining a higher level qualification. This approach is followed in the analysis of SES and LFS data discussed in the following chapters. As the marginal returns are estimated to the highest qualification, information on all the previous qualifications withhold by the individual is 'lost'. For example, someone with a level 4/5 qualification who subsequently obtains a degree would be counted as a degree holder. An alternative approach, (if data are available on all the qualifications of an individual, not just the highest one), involves estimating the average wage returns to qualifications, including all qualifications in the model. The premium to a qualification is estimated by comparing wages of those with the specific qualification to all those without it (Dearden et al., 2002; McIntosh, 2004; Dickerson and Vignoles, 2007). The qualification of interest can be any qualification held. This approach allows the returns to vocational qualifications to be identified even when topped up with a degree. However, it requires detailed information on educational history, which is not readily available in all datasets.

### 1.2.3. Review of UK literature on the outcomes of HTE qualifications

Definitions of vocational qualifications in the UK differ across research studies. Some focus on specific qualifications and provide estimates of wage returns to individual qualifications, while others group qualifications by level and type (e.g. Level 4 vocational qualifications). Unless otherwise specified, for convenience, in this literature review we will be referring to any qualification (technical and otherwise) at level 4 and 5 as HTE.

Returns to different vocational qualifications have been extensively studied in the UK. The evidence suggests that HTE qualifications yield larger benefits than lesser qualifications but fewer benefits than those associated with degrees, after accounting for observable wage determinants. Naturally, the returns to HTE depend heavily on the specific qualification and area of study.

Dearden *et al.*, (2002) use LFS data and National Child Development Study (NCDS) datasets to estimate returns to individual academic and vocational qualifications, rather than to qualifications aggregated by level, to account for diversity in the UK qualifications and associated wage premium. NCDS, a national longitudinal cohort study[5], provides rich information in regards to health, physical, educational and social development and economic circumstances, among others. The novelty of the study by Dearden *et al.*, (2002) is that by using information from NCDS, it controlled for various individual characteristics, such as ability and family background, which are often difficult to observe, and which are correlated with the choice of an educational programme. The authors estimated the biases resulting from the omission of these variables and conclude that an analysis with and without controls for individual characteristics yield similar results, as different biases cancel each other out.

Dearden et al. (2002) find that while the NVQ below level 3 qualifications yield no premium, HTE qualifications are associated with positive outcomes. The authors also show that academic qualifications yield a higher wage premium than vocational qualifications of the same level.

McIntosh (2004) estimated average returns (with all qualifications included) to various qualifications and found that in 2002 the wage premium for a first degree was 23-25%, and for professional qualifications (e.g. accountancy, law) around 40%, when age, age square, ethnicity, region, workplace size and public sector were accounted for. HTE qualifications yielded lower benefits and the wage premium varied to a greater extent between men and women. Among HTE qualifications, HNC/HND led to the highest wage premium (as compared to those without these qualifications) of 6% and 13% for women and men accordingly. An RSA (The Royal Society of Arts) higher qualification was associated with the lowest wage increment, approaching zero in the case of men. These estimates are in line with those provided by Dearden et al. (2002).

In a more recent study, Mcintosh and Morris (2016) exploit 1997-2015 LFS data to estimate wage benefits to vocational qualifications. The authors show that after accounting for individual and workplace characteristics, as well as geographical area and year, workers with level 4 and 5 vocational qualifications (with these qualifications representing their highest educational attainment) earn between 37% and 60% more than those with no qualifications, depending on the type of HTE qualification. The wage premium drops significantly when the earnings of those with HTE qualifications are compared to those of individuals with level 3 qualifications, reaching at most 13%, depending on the specific qualification.

One well-recognised challenge faced by studies drawing on survey data is that individuals are not randomly distributed across qualifications, as entry to programmes depends on individual choice and entry criteria. This means that unless all the relevant individual characteristics are accounted for, the estimates are

[5] NCDS follows the lives of around 17000 people born in England, Scotland and Wales in a single week of 1958.

biased. In this respect, administrative data can provide some advantages. They provide the advantage of large sample sizes and the ability to run subgroup analysis. Administrative data also often include excellent measures of prior achievement and so can control for the individual's academic ability, which is one major driver of individuals' decisions to take particular qualifications.

Espinoza and Speckesser (2019) use Longitudinal Education Outcomes (LEO) data, which link earnings from administrative data to individual records from England's central education register covering all stages of education. LEO provides very detailed information on each individual, resulting in a large number of predictors and a complex model. Including many regressors may lead to overfitting, whereby the model has a low bias and a high variance. To reduce the model complexity the authors apply LASSO (Least Absolute Shrinkage and Selection Operator) regression, a regularisation technique. Espinoza and Speckesser (2019) drawing on LASSO results chose the following covariates: gender, work experience, ethnicity, Free School Meal eligibility, region, Index of Multiple Deprivation at the Lower Layer Super Output Area level, GCSEs results, broad subject area, and school type. This set of variables provide an indication of individual features that have a strong bearing on wages. Espinoza and Speckesser (2019) look at earnings associated with 'higher vocational and technical education' and how they relate to graduate wages[6], issues that are also addressed in our research. The authors focus on the earnings of individuals who completed their secondary education in 2003 up to the time when they reach the age of 30. Their study confirms that ability as measured with school tests (English and Mathematics performance at KS2, KS3, and GCSE's outcomes) is highly correlated with subsequent qualification attainment. As expected, the prior achievement of the group with level 5 qualifications is higher on average than that of those with qualifications level 4, but lower than that of individuals with qualifications at level 6. Among graduates, those who completed Russell group universities have the highest previous level of school performance. Wage return estimates to qualifications ignoring that individuals are allocated to different education paths by ability, would therefore risk producing biased estimators. Regarding the wage premium, among men with similar ability, the earnings of those with higher vocational/technical education are comparable to the earnings of graduates from non-Russell universities, but they are below the graduate wage if the degree was obtained in a Russell institution. Female graduates, regardless of the type of institution, earn more than women with higher vocational/technical qualifications.

A more recent study by Espinoza et al., (2020) provides important insights into the labour market performance of individuals with qualifications level 4 and 5 as compared to those with other qualifications[7]. The study exploits a range of longitudinal data sets, such as: the National Pupil Database (NPD), the

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[6] Higher vocational education refers to qualifications level 4 and 5 that are typically achieved upon completion of programmes lasting one to two years. Following qualifications are included in this category: Higher National Certificates (HNC)/Higher National Diplomas (HND), Level 4 and 5 National Vocational Qualifications (NVQs). Academic programmes are mainly bachelor's degrees and a few other level 6 three years programmes.

[7] Level 4 and 5 qualifications discussed in Espinoza et al. (2020) overlap with our definition of the HTE drawing on LFS data but does not match it perfectly. For example, in our analysis foundation degrees are amalgamated with degrees.

Individualised Learner Record (ILR) and Higher Education Statistics Agency (HESA) data. This information is linked to HMRC tax records. The authors observe educational and labour market trajectories of cohorts who completed their GCSE's in 2002-2006 education. Similarly to (Espinoza and Speckesser, 2019) they find that individuals opting for level 4 and 5 qualifications have a different profile than those with level 6 qualifications, with the former having obtained lower GCSE results than the later. The study finds that level 4 and 5 qualifications yield a substantial premium at the age of 26 as compared to those with level 3 qualifications, after accounting for observable differences. Women qualified to level 5 earned on average 57% more than those with qualifications at level 3 only. Among men with qualifications at level 4 the wage premium is 42%. Surprisingly, wage benefits associated with level 4 and 5 qualifications in some subject areas exceeded those of degree holders. The authors note that this wage differential decreases with age and reverses later on. Graduate earnings thus rise faster by age than the earnings of holders of level 4 and 5 qualifications. The initial wage difference between level 6 on the one hand, and level 4 and 5 on the other may be related to young adults with qualifications at level 4 and 5 spending more time in the labour market than young graduates as qualifications at level 4 and 5 are of shorter duration than degrees, leaving more time for work. The higher average age of completion among individuals opting for level 4 and 5 qualifications suggests that they may often have had some work experience before embarking on their higher technical programme.

Positive outcomes from level 4 qualifications are also reported in (Patrignani, et al., 2017). The authors use various administrative data (such as the Longitudinal Education Outcomes (LEO), National Pupil Database (NPD), Individualised Learner Record, Higher Education Statistics Agency (HESA) and Work and Pensions Longitudinal Study) to construct credible counterfactual estimations. The counterfactual is what would have occurred if the individual had not obtained a level 4 qualification. The counterfactual labour market outcomes are therefore compared with outcomes of those who got the qualification. They find that a level 4 qualification, as compared to level 3 qualification, yield a substantial wage premium, though lower than that reported in (Espinoza, et al., 2020). They also point to other benefits associated with being educated to level 4, such as higher employability rates.

Wage benefits to higher level vocational and technical qualifications vary by area of study. Espinoza et al. (2020) finds that men and women with level 4 and 5 qualifications chose different areas of studies, and that wage premia to these qualifications vary greatly by subject. These findings echo results presented in (Greenwood, et al., 2011; Espinoza & Speckesser, 2019). Espinoza and Speckesser (2019) demonstrate that men who obtained their higher vocational and technical qualifications in "STEM" areas tend to earn as much or more than graduates with 'STEM' specialisations. Greenwood, Harrison and Vignoles (2011) found that, ceteris paribus, the HNC/HND qualified in STEM areas earned 8% on the top of the average HNC/HND wage premium and that the premium was the highest for those HND/HNC-qualified who studied STEM specialisations and who were working in STEM sectors, the sector therefore matching their specialisation. Aucejo, Hupkau and Ruiz-Valenzuela (2020) evaluate the value added of Further Education Colleges in terms of labour market performance and academic achievement controlling for a rich set of counterfactuals. They find large variations in the returns to vocational programmes by area of study.

However, among those in vocational programmes the majority pursue vocational qualifications level 2 and 3, with only few following level 4 programmes.

### *1.2.4. Overview of literature on changes in the labour market for skills*

Our research explores how the demand for skills associated with HTE qualifications has changed over time. It therefore draws on a body of evidence that discusses how labour markets have been changing over time in developed countries. Here we summarise main findings, theories supporting them and discuss the demand for technical skills within this context.

In many developed countries labour markets have become more polarised, in the sense that many more routine middle skilled jobs are being eliminated through automation, while employment in high skilled jobs, and to some extent in non-routine low paid occupations, has been rising. This development is associated with the metaphor of an hourglass shape to the labour market, compressed at midlevel. The last decades have also been marked by rising enrolment in post-secondary education in the UK and other developed countries and labour market demand for higher level education and skills. However, in the UK despite the sharp increase in the supply of university graduates the wage differential between university and lower level qualifications holders was maintained or increasing up to the mid 2000's corresponding roughly with the entry of the 1975 cohort to the labour market (Blundell et al. 2016).

Some theories such as Skills Biased Technological Change (SBTC) theory explain observed wage polarisation as the result of differences in skills pricing triggered by technologies (Katz & Murphy, 1992; Goos & Manning, 2007; Autor, et al., 2008; Acemoglu & Autor, 2011). For a historical overview see for example Vivarelli (2012). According to SBTC theory, the declining cost of computing technologies allowed their massive introduction in workplaces, and increased the demand for labour that was complementary to the new technologies. Other approaches focus on the role of the supply side, and notably the rising supply of highly educated labour in explaining changes in the job content and in the occupational structure. It is expected that in response to an increasing supply of higher education graduates firms will shift production methods to make greater use of high level skills (assuming education contributes to skills development) (Beaudry, et al., 2006; Blundell, et al., 2016; Salvatori, 2018). Blundell, Green and Jin (2016) in a study of LFS data over time (repeated cross-sections) explain the sustained wage premium to higher education in the UK, despite a growing supply of graduates, as reflecting changes in work organisation, whereby firms increase managerial positions in response to the inflow of HE graduates to the labour market. The authors also test and consider as unlikely alternative explanations such as the effect of cohort characteristics on the wage distribution[8].

[8] Other factors such as offshoring, migration and change in labour market institutions (e.g. unionisation, minimum wage) are also explored in the context of wage distribution and employment patterns (Card & Dinardo, 2002)(Mandelman & Zlate, 2014) (Salvatori, 2018).

There are some signs that the pace of growth in the demand for educated labour has ebbed. Studies looking at occupational changes over time in the UK show that, since early 2000’s, employment in top paid occupations has been declining (Cristini, et al., 2017). Henseke et al. (2018) drawing on UK Skills and Employment Surveys (repeated cross-sections) show that overall, since 2012, skills requirements in respect of numeracy and literacy have declined, the demand for higher education qualifications has stopped growing, and the amount of training and learning received by newcomers decreased. However, this should be interpreted with caution. The lower amount of training and learning received by an individual who has just started on the job could reflect the fact that new employees are now better skilled and trained than in the past and so require less training to become fully productive.

The impact of described changes on HTE is not clear as the majority of the research do not distinguish between different post-secondary qualifications. Spitz-Oener (2006) looks at employment patterns in Germany of those with ‘medium’ levels of education by aggregating secondary vocational upper-secondary and post-secondary credentials. She finds that individuals with this type of education tend to be concentrated in routine midlevel jobs, where demand for these occupations has been shrinking.

Traditionally, secondary vocational education and training prepared for mid-level occupations. Some of these occupations have been most affected by automatization, and employment in these sectors has therefore been shrinking. It can therefore be assumed that the demand for skills associated with this type of education has been falling. While our research concerns higher technical education at postsecondary level, some of the jobs targeted may also have been strongly affected by automatization. Our research indirectly explores how those with level 4/5 qualifications have been affected by the technological innovation. It therefore looks, for example, at whether those qualified at this level are more likely than in the past to perform the managerial tasks associated with high level jobs of professionals, or whether they have been displaced to low paid jobs.

Research looking at employment in the context of technological change decomposes jobs into routine and non-routine tasks and examines the extent to which individual tasks can be automated (Acemoglu & Autor, 2011; Green, 2015). As shown by Green (2015), this allocation of tasks is prone to error and involves subjectivity. Frey and Osborne (2013) apply a more granular approach to skills and recognize that nominally the same skill may or may not be automated depending on the context. For example, manual skills used by workers at an assembly line in a car factory can be easily automated, but a machine cannot yet replace a plumber using his manual skills in diverse and often cramped spaces.

The above review covers key literature that this research also contributes to. Further, more targeted, literature reviews are provided in each subsequent chapter. Before these chapters, however, the theoretical underpinnings of the research are discussed.

## 1.3. Theoretical model

Our research looks at the changing demand for HTE qualifications by exploring the labour market outcomes associated with different qualifications. This section presents the theoretical foundation and clarifies key concepts applied in this work.

### *1.3.1. The demand and supply of labour*

The demand and supply of labour have been extensively studied in economic literature, usually in the context of companies seeking to maximise their profits by choosing an optimal combination of production factors such as labour and capital; and in relation to individuals maximising their utility by choosing between leisure and employment generating income.

The aggregated demand for labour can be expressed as the sum of all the existing jobs and job openings in the economy, with vacancies providing an indication of the unmet demand for labour. Demand for labour is often depicted in relative terms as a proportion of the population in the labour force (employed and unemployed) or in employment.

The demand for labour is closely related to its supply, i.e., the number of individuals available for work, which partly reflects demography. Stagnating employment growth may be explained with a lack of job openings, but it may also reflect a low supply of qualified labour despite employer' willingness to hire. A study of wages helps to better understand labour market dynamics.

Higher wages encourage more individuals to work, and to work longer hours, so that, plotting wages against labour supply, the supply curve slopes upwards. But, higher wages also make production costlier for firms pushing them eventually to cut employment. Plotting wages against labour demand, the demand curve slopes downward. In a perfect market, the equilibrium wage is defined by the point where the supply and demand curves cross. In reality, markets are imperfect and the supply and demand for labour are also affected by various other factors. For example, a firm that is the only employer for those with particular skills in a large geographic area has a monopoly power over workers' wages. Despite these market imperfections, wages are still a valuable indicator of the supply and demand for labour as they tend to increase when the demand for labour exceeds its supply, and to fall when there are more employees available to work than jobs on the market.

In principle, under perfect competition, wages should reflect worker productivity, with employees who are more productive receiving higher wages. The capacity of any worker to produce goods and services depends on their stock of knowledge, skills and other characteristics (such as physical strength), often referred to as human capital (Becker, 1962). Assuming that markets are competitive, the wage of a worker with a given skillset equals the value of the marginal product of a worker with that skillset. More highly skilled employees are more productive and therefore receive higher wages. Given varying individual levels of human capital, wages will differ across employees depending on their skills, and the technology available to make use of those skill. I.e. in a competitive market wages are determined by the marginal product which is possible in principle given technology (some technologically backward firms may not be able to realise this marginal product but will still have to pay the going wage).

Wages also depend on the relationship between the demand and supply of required skills. Wages associated with skills for which the demand exceeds the supply, would typically increase. The wage premium associated with a skill may thus provide an indication of the demand for this skill, relative to its supply.

The labour market demand for individuals with a specific qualification also depends on the availability and price of labour with different qualifications. For example, an increased wage for university graduates could push employers to substitute graduate employees with lower qualified but cheaper labour. Evidence confirms that there is some substitution of highly educated by those with lower education attainment if the wage paid to educated labour increases (Ciccone & Peri, 2005). However, the elasticity of substitution tends to decrease in education, which means that those with lower levels of education can be more easily replaced than those with higher qualifications (Mollick, 2011).

### *1.3.2. The human capital model*

This research uses a framework provided by the human capital theory first formulated by Becker (Becker, 1962). Human capital refers to the stock of knowledge, skills and other characteristics that make individuals productive and is reflected in their earnings. Individuals invest in education and training to boost their stock of human capital and to increase future earnings. The choice of different levels and types of educational attainment is informed by demand factors and the stock of human capital available on the labour market (Heckman, et al., 1998; Fleischhauer, 2007).

Under this theory, the individual decision to invest in education is based on a comparison of the additional earnings[9] resulting from the education with the current cost of education, including both direct costs such as fees and foregone earnings. Individuals therefore have incentives to go on investing in education until, because of diminishing marginal returns, the marginal cost of education is equal to the marginal return (Harmon, Oosterbeek and Walker, 2020). In the UK, Dearden (1998) estimated that an additional year of education yielded increased wage returns of 5-9% on average. The OECD estimates average rates of return to university education in the UK in 2016 of around 13%, relative to those with just upper-secondary (level 3) education as their highest qualification[10] (Organisation for Economic Co-operation and Development (OECD), 2019).

[9] Future earnings refer to the present value of the stream of future incomes. Future earnings are discounted at the discount rate, and the higher the discount rate, the lower the present value of the future earnings.

[10] The rate of return to education compares the value of lifetime earnings to the cost of education.

The relationship between earnings and human capital is often expressed as a Mincerian wage equation (Mincer 1974), with the functional form:

Wage = F(Schooling, Experience)

Taking the log of wages as the dependent variable, the coefficients of independent variables may be interpreted as the percentage change in income arising from a one-unit increase in the independent variables. The log of individual earnings at a given point in time can be modelled as a linear function of education, experience and squared experience. More formally:

$$\ln(\mathrm{w}) = \alpha + \beta_1{}'S + \beta_2' E + \beta_3' E^2 \quad + e \ (1)$$

w – wages

$\alpha$ - intercept

S – Schooling measured with qualifications (dummy variable)

E – Experience

E^2 – accounts for the fact that the relationship between experience and earnings tends to be nonlinear (concave)

e – residuals

This general model will be used throughout the research, but adjusted to the constraints of different data sets. Our research draws on three data sources: the Skills Employment Survey, the Labour Force Survey and job vacancy data. While each of these data sources has limitations, together they provide a powerful way of triangulating estimates, and arriving at robust conclusions.

Employer demand for HTE relative to the supply of HTE will be estimated through the wage premium associated with HTE. The HTE wage premium is a percentage gain in earnings associated with this type of education, as compared to those with lesser qualifications (usually level 3), but also sometimes in relation to graduate wages (where the premium is usually negative). The HTE wage premium will be positive if individuals with HTE earn on average more than those with other qualifications, and negative if they earn less. By estimating changes in the wage premium over time we observe changes in the productivity of individuals with HTE qualifications, for wages are a proxy for productivity. The measured wage premium is relative to other levels of educational attainment, so changes in the relative demand for those with other qualifications may also affect the observed HTE wage premium.

Distilling out the effect of education from other factors that are not observed but are correlated with both education and wages is one of the major challenges. Individual ability is one such characteristic. If the analysis does not account for the impact of these other factors, the education coefficient will reflect both the effect of education on productivity and the effect of the unobserved variable that is correlated with education. There are different strategies to overcome this challenge including using instrumental variables, and accounting for a rich set of covariates. Despite these endeavours, our research may still suffer from some degree of omitted variable bias, implying a need for careful interpretation of results and formulation of conclusions.

### *1.3.3. An alternative model of assortative labour market*

In this research, following a neoclassical approach, employers are considered as wage takers – firms pay the same price for workers with similar characteristics (Card, et al., 2016). An alternative approach recognises that firms play a role in wage setting and that workers with equivalent observable characteristics may receive a different wage depending on the employer. Moreover, labour market frictions create opportunities for firms to set wages below worker's marginal productivity. This can result for example from a firm being the only employer in the local market (monopsony) and employers agreeing on the wage setting (oligopsony) (Card, 2022). In the past, lack of firm and employee data was one of the obstacles to measuring the influence of firms on wages.

Improvement in data collection and availability of matched employer-employee data permitted researchers to explore factors behind heterogeneity in wages and more broadly in employment outcomes observed among nominally similar individuals. An influential study by (Abowd, et al., 1999) estimated both person and firm elements of wage setting, by including observable and unobservable characteristics of workers and firms. They found that individual unobservable effects explain a large part of the wage variation. However, the study failed to demonstrate a positive association between workers and firm productivity - positive assortative matching (PAM). In a more recent study (Abowd, et al., 2014) adjusted the initial model and found that more productive workers were employed in more productive industries. Other research studies confirm the assortative matching between firms and workers. For example, (Bartolucci, et al., 2018) use workers mobility to identify the strength of the assortative matching. (Mendes, et al., 2010), explore PAM by focusing on the firm output rather than wages. (Dauth, et al., 2016) show that there is a better matching between workers and firms in dense local labour markets. The evidence thus tends to confirm that there is a positive association between workers and firm types. In the context of our research PAM would mean that HTE and employees with other qualifications are matched with different employers (e.g., by firm technology, their market power or managerial skills of their CEO and other unobserved characteristics), which can explain the observed differences in wages while keeping education and other individual observable characteristics constant. This hypothesis is not directly addressed in this research but is suggested as a topic for future examination. The first two studies of this research draw on the SES and LFS datasets, which lack sufficient employer information to explore this issue further. Findings from the third study using the BGT data point to differences in qualification requirements in nominally similar job ads (in terms of skills) and suggest that these differences in qualification requirements may be explained by firms' characteristics (e.g., geographical location, size). The BGT study does not explore the issue further but endorse it as a topic for further research.

### *1.3.4. A theoretical framework for interpretation of the results*

This section looks in more detail at Skills Biased Technical Change (SBTC) theory, namely the idea that technological change has increased the demand for skills over time. The theory, supported with empirical evidence (see for example Autor, Katz and Kearney (2006), Machin (2001), Autor, Levy and Murnane (2003)) suggests some reasons why the relative demand for HTE holders might increase or fall relative to the demand for graduates. It also helps to explain why demand for graduates has increased, despite the rising supply of graduates.

The SBTC model does not guide the empirical analysis that follows but provides a conceptual framework for interpretation of the results. Empirical tests of hypotheses suggested by the SBTC model are typically performed at an occupation or sector level within which relative wages and labour supply can be observed. Our analysis in the following chapters is carried out on individual data and does not directly explore the impact of technology on the demand for labour. It does assume though that some of the observed changes in tasks and skills requirements in jobs result from the introduction of new technologies. The SBTC model has recently been subject to revision as it failed to predict some recent employment and wage developments in developed countries (see for example, Acemoglu and Restrepo, 2018). However it remains a useful theoretical framework for this research.

The relationship between technology, skills and education has been addressed in many macroeconomic models of growth and is a perennial topic in economic analysis of the labour market. Technological innovation introduces new job tasks that potentially enhance labour productivity, but the same innovations create new challenges for workers who need the skills for the new set of tasks. Any lack of the skills necessary to handle new technologies will impede the successful adoption of technical innovations. (Nelson and Phelps, 1966; Tinbergen, 1974) argued that the adoption of technologies depends on the ability of the population to learn, and that technological development stimulates the demand for skilled labour. Empirical evidence from developed countries including the UK confirms that the spread of technologies, and in particular IT technologies, favoured skilled workers and negatively affected the labour market outcomes for those with lower level of skills (Acemoglu, 2000; Machin, 2001; Autor, Katz and Kearney, 2006; Goos and Manning, 2007; Acemoglu and Autor, 2010; Håkanson, Lindqvist and Vlachos, 2015). Typically, the contribution of different types of labour to the production function of the aggregate economy may be presented in the stylised form.

$$Y_t = F(K_t + H_t + L_t)$$

Where Y is the output produced at time t, H are high-skilled and L are low-skilled workers, with skills typically proxied with education. K represents the capital at time t. Focusing on the labour factors yields a canonical skill-biased technical (SBTC) change model.

$$Y_t = [(A_{lt}L_t)^\rho + (A_{ht}H_t)^\rho]^{1/\rho}$$

$A_{lt}$ and $A_{ht}$ are factors augmenting technology, $\rho$ is a substitution parameter. Technological change can improve the productivity of skilled labour, unskilled labour or both. Typically, it is assumed in the literature that the elasticity of substitution between labour factors is constant (CES) (Acemoglu, 2000; Mollick, 2011), such that $\sigma = 1/(1-\rho)$. In this framework, depending on the value of σ (elasticity of substitution), technology and the relative supply of labour would have a different effect on the demand and wages of workers with particular skills.

From the production function, we can estimate the optimal wage of skilled ($w_h$*) and unskilled workers ($w_l$*), under the assumption of competitive labour markets and two types of labour.

$$w_l * = \frac{\partial Y}{\partial L} = A_l^{\rho}[A_l^{\rho} + A_h^{\rho}(H/L)^{\rho}]^{(1-\rho)/\rho}$$

$$w_h * = \frac{\partial Y}{\partial H} = A_h^{\rho}[A_h^{\rho} + A_l^{\rho}(H/L)^{-\rho}]^{(1-\rho)/\rho}$$

By combining the two we obtain the relative wage of skilled versus unskilled employees.

$$\omega = w_h/w_l = (A_h/A_l)^{\rho}(H/L)^{-(1-\rho)}$$

$$= (A_h/A_l)^{(\sigma-1)/\sigma}(H/L)^{-1/\sigma}$$

For ease of interpretation, the relative wage $\omega$ can be presented in a logarithmic form, with the last term on the right-hand side standing for the relative supply of labour

$$\ln(\omega) = \frac{\sigma-1}{\sigma} ln(A_h/A_l) - \frac{1}{\sigma}(H/L)$$

Elasticity of substitution is between 0 and infinity, $\sigma[0,\infty)$. When $\sigma \to 0$, unskilled and skilled labour are perfect complements (Leontief framework), whereby factors are used in fixed proportions to produce a unit of output. HTE and degree holders would be Leontief if for example it was required for every dentist (degree holder) to work with exactly one dental technician (HTE-qualified) and if a career change was impossible. Obviously, this example is highly stylised. At the other extreme, where $\sigma \to \infty$, two types of labour are perfect substitutes. When two types of labour are perfect substitutes the relative wage is not affected by their relative supply.

The assumption of perfect substitution between graduates and non-graduate labour is adopted by O'Leary and Sloane (2016) who estimate the demand and supply of graduates across different occupations. More commonly though, different types of labour are seen as neither perfect substitutes nor complements in the production process. Empirical evidence tends to situate the elasticity of substitution between skilled and unskilled labour in a range between 1 and 2 (Katz & Murphy, 1992; Acemoglu, 2000; Ciccone & Peri, 2005). However these results may not be very meaningful as the definition of skilled and unskilled labour is not consistent across different studies. Katz and Murphy (1992) compare wages of US college (degree) and high school graduates (equivalent of level 3 qualifications), whereas Ciccone and Peri (2005) focus on individuals with high school and above as compared to high school dropouts. Mollick (2011) using cross country data provides different estimates depending on the definition of skilled and unskilled labour. The author estimates the elasticity of substitution between low skilled labour including individuals with no education or some primary, and skilled labour defined in three ways: completed primary, upper-secondary (equivalent of GCSE A-C*) and college. He concludes that the higher the level of education, the lower the elasticity of substitution. Highly skilled employees are therefore more difficult to replace than low skilled workers.

In the SBTC model the relative marginal productivity of the two types of labour depends on their relative supply and technology augmenting factors. When two types of labour are imperfect substitutes (at $\sigma$ >1) at a given level of technology, an increase in the relative supply of skilled versus unskilled labour H/L results in a falling skilled wage premium.

$$\frac{\partial ln\ \omega}{\partial\ ln\left(\frac{H}{L}\right)} = -\ \frac{1}{\sigma} < 0$$

Keeping relative supply constant, growth in the technology bias favouring skilled labour boosts the skilled labour wage premium.

$$\frac{\partial ln\ \omega}{\partial\ ln\left(\frac{A_h}{A_l}\right)} = \frac{\sigma - 1}{\sigma} > 0$$

Technology requiring a high level of skills drives the wage premium of the skilled labour up while the rising relative supply of highly skilled labour suppresses it. Depending on which factor prevails the skill premium will either grow or fall. Use of new technologies, production and management methods favouring skills commonly found among graduates may therefore maintain the demand for graduates despite their rising supply.

## 1.4. Ethical considerations

A series of ethical concerns arise in this research related to the source of funding and the use of data.

This research was conducted with the support of Gatsby Charitable Foundation, which provided funding and defined the topic of this research. By funding this research the Foundation intended to advance knowledge on the labour market demand for technical skills, and more broadly to promote research on vocational education and training in England. The terms of this sponsorship, including rights and duties of the parties involved, were defined in an agreement signed by the University of Cambridge, the Foundation and myself. At no time did the Foundation seek to influence the way the research was conducted or its findings.

Data ethic “studies and evaluates moral problems related to data, algorithms and corresponding practices in order to formulate and support morally good solutions (e.g. right conducts or right values)” (Floridi & Taddeo, 2016, p. 1). In other words, it is about the impact of activities related to data on people and societies.

This research relies on secondary data. Unlike primary data collected by the researcher with the purpose of informing her research study, secondary data are gathered by a body or person external to the researcher, usually for the purposes not related to the researcher’s study. Depending on the type of secondary data different ethical consideration emerge. Law (2005) makes a distinction between large scale publicly funded data, such as the LFS and SES, and smaller scale data collected and funded by the researcher. She notes that “there is general agreement that the first should be shared and made generally available in a “timely” fashion, but there is little agreement about the second” (Law, 2005, p. 1).

(Morrow, et al., 2014) show that over time approaches to data treatment changed from a very restrictive one whereby researchers were often expected to destroy the data after the end of the study to data archiving and data sharing. Data archiving and sharing was made possible by digital technology facilitating the storage of data (Morrow, et al., 2014). At the same time major public and not-for profit data producers, such as the Office for National Statistics in the UK, have developed a policy regulating archiving and access to data to ensure that ethical conditions are met and to maximise the use of the data.

“*Publicly funded research data are a public good and produced in the public interest. They should be made openly available with as few restrictions as possible in a timely and responsible manner*” (UK Research and Innovation , 2022, p. Common principles on research data)

Sharing research data has many benefits (UK Data Archive, 2011). Existing data can be used for various purposes to test new hypotheses and answer research questions without new data collection being necessary. This saves time and resources. The use of publicly funded secondary data thus maximises the value of public investment if the data collection is publicly funded. Another benefit is that methods, approaches and findings obtained with the secondary data can be verified and replicated, contributing to more transparency and accountability in research.

The major ethical risk of using secondary data is related to identification of individuals participating in data collection. Independently of this risk, Floridi & Taddeo (2016) point to the risk of group identification and targeting, whereby specific groups (by age, ethnicity) might be subject to discrimination and violence. Lack of informed consent by respondents to reuse the data represents another concern (Law, 2005). To address these issues, use of secondary data must meet some key ethical conditions (Data Big and Small, 2015):

- Data must be de-identified before release to the researcher
- Consent of participants can be reasonably presumed
- Findings from the analysis must not allow the re-identification of respondents
- Use of the data must not result in any damage or distress

Misinterpretations of the results can also pose an ethical threat. Research in social sciences aims to influence social policy and social reality. Policy that is based on false claims and wrong conclusions is likely to be inefficient and result in a waste of public money. To avoid such misinterpretations the current research systematically pinpoints the limits of the performed analysis.

In our research we analyse three data sets: two large scale survey data publicly funded and managed by the UK Data Service (LFS and SES), and data extracted from online job vacancies by a commercial company BGT. These datasets have distinctive characteristics and pose different challenges in relation to data ethics.

### *1.4.1. Ethical issues associated with the SES and LFS*

The Labour Force Survey (LFS) and Skills and Employment Surveys (SES) are publicly funded large scale sample data stored and managed by the UK Data Service. The UK Data Service has rules regulating access to data to minimise re-identification and disclosure risks, and agrees on access with the data owner. SES is funded by public entities including the Economic and Social Research Council, the Department for Education, whereas LFS is conducted by the Office for National Statistics (Office for National Statistcis, 2022). UK Data Service provides three different types of access depending on the data. Data can be: open access, safeguarded and controlled (secure) (UK Data Service, 2022). Both SES and LFS have a safeguarded status.

*"Data licensed for use in the 'safeguarded' category are not 'personal data', but the data owner considers there to be a risk of disclosure resulting from linkage to other data, such as private databases. The safeguards include knowing who is using the data and for what purpose. The End User Licence (EUL) outlines the restrictions on use for a particular data collection*." (UK Data Service, 2022, p. Legal definitions)

Further to the regulations, to access the SES and LFS data we registered with the UK Data Service, submitted a description of the research to explain which SES and LFS data would be used, and demonstrated that we have the appropriate knowledge and skills to manipulate and analyse the data. We signed up to terms and conditions set out in the EUL, which we observed through the research. Approaches we applied to data analysis and interpretation of findings were consistent with that proposed by the data owners. For example, we weighted the LFS data following ONS guidance.

### *1.4.2. Ethical issues associated with online vacancy data*

Burning Glass Technologies is a commercial US labour market analytics company[11]. BGT data are collected by web-scraping of job advertisement sources. There are two major ethical issues that apply to any data collection. First, participants should consent to data collection, and second participants' confidentiality and anonymity should be preserved. Regarding the first issue, informed consent implies that participants decide whether they want to participate in the study. Obtaining informed consent is not essential in covert research whereby individuals' behaviour takes place in the public space (Sugiura, et al., 2016). Information on job vacancies comes from job platforms or other sites that are in a public domain and for that reason seeking consent of employers posting open job vacancies is not required. Contributions to the job platforms can therefore be compared to observing individuals in a public space (Rodham & Gavin, 2006). Similar arguments apply to confidentiality and anonymity requirements. Employers or other bodies posting job vacancies are fully aware of the public status of their contribution posted in online public space. A different approach would naturally apply to information collected on online forums where participants may want to preserve anonymity (Sugiura, et al., 2016). This is however very different from the majority of online job vacancies where details on the employer and job are disclosed.

Online data gave rise to new ethical considerations. This type of data are characterized by a high volume of often unstructured observations. They are thus more demanding computationally and require much more work to be processed and analysed. To manipulate and order such a wealth of information new data analysis methods are used. Individuals working with online data often apply complex algorithms in the data analysis gradually reducing human involvement and control over the processes of data analysis. Floridi & Taddeo (2016) argue that this raises issues of fairness, responsibility and respect of human rights. BGT job vacancy data come in a structured form being pre-processed by BGT, however the algorithms applied by BGT to structure the data are not publicly available. Difficulty with replicating BGT analysis and verifying the reliability of the provided information raise the risk that BGT data might be flawed, leading to unreliable results. To have a better control over the BGT data we constructed an educational variable by analysing raw job vacancy text and job titles. The results obtained were consistent with the educational variable provided by BGT. We also carried out additional checks of the representativeness of the BGT data by reviewing relevant literature and comparing BGT data with other data sources such as LFS. This process casted doubts on the robustness of over-time analysis with BGT data, reflecting one of our concerns. We therefore refrained from any over time comparison with BGT data.

### *1.4.3. Organisation of the thesis*

The following three chapters present data analysis and its results. Chapter 2 explores Skills Employment Surveys, Chapter 3 focuses on the Labour Force Survey data analysis, and finally Chapter 4 discusses

[11] Since our research was carried, BGT has bought another labour market analytics company EMSI, and changed the name to Lightcast.

analysis of Burning Glass Technology data. Each of the empirical chapters brings in relevant literature that complements the evidence overviewed in the introductory chapter, discusses models and characteristics of the datasets used for the analysis, and finally looks into the results. Chapter 5 concludes. We refer to the whole research including analysis of the three datasets as ‘research’, and to individual analysis of the three data sets as ‘studies’.

# 2 How has the content of jobs performed by HTE-qualified changed over time?

## 2.1. Introduction

The research explores how employer demand for higher technical education (HTE) has changed over time in different occupations. It defines HTE as postsecondary programmes and qualifications at level 4 and 5 in the UK that prepare individuals for a specific occupation and are therefore considered technical. (A minority of level 4 and 5 qualifications are general). HTE programmes typically last 1-2 years (full-time equivalents). HTE therefore normally leads to jobs requiring some post-secondary education but not necessarily a full bachelor's degree.

The research looks at whether employment opportunities of individuals with HTE have worsened over time, a trend which may, setting aside other potential factors, imply falling demand for these qualifications relative to supply; or whether the reverse is true. Low take-up by students of programmes leading to HTE qualifications could be related to low demand for these qualifications from employers, for example because the skills provided by relevant programmes poorly match job requirements. Equally, it may also be that the demand from employers for these qualifications exceeds the supply, if for example students are not well informed about HTE programmes on offer, or there are institutional barriers (e.g. if there are financial incentives encouraging training institutions to provide programmes other than HTE ones).

Three data sources are used in the research: the Skills Employment Survey (SES), the Labour Force Survey and Burning Glass Technologies job vacancy data. The analysis of the three datasets is reported in separate chapters.

This first empirical chapter describes the analysis of the SES data. The Skills Employment Survey is a cyclical representative sample survey of workers in the UK. It provides information on tasks performed on the job and job characteristics, as reported by individuals in employment, alongside background demographic information and educational attainment. In our research, we use the 2001, 2006, 2012 and 2017 data.

This study, drawing on the SES data, defines the following highest qualifications as HTE: NVQ LEVEL 4 (or SNVQ 4) and HNC/HND (or SHNC/SHND)[12]. Many qualifications that are typically seen as HTE, such as foundation degrees, certificate and diploma of higher education, and higher level apprenticeships, are not included in the HTE category since they could not be clearly identified in the data. As they are not included in the HTE group they are inevitably part of other qualification categories, such as qualifications at level 3 or degrees. For example, all apprenticeships are classified at level 3 in the SES. This means that individuals reporting higher apprenticeship as their highest qualifications were probably classified as holding level 3 qualifications. Degree (or university degree) refer to qualifications level 5 and above other than those included in our definition of HTE (such as foundation degrees), and a graduate is a person with a degree.

This study uses the SES to explore whether, and to what extent, changing job requirements may explain some of the observed shifts in the HTE wage premium and so the relative demand for HTE. It aims to better understand the effect of various job tasks on earnings, the prevalence of these tasks in jobs performed by HTE holders and any changes over time. Separately, it looks at changes in specific jobs over time, in terms of their task composition, and expected qualifications of jobholders. To this end it exploits the unique feature of the SES data, namely the information it provides on tasks performed within different job roles. The novel feature of this study lies in its focus on job content and how job tasks are associated with wages among those with HTE qualifications. While research studies in the UK have explored the relationship between educational qualifications and the skills required on the job, including studies that have used these SES data, previous work did not focus specifically on HTE.

In the SES, skills ‘applied in the workplace’ are synonymous with tasks performed on the job. Skills applied on the job will typically be a subset of skills possessed by jobholders. In addition, an individual may possess other skills that are not directly used on the job. Those skills that are not applied on the job are not reported in the SES.

When a person lacks the skills necessary to successfully perform job-related tasks, there is a mismatch between the individual’s skills and those required on the job. Such a person is obviously less likely to be employed in the relevant job in the first place, and if employed in that role, her/his productive contribution would be lower than that of a person whose skills are well matched.

This SES study starts with a presentation of research questions and how they feed into the whole research. Second, a theoretical model of human capital and wages is discussed, as well a concept of skills drawing on the SES data. Third, the chapter focuses on the SES data and the data transformation for the analysis. Fourth, it focuses on empirical analysis and resulting findings. It ends with conclusions.

[12] See Boniface, Whalley and Goodwin (2018) and Field (2019)for a discussion of HTE qualifications in the UK.

## 2.2. Research questions

This SES study seeks to test some hypotheses suggested by the theoretical and empirical literature:

- As earnings tend to increase with education level, we expect that the skills used on the job that show the strongest positive association with wages would be those that are more prevalent among university graduates. We may also find that in response to the apparent strong demand for these skills university graduates will increasingly report the use of such skills in their jobs over time. This is consistent with evidence that the demand for degree holders in high paid employment has been rising and that the wage premium from a degree has remained positive despite an increase in the supply of graduates (Blundell, et al., 2016)[13]. We might also see that the use of these skills by HTE jobholders increased over time, again reflecting the strong demand for such skills in the labour market. However, if such skills are generally considered “graduate skills”, in the sense of skills expected from those with university degrees, we might also find that those with HTE qualifications remain less likely to secure jobs that use these skills than graduates, and hence that the growth in the use of these skills would be slower for the HTE group.
- Conversely, we expect to see a drop over time in the use of skills associated with mid-level blue collar occupations (such as physical strength, manual skills and ability to use hand tools). This is because jobs that require these skills have been the most affected by automation and hence the number of jobs requiring such skills has been shrinking. While HTE in principle should prepare workers for higher-level jobs rather than mid-level blue collar work, we might also expect that some more routine jobs associated with HTE qualification, have been ‘hollowed out’ by automation and technological change, reducing employer demand for the HTE qualification in question.
- With the increase in the supply of graduates, it is possible that workers with HTE qualifications who might have been doing higher level technical jobs have been displaced by graduates and forced to take less skilled employment. If this phenomenon is widespread, we may observe HTE holders increasingly undertaking on-the-job tasks that are more low level, and therefore negatively associated with wages.

## 2.3. Review of the literature drawing on SES

SES data have been extensively analysed to understand changes in job content, the mismatch between the demand for and supply of skills, productivity, and changes in the demand for skills required on the job over time. Whilst this body of work also explores the relationship between education type and level, and the tasks performed on the job, it does not address the issue of qualifications. This section describes

[13] The authors define university graduates as those with Bachelors’ degrees (and equivalents) and higher-level degrees.

relevant findings from the SES literature and indicates how the analysis reported in this chapter complements this existing evidence.

SES data demonstrate that the labour market demand for higher levels of educational attainment has increased, but that the returns have become more heterogenous. According to Felstead et al., (2007) in 2006, 30% of individuals in employment reported that qualifications at level 4 and above were required to get their jobs, representing an increase of ten percentage points as compared to those reporting this in 1986. In parallel, during this period there was an increase in individuals with qualifications at level 4 and above doing jobs where lower level qualifications were required (self-reported). If the supply of qualifications at level 4 and above had grown faster than demand, one would expect the return to these qualifications to have fallen over the period. This has not happened. An alternative explanation is that while the average return to qualifications at level 4 and above has been maintained, the variation in returns has increased with some of these qualifications providing skills that poorly match the skills required in jobs traditionally associated with qualifications level 4 and above. Felstead et al., (2007) do not discuss HTE qualifications specifically. It might however, be speculated that the observed increase in jobs requiring qualifications at level 4 and above was driven by a higher demand for degree holders rather than HTE, as the supply of the former was increasing rapidly, while the supply of HTE qualifications remained stable over time.

Job roles and the skills required to perform job tasks explain some of the variation in returns both between and within educational groups. Existing research shows that different skills used on the job are differently priced on the labour market, even after accounting for differences in occupation and education, i.e. two people with the same level of education and working in similar occupations will receive a different wage if the tasks they perform on the job require a different set of skills (Green, 2012). The analysis in this chapter aims to identify how skills used on the job explain differences in earnings between those with HTE and those with other qualifications, and indeed explain wage differences among those with HTE.

Increasing skill requirements in any individual job role typically result in a growing share of highly educated labour in that job. (It may also be that an inflow of highly educated labour into the labour market contributes to job upskilling). Felstead et al., (2007) observe an increase in the average level of skills applied on the job between 1997-2006, except for physical skills which remained stable in absolute terms. The education level of workers was positively correlated with the cognitive skills used on the job, and negatively related to physical tasks. This association was observed between occupations and within occupations (Green, 2012).

Computer-related job tasks have grown particularly fast. Green, Felstead and Gallie, (2003) demonstrate that the increase in educational attainment and training intensity among employees that occurred at the end of the 1990s was mainly driven by a massification of computer use in the workplace. This is consistent with other evidence showing that the introduction of computers and automation at work contributed to a higher demand for complex cognitive skills. However, recent data suggest that the growth in computer skills used on the job may have stalled, with a similar pattern observed in some other job-related skills

(Henseke, et al., 2018). Previously, technological change (introduction of new communication, computerised or automated equipment in the workplace) appears to have driven an increase in the demand for complex cognitive skills (Henseke, et al., 2018). But more recently this trend seems to have weakened, possibly because of the maturing of ICT technologies and a high penetration level of technologies in the workplace, reducing the scope for further increments of demand. Organisational change that provides employees with greater levels of job control and that enhances their involvement in work processes has also been associated with higher levels of skill, however again the pace of these kinds of workplace changes is declining (Green, 2012; Henseke, et al., 2018). Overall, 2017 SES data show a stagnation or even a decline in some skills used on the job.

These findings would suggest that we should observe an increase in the use of computer, cognitive and academic job-related skills and a decline in the use of physical skills among those with HTE qualifications, but with these trends weakening from 2017. To test these hypotheses, we will explore how skills use in jobs held by HTE-qualified workers have changed over time and compare them with changes in skill use observed in the total population.

Some job-related skills, such as teamwork are common in the majority of jobs, whereas other skills, such as numeracy, are particularly important in fewer jobs (Felstead, et al., 2007). The use of skills on the job is highly variable across occupations (SOC) and sectors (SIC). Overall, occupations associated with higher levels of education (e.g. professionals and managers) show a higher level of skill intensity (as reported by respondents). Given these large differences across occupations and sectors we will also explore whether changes in tasks performed on the job by HTE holders can be explained by the fact that HTE holders are more likely to be found in specific occupations. A similar approach was adopted in Green (2012). However, unlike Green (2012), our focus is on the relationship between HTE qualifications and skills used on the job.

## 2.4. Theoretical model

### *2.4.1. The Mincerian wage function*

This analysis is performed within a framework of a Mincerian wage function, whereby wage is a function of the worker's human capital proxied by education level (qualifications) and labour market experience.

As outlined above in the section describing the theoretical background to all the research reported in this thesis, the Mincerian wage function simply sees wages as a function of education and experience.

Wages= F(Education, Experience)

The model measures the effect of HTE on wages relative to other qualifications, and provides an indication if, from an individual point of view, investment in HTE is likely to yield positive wage returns. It also allows us to estimate the demand for HTE relative to its supply by examining changes in the wage premium associated with HTE qualifications over time. Increasing wage premia tend to be associated with growing relative demand, while decreasing premia imply the opposite.

To account for the fact that wages are influenced by various characteristics, many Mincerian-type models include independent variables other than education and work experience (Polachek, 2007). Factors such as gender and migration background are often associated with a choice of a career and so of an educational programme. These factors may also impact wages directly if gender and migration background are vectors of discrimination on the labour market. Following this approach our model controls for the effect of gender, as women and men tend to perform different types of job, and obtain different wage rewards. Our analysis does not control for migration background as this information is not available in the SES.

This research assumes that employers are not important in wage setting with wages being defined by the market. Card (2022) in his recent review of literature demonstrates that this assumption may not hold as firms are actively involved in wage determination. As argued above, this research does not address this issue directly. However, it acknowledges its importance and endorses future research in this area.

### *2.4.2. The wage is also a function of skills applied on the job*

The model can also incorporate information on tasks performed on the job and skills applied to perform them. More highly skilled employees receive higher wages as they can undertake more productive tasks. Wages also reflect availability of skills, with scarce skills attracting higher wages. In our estimation, individual wages are a function of education and skills applied on the job (these skills are indicated as $S_j$ in the scheme below), controlling for other factors.

Jobs that rely on a variety of skills and knowledge yield high revenues for the employer and can be expected to pay higher wages. Employees found in these jobs are typically highly educated and often with substantial work experience. Conversely, jobs that involve less complicated tasks can be carried out by workers with fewer and less advanced skills. Assuming education and training contributes to the development of skills and knowledge, workers in jobs involving fewer and simpler tasks can be expected to have received less education and on-the-job training than those in more complex jobs. It can also be expected that the supply of workers to perform low-skilled tasks relative to the demand will exceed the relative supply of employees capable of performing more challenging tasks, since highly skilled jobholders can substitute for the less-skilled workers but not the other way round[14]. For example, in principle it should be easier (in terms of acquiring new skills) for a dentist to replace a dental assistant than for a dental assistant to carry out a dentist's job. A falling share of those qualified at HTE level in jobs involving a range of highly paid tasks may therefore imply that their comparative advantage on the labour market is declining – if for example there is an abundance of more skilled graduates who are able to replace them.

While recognising a lack of consensus across disciplines regarding the meaning of 'skills', and evolution of the term over time, we adopt here a broad definition of 'skills' (Payne, 2000; Green, 2015). The skills applied on the job, as reported in SES, correspond to tasks that respondents carry out on the job, with tasks defined as units of activity producing an output (Green, 2012). In SES, respondents were asked to

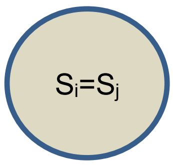
[14] We assume that individuals prefer to work than not to work.

rate the importance of a specific task X in their jobs (e.g. *In your job, how important is reading written information such as forms, notices or signs?).* Ideally one might have preferred that individuals are asked what tasks does this job require and, separately, what skills do you have to do said tasks. However, the data does not permit this. Hence it is assumed that individuals reporting a task X as important had the ability and skills ($S_j$) required to perform said task X. The 'tasks performed for the job' and 'skills applied on the job' to perform these tasks are therefore used in this chapter interchangeably. We assume that if the jobholder does not have a skill, which in principle could be usefully applied on the job, this skill is reported as not at all important or irrelevant to the job. Below, we discuss a relationship between skills used by individuals to perform tasks on the job, and other skills and abilities they possess. We also discuss the relationship between on the one hand, the set of skills that are in practice used by individuals on the job, and on the other hand a theoretically optimal set of skills that can be applied on the job to maximise the company profit.

### *Skills used on the job by an individual vs. skills held by the individual*

While skills performed on the job may overlap with skills possessed by jobholders, they are not identical. If there are two sets, with a set of individual skills $S_i$ (circled in blue), and a set of skills applied to perform job tasks $S_j$ (filled in grey) the relationship between the two can be described as following:

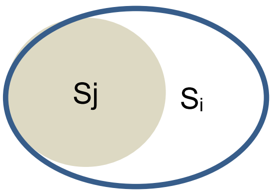
1. Perfect overlap, whereby individual skills Si equal skills used on the job $S_j$. This situation is optimal for individuals since they get to use and earn a return to all their skills.




$$Si \cap Sj, \qquad with \;\; Si = Sj$$

2. Individuals have the skills to perform jobs tasks plus some other skills

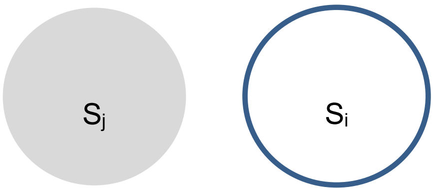
$$Sj \subseteq Si, \;\; and \; Si > Sj$$



Individual skills Si that are not part of Sj are not reported in the SES. However, if they impact wages and are not randomly distributed across individuals they may bias the results, particularly if they are correlated with qualification types or levels. For example, if graduates are more assertive than those with other qualifications, and assertiveness (not observed) is rewarded in the labour market, the wage premium associated with a degree will be overestimated. This is because although assertiveness is not (by assumption) taught or acquired during a degree programme, a degree signals the likelihood that the degree-holder is assertive, and since that assertiveness is attractive to employers, they are prepared to offer degree-holders a higher wage independently of any skills acquired as a result of a degree programme. The observed wage premium for a degree is therefore greater than the productive value of the skills acquired through the degree programme. Case 2 also describes a situation when an employee is over-skilled for the job. The worker possesses skills that could yield a higher wage premium if the person was in a different job. The issue of overskilling, important as it is, will not be developed further as the SES does not allow for an identification of those who are over-skilled.

3. Individuals do not have skills to perform job tasks.

$$Si \cap Sj = \emptyset$$




In principle, this situation should not be captured in the data as the sample consists of individuals in employment. Assuming, a job cannot be entirely taskless and a worker cannot spend all his work time being idle, workers will report using at least some sort of skills on the job.

### *Skills used on the job by an individual vs. an ideal set of skills required on the job*

Our definition of skills used on the job implies that on-the-job tasks, and so skills used to perform these tasks may vary across two nominally identical jobs depending on the ability and skills of the individuals. If $S_j$ refers to a set of skills applied by an individual on a job, and $S_{jt}$ refers to a theoretical optimal set of skills required in a given job, with $Sj \leq Sjt$,

1. $Sj = Sjt$ yields a solution optimal for the employer, as the jobholder has exactly the skills that maximise the output at a given wage.
2. $Sj < Sjt$ is sub-optimal for the employer. Tasks an individual can perform on the job do not cover a whole range of tasks required by the employer on this job.

In a specific job, a person, whose skills $S_j$ applied on the job are below $S_{jt}$, is less productive than an individual using on the job skills $S_j$ that perfectly match all the job requirements $S_{jt}$. If over time $S_j$ declines as compared to $S_{jt}$ in an educational group, this may imply that the productivity of individuals with the specific educational qualification declines too. This may happen because $S_j$ is decreasing, $S_{jt}$ is growing, or both. At a constant wage, employers would have strong preference for labour with a ratio $S_j/S_{jt}$ of 1 or close to 1.

Skills applied on the job ($S_j$) are added to the model on the grounds that, as the literature above demonstrates, job tasks and the skills required to perform these tasks are associated with wages. One of the difficulties in measuring the impact of skills on wages is that skills are correlated with education level and type. Hence controlling for both education and job tasks in the model indicates the extent to which some of the wage variation observed between individuals with different qualifications is largely attributable to the specific skills used on the job. More crucially, the model allows us to consider the demand for skills simultaneously with the demand for specific qualifications such as HTE, which is at the core of this research.

### *2.4.3. Caveats*

Observed statistical relationships between wages and education are not always causal; the analysis may suffer from omitted variables bias, whereby other, unobserved factors that affect both productivity and wages are not accounted for. If these factors are unequally represented among individuals with different qualifications, the wage estimate associated with the qualifications will be biased. For example, if those with higher ability are more likely to opt for a degree rather than for a HTE qualification and ability is not accounted for, graduate returns will be overestimated. They will be larger than if ability was randomly distributed across qualifications.

By the same token, observed associations between tasks performed on the job and wages, and between tasks performed on the job and qualifications, are not necessarily casual. A declining relative demand for HTE in occupations making use of tasks that are highly priced on the market could reflect a deterioration in the quality of HTE provision, whereby HTE programmes are failing to provide students with the skills that are in demand among employers. But it may also be because of a falling ability among HTE holders. In practical terms it means that those who in the past chose HTE now can enter university and many indeed do. Despite the fact that our models are not necessarily causal - they cannot pinpoint the exact causes of the observed changes, this analysis should help to cast light on how HTE employment patterns, as explained by the job content, have changed. It also improves our understanding of changes in skills used on the job by those with HTE qualifications, a little-researched field.

## 2.5. Data and measurement

The Skills and Employment Survey (SES) is a representative sample survey of workers in the UK and is one of the few datasets to provide quantitative information on tasks performed on the job in the UK. The SES provides rich information on job relevant skills and job characteristics, as reported by individuals in employment, alongside background demographic information and educational attainment. The fact that questions were partially repeated in consecutive SES waves allow changing patterns of job quality and job skills to be analysed.

The survey has been carried out roughly every five years in 1986, 1992, 1997, 2001, 2006, 2012 and 2017. This analysis uses the 2001, 2006, 2012 and 2017 data, where information on a range of skill variables was introduced. The numbers of respondents in the selected surveys were: 4,470 in 2001; 7,787 in 2006; 3,200 in 2012; and 3,306 in 2017 (Henseke, et al., 2018).The surveys targeted a representative sample of population aged 20-60-year-olds. In 2001, 2012 and 2017, 61-65-year-olds were additionally sampled. All surveys cover 12 UK regions: North East, North West, Yorkshire and the Humber, Eastern Midlands, West Midlands, East of England, London, South East, South West, Wales, Scottish Lowlands. The 2006 Survey was extended to Highlands and Islands, and Northern Ireland (Henseke, et al., 2018). To make the data consistent across the waves we restrict the sample to individuals aged 20-60 and remove Highlands and Islands, and Northern Ireland.

As noted by Felstead, Gallie and Green (2015) issues of work content, skills and ability of individuals, and interactions between the two have been addressed by other research studies typically applying qualitative methods proper to social sciences such anthropology, psychology, or sociology. Quantitative information provided by the SES's is complementary to this existing body of research.

### *2.5.1. The wage variable*

In this analysis wages are expressed in terms of a gross hourly nominal wage. This is derived in two steps. First, a yearly wage variable draws on other wage variables (e.g., daily, weekly, monthly wage); second, the nominal yearly earnings are divided by the number of hours of work during a year. The number of hours includes paid and unpaid overtime. The derived hourly wage may therefore be less than the worker's official hourly rate, if the hours reported include a lot of unpaid overtime. Information on the hours worked was not available for individuals who responded that the number of hours at work 'varied'. For those individuals who identified their employment as full or part-time we imputed hours worked by replacing missing values with an average number of hours worked in full-time and part-time employment drawing on information provided by the Office of National Statistics (Office for National Statistics, 2019).

The wage distribution in all four years is skewed to the right - wages are compressed at the bottom with a long tail at the top end. Wage outliers were dropped, namely wages at and above the 99th percentile and wages at and below the 1st percentile. Given that the nominal wage increased over time the data were trimmed for outliers for each year separately.

### *2.5.2. The highest qualification obtained*

SES data do not distinguish HTE from other qualifications as level 4/5 qualifications are amalgamated with qualifications at level 6 and above into one category. Since this research focuses on HTE and the associated labour market outcomes, an attempt is made to separate qualifications at level 4/5 from qualifications at level 6 and above. Out of level 4/5 qualifications the data allows to distinguish NVQ level 4 (or SNVQ 4), HNC/HND (or SHNC/SHND). Other level 4/5 qualifications such as foundation degrees, certificate and diploma of higher education, and higher-level apprenticeship cannot be precisely identified in the SES data and are therefore not counted as HTE here. It should therefore be kept in mind that the HTE qualifications as defined in this study represent only a fraction of all level 4/5 qualifications, and that these other level 4/5 qualifications are inevitably included in other qualification categories. For example, apprenticeships are classified at level 3 in the SES. This means that an individual reporting having a higher apprenticeship probably was classified as holding a level 3 qualification.

Overall, this study divides qualifications into 4 categories: 1). qualifications level 5 and above, other than those included in the HTE category, 2). HTE as above, 3). qualifications at level 3, 4). qualification at level 2 and below[15]. The first category - qualification level 5 and above, are referred to as degrees or university degrees, and a person with a degree is referred to as a graduate. A precise allocation of individual qualifications to educational categories is shown in Table A1.1 in Annex A.1.

### *2.5.3. The skills data reduction*

There are 48 occupational skill variables in the Survey. We make use of variables that are available in the four consecutive waves as our goal is to compare skills distribution over time. The variables with missing observations were dropped leaving 31 skill variables in the data (see Table A1.2 in Annex A.1). Individuals participating in the SES were asked how important the specific task was on the job, and to rate the importance of the task on a scale 1-5 (1-essential, 2-very important, 3-fairly important, 4-not very important, 5-not at all important/does not apply). Following Green (2012), we recoded the variable by allocating higher values to the more intensive use of skills (4-essential, 3-very important, 2-fairly important, 1-not very important, 0-not at all important/does not apply).

Multicollinearity issues arise if the analysis is performed on a large number of intercorrelated independent variables. Such an analysis risks returning poor accuracy of results. It can be expected that on-the-job skill variables identified in the SES are interrelated. Previous research studies working with a large number of on-the-job skill variables applied various methods to address the issue of multicollinearity and to reduce the dimension of the skill vector. Dickerson and Damon (2019) apply the O*NET description of US jobs to UK occupations[16]. They aggregate 35 skill measures into three indices corresponding to the 'data-people-things' taxonomy, as defined in the US Dictionary of Occupational Titles (DOT). Some other studies remove redundant information from the data by applying data driven methods such as Principal Component

[15] In the SES, respondents reporting 'other qualifications' are coded as having highest qualifications level 2 or below. However, in our analysis we code as missing those who reported obtaining other qualifications when they were older than 15. This is based on a conservative assumption that qualifications obtained when an individual was at least 16 could be above level 2.

[16] The Occupation Information Network (O*NET), sponsored by the US Department of Labour, describes worker attributes, including technical skills, for each occupation in the labour market (https://www.onetcenter.org).

Analysis (PCA) and Factor Analysis (FA), which do not presuppose any particular relationship between the variables. PCA and FA are data reduction techniques and aim to use the common variance across variables to reduce the number of items into a smaller set. In comparison to PCA, which finds a linear combination of variables explaining the maximal variance, FA is a statistical model expressing the relationship between variables with latent constructs which is arguably more appropriate for psychological concepts such as skills. Dickerson and Green (2004) discuss the principles of FA as well as PCA in more detail in the context of the SES.

Espinoza and Speckesser (2019) adopt an alternative data reduction method, mainly LASSO (Least Absolute Shrinkage and Selection Operator) regression. The choice of this method is dictated by the characteristics of their data and objective of their analysis. The authors focus on earnings associated with 'higher vocational and technical education' and how they relate to graduate wages[17], issues that are also addressed in our research. Espinoza and Speckesser (2019) use the Longitudinal Education Outcomes (LEO), which link earnings from administrative data to individual records from England's central education register covering all stages of education. LEO provides very detailed information on each individual resulting in a large number of predictors and a complex model. Including many regressors may lead to overfitting, whereby the model has a low bias and a high variance. To improve the predictability of the model the authors apply LASSO (Least Absolute Shrinkage and Selection Operator) regression, a regularisation technique that reduced the model complexity by decreasing the model variance at a cost of increasing its bias[18]. This technique results in data reduction, similarly to the Factor Analysis (FA) approach that we applied in the analysis of the SES data discussed in this chapter. Sharing the same aim – data reduction, the two techniques serve different purposes. While LASSO improves the predictive performance of the model, FA attempts to explain the relationship between the variables with latent constructs. Contrary to LASSO, which selects a subset of covariates from the existing set, FA yields new variables (factors) derived from the original ones, without altering their original variable structure (Euclidian distances between variables).

We reduce the dimensionality of the skills vector in two steps. First, we apply a FA to select variables showing the strongest relationship with unobserved latent constructs. Second, we estimate associations between the selected skill variables and wages to identify skill variables that are significantly associated with earnings.

---

[17] Higher vocational education refers to qualifications level 4 and 5 that are typically achieved upon completion of programmes lasting one to two years. They include following qualifications in this category: Higher National Certificates (HNC)/Higher National Diplomas (HND), Level 4 and 5 National Vocational Qualifications (NVQs). Academic programmes are mainly bachelor's degrees and a few other level 6 three years programmes.

[18] In Ordinary Least Square (OLS) estimation, parameters are estimated by minimizing the sum of squared residuals, whereby the following objective function S is minimised $Sols(\hat{\beta}) = \sum_{i=1}^{N}(y_i - x_i'\hat{\beta})^2$. In the LASSO regression a penalty term lambda is added to the objective function to penalize the size of parameter estimates, $S_{lasso}(\hat{\beta}) = \sum_{i=1}^{N}(y_i - x_i'\hat{\beta})^2 + \lambda \sum_{j=1}^{P} \parallel \hat{\beta}_i \parallel$, If $\lambda$=0, then $\hat{\beta}_{lasso} = \hat{\beta}_{ols}$

*First step: Factor Analysis (FA)*

Most of the studies examining SES apply the FA method to reduce skill data dimensionality. This method explains covariation between variables of interest with a linear combination of unobservable/latent characteristics (factors). For example, it can be presumed that counting, statistical calculations and any other mathematical operations performed on the job are related to person's quantitative skills or mathematical ability, and a job with a quantitative focus involves a range of quantitative tasks. In this example, the quantitative skills are therefore the underlying latent variable.

Dickerson and Green (2004) identified 10 skill factors through a FA on 1997 and 2001 survey data. The selected 10 factors account for 70% of the variance in the variables. Another SES study identified eight factors through a FA (Green, 2012). The author defined skill indices for further analysis by averaging scores from the responses to the component item. (See table 1 in (Green, 2012) for an allocation of skill variables to different factors). Felstead et al., (2007) and Forster, Bol and van de Werfhorst (2016) also apply FA to SES data. They constructed skills indices by averaging across the items in each group rather than using the factor scores themselves as the skills indices.

To select an appropriate data-reduction method we explored the relationship between skill variables. PCA and FA are appropriate statistical approaches if the variables are closely correlated. Spearman rank-order and Pearson correlations show that some SES skill variables are indeed highly correlated. Skill variables are ordinal and Spearman rank correlation may represent a better fit for this type of data. However, the two approaches yield similar results.

Similarly to previous SES studies, in this research a FA is applied to reduce the dimensionality of the skill data. FA is performed on all datasets (2001-2017) to obtain consistent skill measures across all waves. This approach assumes that the relationship between skill variables is stable over time. Carrying out a FA for each year individually represents an alternative approach. It relaxes the assumption of a constant association between skill variables across time but may result in a slightly different factor composition for each year making comparison across periods impossible. For this reason, the first approach is privileged. For ease of interpretation, we apply an oblique rotation to original loadings resulting in a new set of factor loadings, without altering the variance and covariance of the original model. An oblique rotation allows factors to be correlated (factors are nonorthogonal). Based on the results of the FA, the dimension of the skill vector is reduced from 31 to 18 variables. Seven factors with loadings (relationship of the variable to the factor) >= |0.5| are selected. Indices of the constructed variables are generated by averaging scores from the responses to the component items and rounded[19], as in Green (2012). As for the original scale on which skills are rated, the new constructed skill domains can take one of the 5 values: $\{0,1,2,3,4\}$. An

[19] If the first digit is exactly 5, R applies a rule common in programming languages whereby the number is rounded to the nearest even number (e.g. both 3.5 and 4.5 are rounded to 4). We derogate from this rule by rounding up to the nearest integer number (e.g 3.5 is rounded to 4 and 4.5 is rounded to 5).

alternative approach would be to directly construct factor indices with factor scores. Green (2012) notes that both methods yield similar results, with the former being more transparent and easier to interpret. Variables that do not show a strong association with any of the factors (with loadings <|0.5|) enter the model as individual variables. These variables tend to have a high uniqueness score, whereby all the factors jointly explain only a small percent of the variance in a given variable. Table 2.1 below provides a list of the resulting 18 variables including 7 constructed (in bold) and 11 individual variables.

### Table 2.1. Skills variables resulting from FA

| | |
|---|---|
| 1. | **Literacy tasks/skills (Vwrite)**: reading written information such as forms, notices or signs (cread), reading short documents such as short reports, letters or memos (cshort), writing material such as forms, notices or signs (cwrite), writing short documents, for example, short reports, letters or memos (cwritesh) |
| 2. | **Checking tasks/skills (Vsolut)**: spotting problems or faults (cfaults), working out the cause of problems or faults (ccause), thinking of solutions to problems (csolutn) |
| 3. | **Physical and manual tasks/skills (Vphysic)**: physical strength, for example to carry, push or pull heavy objects (cstrengt), physical stamina to work for long periods on physical activities (cstamina), skill or accuracy in using your hands or fingers, for example, to mend, repair, assemble, construct or adjust things (chands) |
| 4. | **Cooperation tasks/skills (Vcoop)**: working with a team of people (cteamwk), listening carefully to colleagues (clisten), cooperating with colleagues (ccoop) |
| 5. | **Planning own tasks/skills (Vplan):** planning your own activities (cplanme), organising your own time (cmytime), thinking ahead (cahead) |
| 6. | **Quantitative tasks/skills (Vnum)**: adding, subtracting, multiplying or dividing numbers (ccalca), calculations using decimals, percentages or fractions (cpercent) |
| 7. | **Influence tasks/skills (Vpersuad):** making speeches or presentations (cspeech), persuading or influencing others (cpersuad) |
| 8. | Knowledge of particular products or services (cproduct) |
| 9. | Dealing with people (cpeople) |
| 10. | Instructing, training or teaching people, individually or in groups (cteach) |
| 11. | Selling a product or service (cselling) |
| 12. | Counselling, advising or caring for customers or clients (ccaring) |
| 13. | Knowledge of how to use or operate tools, equipment or machinery (ctools) |
| 14. | Specialist knowledge or understanding (cspecial) |
| 15. | Knowledge of how your organisation works (corgwork) |
| 16. | Using a computer, 'PC', or other types of computerised equipment (cusepc) |
| 17. | Analysing complex problems in depth (canalyse) |
| 18. | Planning the activities of others (cplanoth) |

Note: the original variable name is provided in brackets.

*Second step: selecting skill variables based on their association with wages*

This second step aims to identify the on-the-job skills that show the strongest association (positive or negative) with the individual wage premium. The idea here is that the on-the-job skills that closely drive the wage premium are therefore the skills that employers are willing to pay for and those that are in greatest demand. These job-related skills, selected with model 1, will be used in the further analysis.

$$\ln(wi) = \alpha + \beta_1 Y + \beta_2\ Gi + \beta_3 Xi + e\text{i} \quad (1)$$

Where, ln (wi) – log wage of an individual i

$\alpha$ - intercept

Y –a vector of year dummies: 2006, 2012, 2017 (2001 reference year)

Gi – gender of an individual i (dummy variable, male – reference group),

Xi – vector of 18 skills/tasks performed on the job by an individual i, including 7 composed variables

ei – residuals

To increase the number of observations the data are pooled across the years. The coefficients of the skill variables returned by the wage analysis on pooled data represent an average effect of the job-related skills during the whole period keeping gender constant (the difference in relationship between job tasks and wages cannot be attributed to a non-random allocation of men and women into different jobs with presumably different job-tasks). The model deliberately does not account for education and age, as we want to explore the effect of education and on-the-job training in further analysis.

To observe if the effect of job-skills on wages varies across periods, and if selecting a one set of job-tasks for all the four years is methodologically appropriate, an analysis is performed separately on 2001-2006 and 2012-2017 data (see Table A1.3 in Annex A.1). Comparison of job skill coefficients in these two time periods shows that their signs are consistent. As a result, eleven job-skill variables significantly associated with wages are selected. They include:

- Physical and manual tasks/skills (Vphysic),
- Planning own tasks/skills (Vplan),
- Influence tasks/skills (Vpersuad),
- Knowledge of particular products or services (cproduct)
- Selling a product or service (cselling),
- Counselling, advising or caring for customers or clients (ccaring),
- Specialist knowledge or understanding (cspecial),
- Knowledge of how your organisation works (corgwork),
- Using a computer, 'PC', or other types of computerised equipment (cusepc),

- Analysing complex problems in depth (canalyse),
- Planning the activities of others (cplanoth).

As expected, and in line with existing literature jobs involving planning, analytical, computer tasks, influencing others, and jobs requiring specialist knowledge yield higher earnings. On the other side of the spectrum are job tasks requiring physical strength and manual ability, and jobs involving selling tasks and relationship with clients. Surprisingly, knowledge of how the organisation works is also negatively associated with wages.

An analysis of residuals versus fitted values (see Figure A1.1 in Annex A.1) shows that there is a cluster of observations that potentially could be influential, i.e. the results would be different if they were excluded from the analysis. In the first instance an attempt was made to associate these data points with characteristics that have not been accounted for, such as type of employment (employed vs self-employed), job stability (permanent vs not permanent), region, education, ethnicity and age, but no specific pattern is revealed. Finally, we run an analysis with and without the potentially influential observations. We keep the full sample as the two approaches yield similar results.

### *2.5.4. Sample weights*

For each survey, weights were computed to take into account a different probability of an individual being selected for each survey, the over-sampling of certain areas and variations in response rate between groups (defined by sex, age and occupation) (Henseke, et al., 2018).

To account for this, weighted data are used to produce descriptive statistics. Application of weights to regression analysis is more controversial (Solon, et al., 2013; Winship & Radbill, 1994). To evaluate the importance of weights in the regression analysis, we compare results from an OLS wage model with weighted and unweighted data. It shows that the coefficients of independent variables are comparable. Model 1 results on weighted data for all time periods (2001-2017) are shown in Table A1.4 in Annex A.1 (please compare with column 2 in Table A.1.3 in Annex A.1). In further regression analysis we privilege the unweighted OLS.

## 2.6. Findings

The objective of the empirical investigation is to examine labour market performance of HTE holders over the last twenty years in the context of a rapidly rising supply of degree holders and a spread of new technology in workplaces. In particular we will focus on an interplay between qualifications and tasks performed on the job, and their relationship with wages. In analysing tasks performed by jobholders with different qualifications over time we exploit the fact that the SES provides consistent worker-level data on tasks in four separate periods.

An empirical investigation in this section will look at how HTE wages compare to wages of those holding other qualifications and how undertaking different tasks performed on the job can explain these differences. It will also aim to explore if the value of skills applied in the workplace depends on the qualification held by the worker, i.e., whether individuals reporting identical tasks on the job but with different qualifications receive the same wage. It will also examine how the range of tasks, each with a different labour market price have changed over time among HTE holders. Finally, it will look at the distribution of qualifications and job-tasks in different occupational groups (SOC digit1) to explore the changes in the distribution of HTE holders across occupations over time, and changes in the distribution of tasks within occupations.

As context for this analysis, we start by describing how educational attainment (by qualification level) has changed over time. We also describe relevant trends in the evolution of wages and tasks performed on the job over the same period.

Drawing on the SES data, Table 2.2 shows that between 2001-2017, the share of graduates among those in employment increased by around 15 percentage points. During the same period the share of employees with HTE oscillated between 5% to 10%[20], and the share of labour with the lowest levels of qualification declined. If trends in the supply reflect trends in the demand, it can be concluded that, consistently with the existing evidence, there was a sharp increase in the demand for graduates, a decline in the demand for low educated workers, with little change in the demand for workers with HTE.

### Table 2.2. Highest qualification level over time, 16-60 year-olds in employment

| Highest qualification | 2001 | 2006 | 2012 | 2017 |
|---|---|---|---|---|
| level 2 and below | 0.43 | 0.38 | 0.31 | 0.31 |
| level 3 | 0.23 | 0.23 | 0.22 | 0.23 |
| HTE | 0.06 | 0.09 | 0.07 | 0.05 |
| University degree | 0.25 | 0.29 | 0.36 | 0.41 |
| NA | 0.02 | 0.02 | 0.04 | - |

Note : The results are weighted. NA – missing or does not apply

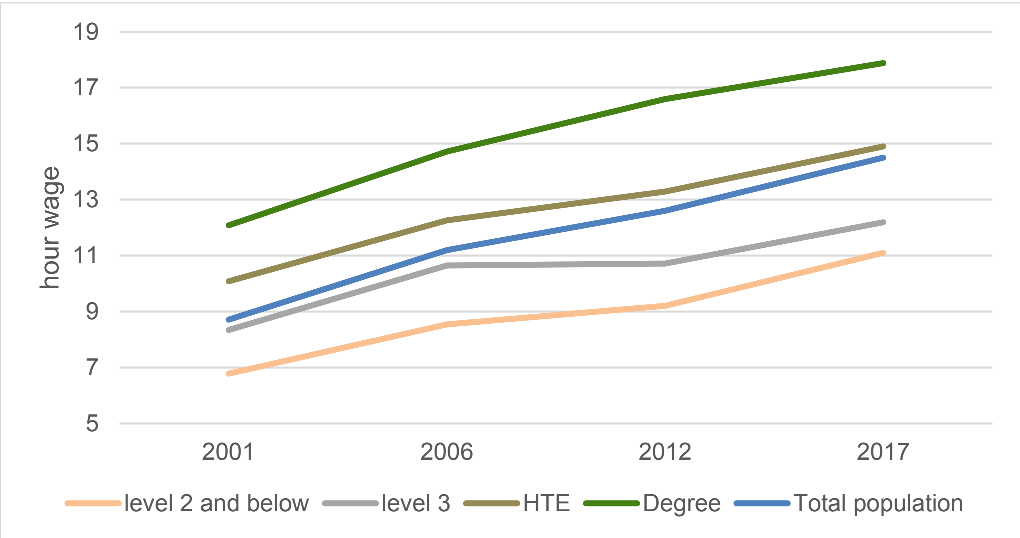
Source: SES data, author's calculations

A growth in graduate wages between 2001 and 2012 does indeed suggest that the demand for HE was maintained over time despite a quickly rising supply of graduates (Walker & Zhu, 2008; Blundell, et al., 2016). The demand for workers with highest qualifications seems to increase faster than the demand for HTE, given the widening wage gap between these two groups (see Figure 2.1). The fastest wage increase (of 63 percent) was recorded among those with the lowest educational attainment (level 2 and below). This

[20] In SES data the differences across years in the share of HTE in the labour force are not statistically significant, which is probably related to a limited cell size. This also explains the variation in the share of HTE qualifications across year. An analysis of the LFS data, discussed in the following chapter, may provide more robust estimates.

is likely to reflect factors other than labour market demand, such as an increase in the minimum wage over time. Since its introduction in 1999, the nominal value of the adult National Minimum Wage (NMW) grew faster than average earnings (The Low Pay Commission, 2016). In 2016, a National Living Wage (NLW), exceeding the NMW, was introduced as a required minimum for workers over 25. Between 2016-2018 the growth in the NLW was much faster than median and mean earnings (The Low Pay Commission, 2017). The growth in the nominal wage among those at the bottom of the earning distribution was therefore faster than a growth in the average wage, and the effect of NMW and NLW on wages of low educated workers who are more likely to be in low paid jobs was probably much stronger than on wages of those with higher educational attainment[21].

**Figure 2.1. Mean hour wage (not adjusted for inflation) 2001-2017, 16-60 year-olds**




Note: weighted data

Source: SES, author's calculations

As part of the background information, we also describe skills used on-the-job over time and wages associated with the intensity of on-the-job skills. The use of the majority of on-the-job skills remained constant or grew over time (the 2017 level as compared to the 2001), except for the tasks of 'advising and caring for clients' (ccaring) (see Table 2.3 below). Notably, there was a steady and fast increase in the use of computers in workplaces over time. Henseke at al. (2018) shows that the importance of the computer use rose over time in jobs in high and middle-skilled occupations. At the same time the authors argue that

[21] An increase in the share of self-employed among low-skilled, as shown by the SES data, could represent an alternative explanation of the relative growth in the wage of those with low education. This would be the case if self-employment yielded higher earnings than regular employment. However, the ONS data show that full-time self-employed, including those with low level of educational attainment, tend to earn less than those in regular employment (ONS, 2018).

the ICT technology in workplaces has recently reached a maturity level as the share of respondents reporting that additional computer skills would help them to do their jobs better has diminished. This may imply that the impact of computer technologies may weaken over time.

### Table 2.3. Tasks performed on the job in the total population, by year, 16-60 year-olds, 2001-2017

The table shows averages of the values the task variables can take. A task variable can take one of the 5 values {0,1,2,3,4}. Higher numbers indicate that tasks are on average used more intensively in the workplace.

| | 2001 | 2006 | 2012 | 2017 |
|---|---|---|---|---|
| Knowledge of particular products or services (cproduct) | 2.78 | 2.88 | 2.89 | 2.93 |
| Physical and manual tasks/skills (vphysic) | 1.89 | 1.84 | 1.79 | 1.87 |
| Planning own tasks/skills (vplan) | 3.01 | 3.09 | 3.08 | 3.11 |
| Influence tasks/skills (vpersuad) | 1.91 | 2.12 | 2.18 | 2.2 |
| Selling a product or service (cselling) | 1.71 | 1.77 | 1.86 | 1.77 |
| Counselling, advising or caring for customers or clients (ccaring) | 2.54 | 2.59 | 2.63 | 2.47 |
| Specialist knowledge or understanding (cspecial) | 3.05 | 3.2 | 3.15 | 3.18 |
| Knowledge of how your organisation works (corgwork) | 2.79 | 2.91 | 2.92 | 3.03 |
| Using a computer, 'PC', or other types of computerised equipment (cusepc) | 2.39 | 2.68 | 2.8 | 2.92 |
| Analysing complex problems in depth (canalyse) | 2.13 | 2.38 | 2.4 | 2.48 |
| Planning the activities of others (cplanoth) | 1.82 | 1.9 | 1.88 | 2.02 |

Note: weighted data

Source: SES, author's calculations

Table 2.4 below shows an average hourly wage by the five level of importance of a specific task on the job. Overall, jobholders intensively using on-the-job tasks that require managerial (or influence), complex cognitive and analytical skills (versuad, canalyse, vplan respectively), and use of computers (cusepc), report the highest wages. These are also the tasks that have been growing over time. It is therefore likely that the demand and supply for the associated on-the-job skills grew simultaneously. Wages associated with physical and manual tasks (vphysic), on the contrary, decreased in their intensity. Wage patterns related to other tasks are less clear.

### Table 2.4. Average hourly wage by tasks performed on the job in the total population, by task importance

2001-2017, 16-60 year-olds

| | Not at all | Not very | Important | Very | Essential |
|---|---|---|---|---|---|

| | important/does not apply | important | | important | |
|---|---|---|---|---|---|
| Influence tasks/skills (vpersuad) | 7.56 | 8.7 | 10.68 | 13.27 | 15.59 |
| Physical and manual tasks/skills (vphysic) | 14.62 | 12.43 | 10.08 | 9.25 | 9.02 |
| Planning own tasks/skills (vplan) | 7.2 | 7.85 | 8.81 | 11.23 | 13.07 |
| Counselling, advising or caring for customers or clients (ccaring) | 9.94 | 11.76 | 11.86 | 11.49 | 11.37 |
| Knowledge of how your organisation works (corgwork) | 7.23 | 8.9 | 10.35 | 11.4 | 12.42 |
| Planning the activities of others (cplanoth) | 8.58 | 10.31 | 11.86 | 12.93 | 12.92 |
| Knowledge of particular products or services (cproduct) | 10.47 | 10.74 | 10.82 | 11.33 | 11.61 |
| Selling a product or service (cselling) | 10.35 | 12.9 | 12.44 | 11.59 | 10.93 |
| Specialist knowledge or understanding (cspecial) | 7.11 | 7.92 | 8.87 | 10.63 | 12.93 |
| Using a computer, 'PC', or other types of computerised equipment (cusepc) | 7.31 | 8.36 | 9.82 | 11.42 | 13.27 |
| Analysing complex problems in depth (canalyse) | 7.69 | 8.8 | 10.18 | 12.32 | 14.51 |

Note: weighted data

Source: SES, author's calculations.

Comparison of coefficients of the skill variables in two time periods (Annex A.1, Table A.1.3) suggests that indeed jobs involving a lot of physical tasks (vphysic), requiring influencing of others (vpersuad) and an intensive use of computers (cusepc) show the strongest association with wages across the time. These findings are consistent with labour market literature suggesting that the share of cognitive, managerial and computer skills among on-the job tasks was growing while the share of physical and manual tasks declined.

A further analysis aims to 'unpack' wages into various factors that may explain differences in earnings between populations with different qualifications. To this end we use the Mincerian wage function, which estimates the association between wages and qualifications. In particular, we are interested in the impact of on-the-job skills on earnings. We expect individuals with different qualifications to be channelled into different job roles requiring a different combination of skills and attracting different pay-offs. This is because through education individuals develop skills and knowledge that are useful on the job, with longer periods of education presumably developing stronger cognitive skills. It can also be that there is selection into different educational pathways, whereby more able individuals are channelled into prestigious institutions and programmes leading to high status jobs (e.g. doctors, lawyers, engineers). This last dimension, selection by ability, is typically very difficult to measure with the data. It is also absent from this SES analysis.

### *2.6.1. Tasks performed on the job explain part of the variation in earnings between HTE and other qualifications*

An analysis without accounting for tasks performed on the job shows that those with HTE qualifications earn more than those with lesser qualifications but less than graduates. This relationship is estimated with a standard wage model at two points in time (2001-2006 and 2012-2017), whereby wages (in logs) are a function of education controlling for individual characteristics such as age (proxy of experience), age squared and gender (model 2). This model provides information on wages of HTE-qualified relative to earnings of those with other qualifications.

$$Ln(w_i) = \alpha + \beta_1 Y + \beta_2 Ei + \beta_3\ Gi + \beta_4 Ai + \beta_5 A_i^2 + e\text{i} \quad (2)$$

Where, wi is wage (in logs) of an individual i

$\alpha$ - intercept

Y –year dummy

Ei- Education dummy (HTE – level of reference)

Gi – gender of an individual i (male – reference group),

Ai – age of individuals and Ai^2 – age squared

ei – residuals

In the two periods graduates earn more than HTE-qualified workers but this difference tends to decrease over time. Wages also increase with age for all workers, up to a certain point when they start to decline, as indicated by the negative coefficient of the age squared term. (See table 2.5 below, columns 2 and 4)

The wage premium associated with HTE decreases when gender is accounted for. This reflects the fact that compared to other levels of educational attainment the share of men is the highest among HTE holders, and that men and women tend to choose different professions associated with different earnings. These findings are in line with other evidence on the relationship between wages, education, gender and age. Further analysis then explores in more detail the relationship between wages and skills required to perform job tasks.

Model 3 estimates the relationship between the selected on-the-job skills hold by an individual Xi, qualifications and wages.

$$Ln(w_i) = \alpha + \beta_1 Y + \beta_2 Ei + \beta_3\ Gi + \beta_4 Ai + \beta_5 A_i^2 + \beta_6\ Xi + e\text{i} \quad (3)$$

It examines if the mix of tasks performed on the job can explain the variation in wages among those with different qualifications, and among individuals with the same qualification. It may be that wage premia associated with specific qualifications to some extent do no more than capture the sorting of individuals with different qualifications into different jobs. However, we also expect to see large differences in the tasks carried out on the job among individuals with similar qualifications. Since qualifications are defined very broadly in this research, the associated returns would vary depending on the level and field of specialisation of the 'sub-qualification'.

Tasks identified in the SES are not specific to one job and may apply across a range of different jobs. But while some more generic tasks cannot be associated with a specific level of educational attainment, others tend to increase or decrease in the level of educational attainment (see Table 2.5). This is particularly true of tasks significantly associated with wages. On average respondents in jobs requiring different levels of education state that dealing with people (cpeople) is a very important or essential part of their jobs (this skill variable is not shown in Table 2.5 as its association with wages was not significant). This is true of medical doctors who have to interact with and look after patients, care workers looking after the elderly, salespersons dealing with clients, and many others. Dealing with people is common in diverse jobs that require varying levels of education, and attract very different wage levels. Given that this skill is required across most jobs, it is not surprising that the salience of people tasks in a job is only weakly associated with wages. Applying specialist knowledge to solve complex tasks is also transversal but more likely to be clustered in jobs with highly educated work force. Jobs making intensive use of analytical tasks tend be associated with higher levels of education and higher earnings. Respondents stating that analytical tasks are essential in their jobs had wages 30 percent higher than the average wage (all skills combined). (See Table A1.5 and A1.6 in Annex A.1). They were also more educated on average. Some of the tasks identified in the SES data, such as this one, clearly show a strong association of on-the-job skills with education.

## Table 2.5. Average on-the-job tasks intensity by qualifications

2001-2017, 16-60 year-olds

The table shows averages of the values the task variables can take. A task variable can take one of the 5 values {0,1,2,3,4}. Higher numbers indicate that tasks are on average used more intensively in the workplace.

| | level 2 and below | level 3 | HTE | degree |
|---|---|---|---|---|
| Physical and manual tasks/skills (vphysic) | 2.19 | 2.04 | 1.75 | 1.32 |
| Planning own tasks/skills (vplan) | 2.75 | 3.05 | 3.22 | 3.43 |
| Influence tasks/skills (vpersuad) | 1.60 | 1.94 | 2.25 | 2.74 |
| Selling a product or service (cselling) | 1.72 | 1.83 | 1.83 | 1.77 |

| | | | | |
|---|---|---|---|---|
| Counselling, advising or caring for customers or clients (ccaring) | 2.35 | 2.52 | 2.52 | 2.86 |
| Knowledge of particular products or services (cproduct) | 2.76 | 2.99 | 3.13 | 2.83 |
| Specialist knowledge or understanding (cspecial) | 2.77 | 3.15 | 3.34 | 3.54 |
| Knowledge of how your organisation works (corgwork) | 2.70 | 2.94 | 3.04 | 3.08 |
| Using a computer, 'PC', or other types of computerised equipment (cusepc) | 2.06 | 2.58 | 3.18 | 3.38 |
| Analysing complex problems in depth (canalyse) | 1.85 | 2.27 | 2.67 | 2.88 |
| Planning the activities of others (cplanoth) | 1.59 | 1.82 | 2.08 | 2.28 |

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' weighted data

Source: SES, author's calculations

After accounting for job tasks in the model, the coefficients on the education dummies shrink for both time periods – the gap in wages between HTE and those with lower and higher-level qualifications diminishes (Table 2.6, columns 3 and 5). This suggests that part of the difference in wages between HTE and other educational groups may be attributed to education mediating selection of workers into different jobs. This is intuitive as one of the goals of education is to secure a successful career. In some areas the two are intimately linked. Licenced occupations (such as doctors, nurses and teachers) can only by accessed by those with specific qualifications, typically positioned at degree level[22.] These jobs should therefore be strongly correlated with higher level qualifications. In other professions while a qualification may not be formally required it improves chances of entering the profession, especially for those with limited work experience. A qualification that has a value on the labour market signals to the employer that its holder has a minimum set of skills and knowledge that are necessary on the job. Typically, higher level qualifications signal higher levels of skill. However, the relationship between qualification and tasks carried out on the job cannot be interpreted as a pure 'education effect' since selection into different qualifications is not random, whereby individuals with certain characteristics are more likely to opt for a specific qualification in the first place. Some of these characteristics, such as gender and age are accounted for, but others (such as ability, family background) are not reported in the data and are not controlled for.

### Table 2.6. Association between wages (log), qualifications, and job tasks in two time periods

16-60 year-olds

In column 2 and 3 the reference group are men with HTE, 2001 is the reference year. In column 4 and 5 the reference group are men with HTE and 2012 is the year of reference

[22] Although this was not always true. Field (2019) describes how professions like engineering and nursing shifted from being HTE to level 6 professions.

| | (2) | (3) | (4) | (5) |
|---|---|---|---|---|
| | 2001, 2006 | 2001, 2006 | 2012, 2017 | 2012, 2017 |
| Intercept | 1.048 (0.092)*** | 0.99 (0.09)*** | 1.217 (0.11)*** | 1.272 (0.108)*** |
| Knowledge of particular products or services | | -0.005 (0.005) | | 0.009 (0.007) |
| Physical and manual tasks/skills | | -0.06 (0.006)*** | | -0.06 (0.006)*** |
| Planning own tasks/skills | | 0.02 (0.008)** | | 0.01 (0.009) |
| Influence tasks/skills | | 0.06 (0.007)*** | | 0.06 (0.008)*** |
| Selling a product or service | | -0.02 (0.004)*** | | -0.02 (0.005)*** |
| Counselling, advising or caring for customers or clients | | -0.03 (0.005)*** | | -0.03 (0.006)*** |
| Specialist knowledge or understanding | | 0.036 (0.007)*** | | 0.04 (0.009)*** |
| Knowledge of how your organisation works | | -0.001 (0.007) | | -0.03 (0.009)*** |
| Using a computer, 'PC', or other types of computerised equipment | | 0.04 (0.005) *** | | 0.05 (0.006)*** |
| Analysing complex problems in depth | | 0.028 (0.006)*** | | 0.05 (0.007)*** |
| Planning the activities of others | | 0.007 (0.006) | | 0.01 (0.007)* |
| female | -0.19 (0.013) *** | -0.17 (0.01)*** | -0.16 (0.015)*** | 0.13 (0.01)*** |
| age | 0.05 (0.005) *** | 0.04 (0.004)*** | 0.055 (0.005)*** | 0.04 (0.005)*** |
| Age square | -0.0006 (0.000)*** | -0.0005 (0.000)*** | -0.0006 (0.000)*** | -0.0003 (0.000)*** |
| Year 2006 | 0.18 (0.013) *** | 0.15 (0.012)*** | | |
| Year 2017 | | | 0.15 (0.015)*** | 0.14 (0.01)*** |
| Level 3 qualif. | -0.027 (0.025) | 0.01 (0.02) | -0.08 (0.03) ** | -0.046 (0.03) |
| Level 2 qualf. & below | -0.23 (0.024) *** | -0.10 (0.023)*** | -0.23 (0.029) *** | -0.11 (0.028)*** |
| Degree | 0.32 (0.025) *** | 0.21 (0.02)*** | 0.27 (0.029)*** | 0.14 (0.027)*** |
| | 2282 observations deleted due to missingness | 2282 observations deleted due to missingness | 1799 observations deleted due to missingness | 1799 observations deleted due to missingness |

| | | | | |
|---|---|---|---|---|
| | F-statistic: 271.7 on 7 and 8549 DF, p-value: < 2.2e-16 | F-statistic: 156.8 on 18 and 8538 DF, p-value: < 2.2e-16 | F-statistic: 178.7 on 7 and 4212 DF, p-value: < 2.2e-16 | F-statistic: 117 on 18 and 4201 DF, p-value: < 2.2e-16 |

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'

Source: SES, author's calculations

### *2.6.2. Accounting for job-related skills decreases but does not eliminate earning differences*

In the group of individuals with exactly the same job-related skills but different qualifications, HTE holders still earn around 19% less than graduates and 10% more than those with the lowest level of education (all years combined). This suggests that other features associated with the specific education drive the wage premium. It could be because education contributes to development of skills, knowledge and social capital that are not captured in the data but that are associated with jobs and earnings. It could also be because education is associated with other characteristics that are unobserved such as family background and ability of individuals.

### *2.6.3. Individuals with the same level of educational attainment but performing different tasks on the job have different earnings*

Job-related skills explain part of the variance in wages independently of education. Similar findings are reported by Green (2012). This suggests that among individuals with the same qualification, wages vary depending on the tasks performed on the job. This may be associated with differences in the field of study that are not accounted for in this analysis (due to small cell size). Britton et al., (2016), Lindley and McIntosh (2015) report that earnings of graduates depend on the field of study. Espinoza and Speckesser (2019), McIntosh and Morris (2016), and McNally (2018) report similar findings for HTE. A search of career information websites (e.g. planitplus net) confirms that HND qualifications yield very different benefits depending on the field of study. For example, a HND trained software developer can expect much higher earnings than a dental nurse with a similar level of qualification.

### *2.6.4. For the HTE-qualified, there are high wage premia associated with specialist knowledge and analytical skills*

Model 3 forces an association between job-related skills and wages to be identical across qualifications, e.g. two individuals performing identical job tasks but with different qualifications are assumed to receive the same salary. But this assumption does not necessarily hold. Tasks, as defined in SES, are common to many jobs and are self-reported. It is possible that an identical task rated in the same way by two respondents is differently priced depending on the precise nature of the job. Analytical tasks performed on the job by a person with a HTE qualification may be more complex and create a larger output than analytical tasks performed by a low educated worker. Tasks performed by an HTE holder would be associated with higher productivity and would attract higher payoffs than the later. The two tasks may therefore be the same in the relative terms - how important they are in comparison to other tasks performed by an individual, but differ in absolute terms.

To verify if the effect of job requirements on earnings differ by qualification interaction terms are added (model 4).

$$\ln(wi) = \alpha + \beta_1\ Y + \beta_2\ Ii + \beta_3\ Xis + \beta_4\ Siq + \beta_5\ (Xis * Siq) + e\text{i} \quad (4)$$

Where, ln(w) – log wage

α - intercept

Y –year dummy

Ii – a vector of covariates such as gender (male – reference group), age, age square

Xis– skill required on the job as reported by an individual i

Siq – a dummy variable indicating qualification q held by an individual i

Xis*Siq – interaction term between qualification i and on the jobs skill s

ei – residuals

The results (Table 2.7 below) show that in 2001-2017 the HTE-qualified benefited more than those with the lowest education and probably more than graduates from using specialist knowledge and understanding on the job (cspecial)[23]. In other terms, the wage gap between the HTE-qualified who make limited use of specialist knowledge and skills and those who apply them intensively on the job, is the largest among these educational groups. Since HTE in principle prepares individuals for technical jobs, and that would also be an employer’s expectation when hiring a HTE holder, those HTE-qualified who lack these specific skills (or the opportunity to use them) may be particularly penalised on the labour market. This may suggest that HTE provision should be strongly connected to the world of work and provide skills that can be directly applied in the workplace. Inclusion of good quality work-based learning in HTE programmes is one way of achieving this objective. This approach has been advocated in Field (2019). Analytical skills applied on the job yield larger returns to the HTE-qualified than to those with low levels of educational attainment. The wage premium associated with analytical on-the-job skills found among HTE-qualified is similar to that observed among graduates. Conversely, an intensive use of knowledge of a particular product and services (cproduct), and dealing with clients (ccaring) yields larger benefits to less educated

[23] We only show the outcomes for the whole period as the analysis broken down by two periods provides less reliable results due to a smaller sample size.

workers than it does for the HTE-qualified. This may be because for less educated workers, jobs relying on these tasks are relatively skilled as compared to an 'average' job held by an unskilled worker. However, in the HTE group the same job would be considered as relatively low-skilled in comparison to the 'typical' HTE job.

### Table 2.7. Association between wages (log) and job tasks among those with different qualifications

16-60 year-olds.

Men with HTE are the reference group, 2001 is the reference year.

| | |
|---|---|
| Intercept | 0.98 (0.1) *** |
| female | -0.16 (0.01)*** |
| Age | 0.04 (0.003)*** |
| Age squared | -0.0004 (0.000) *** |
| Year 2006 | 0.15 (0.01) *** |
| Year2012 | 0.26 (0.015) *** |
| Year2017 | 0.39 (0.015) *** |
| Level 2 qualif. and below | -0.07 (0.08) |
| Level 3 qualif | 0.05 (0.09) |
| Degree | 0.10 (0.09) |
| Knowledge of particular products or services | -0.03 (0.02) * |
| Physical and manual tasks/skills | -0.06(0.01) *** |
| Planning own tasks/skills | 0.03 (0.02) |
| Influence tasks/skills | 0.05 (0.019)** |
| Selling a product or service | -0.015 (0.011) |
| Counselling, advising or caring for customers or clients | -0.05 (0.01)*** |
| Specialist knowledge or understanding | 0.08 (0.02)*** |
| Knowledge of how your organisation works | -0.027 (0.02) |
| Using a computer, 'PC', or other types of computerised equipment | 0.046 (0.01) ** |
| Analysing complex problems in depth | 0.05 (0.016) ** |
| Planning the activities of others | 0.02 (0.15) |
| Knowledge of particular products or services *qualif level 3 | 0.03 (0.02) |
| Physical and manual tasks/skills * qualif level 3 | 0.002 (0.017) |
| Planning own tasks/skills * qualif level 3 | -0.01 (0.03) |
| Influence tasks/skills * qualif level 3 | 0.01 (0.02) |
| Selling a product or service * qualif level 3 | -0.01 (0.01) |
| Counselling, advising or caring for customers or clients * qualif level 3 | 0.02 (0.01) |

| | |
|---|---|
| Specialist knowledge or understanding * qualif level 3 | -0.03 (0.02) |
| Knowledge of how your organisation works * qualif level 3 | 0.01 (0.02) |
| Using a computer, 'PC', or other types of computerised equipment * qualif level 3 | -0.005 (0.02) |
| Analysing complex problems in depth * qualif level 3 | -0.01 (0.02) |
| Planning the activities of others * qualif level 3 | -0.02 (0.017) |
| Knowledge of particular products or services *qualif level 2 and below | 0.04 (0.019) * |
| Physical and manual tasks/skills * qualif level 2 and below | 0.009 (0.02) |
| Planning own tasks/skills * qualif level 2 and below | -0.008 (0.02) |
| Influence tasks/skills * qualif level 2 and below | 0.004 (0.02) |
| Selling a product or service * qualif level 2 and below | -0.005 (0.01) |
| Counselling, advising or caring for customers or clients * qualif level 2 and below | 0.03 (0.01) * |
| Specialist knowledge or understanding * qualif level 2 and below | -0.06 (0.02) ** |
| Knowledge of how your organisation works * qualif level 2 and below | 0.029 (0.02) |
| Using a computer, 'PC', or other types of computerised equipment * qualif level 2 and below | 0.001 (0.015) |
| Analysing complex problems in depth * qualif level 2 and below | -0.036 (0.018) * |
| Planning the activities of others * qualif level 2 and below | -0.02 (0.016) |
| Knowledge of particular products or services *Degree | 0.038 (0.019) * |
| Physical and manual tasks/skills * Degree | -0.007 (0.016) |
| Planning own tasks/skills * Degree | -0.02 (0.026) |
| Influence tasks/skills * Degree | 0.005 (0.02) |
| Selling a product or service * Degree | -0.002 (0.01) |
| Counselling, advising or caring for customers or clients * Degree | 0.03 (0.01) * |
| Specialist knowledge or understanding * Degree | -0.029 (0.024) |

| | |
|---|---|
| Knowledge of how your organisation works * Degree | 0.01 (0.02) |
| Using a computer, 'PC', or other types of computerised equipment * Degree | -0.009 (0.02) |
| Analysing complex problems in depth * Degree | 0.008 (0.018) |
| Planning the activities of others * Degree | 0.000 (0.01) |
| | 4081 observations deleted due to missingness<br>Multiple R-squared: 0.309, Adjusted R-squared: 0.3061<br>F-statistic: 107.4 on 53 and 12723 DF, p-value: < 2.2e-16 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'

Source: SES, author's calculations

### *2.6.5. HTE-qualified workers increasingly perform tasks requiring lower levels of skills*

In the previous analysis, HTE wages were compared to wages of those with other qualifications. Analysis of the relationship between tasks performed on the job and earnings revealed that some of these tasks have a stronger association with wages than others, and that job-related tasks tend to be unequally distributed among educational groups. The analysis also suggested that some job-related skills attract different wage premia depending on the qualification of the worker.

Further analysis explores how job-related skills have changed over time in populations with the same qualification. It determines if over time those with HTE become more (or less) likely to be in the job roles that use skills that have the strongest association with wages, and that are presumably in high demand on the labour market. Intensive use of management, complex cognitive, and computer skills yield higher wages. Specialist knowledge and analytical skills, when applied on the job, are also associated with higher wages, and particularly among those with HTE. An increase of these skills in those with HTE qualifications (relative to those with other qualifications) may suggest an improved match between tasks on the job and the skills of those with HTE. This would imply that the demand for HTE relative to its supply has probably been growing. Conversely, a relative increase in tasks negatively associated with wages such as physical and manual skills would suggest a worsening position for the HTE-qualified. Analysis of the job tasks performed by HTE over time therefore aims to establish if HTE holders moved over time to less (more) skilled tasks and presumably less (more) skilled jobs.

The change in job related skills among HTE holders is evaluated with the following model

$$s_{ij} = \alpha + \beta_1 Y + \beta_2\ Gi + \beta_3 Ai + \beta_4 A_i^2 + e\text{i} \quad (5)$$

Where, sij is a skill j reported by an individual i (HTE holders only)

$\alpha$ - intercept

Y –year dummies: 2006, 2012, 2017 (2001 reference year)

Gi – gender of an individual i (male – reference group),

Ai – age of individuals and Ai^2 – age squared

ei – residuals

An identical estimation is carried out for all the qualifications combined so that the results for HTE-qualified can be compared with those for the total population. A comparison of year effects ($\beta 1$) in the whole sample and among those with HTE qualifications only shows if job related tasks carried out by HTE holders were growing at the same rate over time as in the whole population. It may be that differences in the use of tasks observed across years are explained by HTE-qualified changing occupations over time, if for example they moved over time to occupations involving fewer highly priced tasks. To account for this possibility, we add an occupation dummy (SOC digit 1 category) to the estimation of the use of tasks on the job by HTE workers.

The results of analyses for the total population and for the group with HTE are shown in Table 2.8 below, column 2 and 3 respectively. Effects of age and gender on the intensity of tasks performed on the jobs are included in all the analyses. Results presented in column 4 control in addition for the effect to tasks distribution across occupations (SOC digit 1) among HTE- qualified.

Our analysis estimating how physical skills (negatively associated with wages) are applied on the job shows that over time, there was no significant change in the use of these tasks in the total population. This suggests that the relative intensity of physical tasks decreased, given that other tasks were growing. Contrary to expectations, HTE holders performed an increasing amount of physical and manual tasks, with the rate of growth accelerating. This may suggest that either a) the HTE-qualified have moved into jobs that are more reliant on physical and manual tasks or b) the jobs they are in have become more reliant on these skills. To explore changes occurring within and between occupations among HTE-qualified, an occupation dummy (SOC 1 digit) is added as a control variable to the model 4. After accounting for the fact that physical and manual tasks are not distributed evenly between occupations, the year coefficients become insignificant and the performance of the model improves (as evaluated with the F test). The first hypothesis, that over time the HTE-qualified workers moved to occupations making intensive use of these physical skills, therefore seems to be the most likely.

### Table 2.8. Intensity of tasks performed on the job among HTE-qualified and in the total population

16-60 year-olds

Men are the reference group. 2001 is the reference year.

| | (2) | (3) | (4) |
|---|---|---|---|
| | Physical and manual tasks (vphysic) | | |
| | Total population | HTE | HTE |
| Intercept | 2.35 (0.139) *** | 3.18 (0.60)*** | 2.23 (0.54) *** |

| | | | |
|---|---|---|---|
| Year2006 | 0.009 (0.02) | 0.13 (0.097) | 0.06 (0.08) |
| Year2012 | -0.036 (0.029) | 0.28 (0.12) * | 0.06 (0.10) |
| Year2017 | 0.025 (0.029) | 0.33 (0.12) ** | 0.08 (0.11) |
| Gender | YES | YES | YES |
| Age and age squared | YES | YES | YES |
| Occupation (SOC digit 1) | NO | NO | YES |
| | F-statistic: 46.56 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 4.941 on 6 and 1050 DF, p-value: 5.359e-05 | F-statistic: 28.34 on 14 and 1042 DF, p-value: < 2.2e-16 |
| | Specialist knowledge or understanding (cspecial) | | |
| | Total population | HTE | HTE |
| Intercept | 1.86 (0.12)*** | 2.53 (0.43) *** | 2.91 (0.44) *** |
| Year2006 | 0.16 (0.021) *** | -0.098 (0.07) | -0.06 (0.07) |
| Year2012 | 0.13 (0.026)*** | -0.006 (0.06) | 0.04 (0.08) |
| Year2017 | 0.16 (0.025) *** | -0.12 (0.09) | -0.05 (0.09) |
| Gender | YES | YES | YES |
| Age and age squared | YES | YES | YES |
| Occupation (SOC digit1) | NO | NO | YES |
| | F-statistic: 43.25 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 1.964 on 6 and 1050 DF, p-value: 0.06799 | F-statistic: 7.46 on 14 and 1042 DF, p-value: 4.544e-15 |
| | Analysing complex problems in depth (canalyse) | | |
| | Total population | HTE | HTE |
| Intercept | 0.81 (0.15) *** | 1.99 (0.56) *** | 2.75 (0.57) *** |
| Year2006 | 0.24 (0.26)*** | 0.15 (0.09) | 0.2 (0.09) * |
| Year2012 | 0.28 (0.03) *** | 0.23 (0.11) * | 0.31 (0.11) ** |
| Year2017 | 0.36 (0.03)*** | 0.17 (0.12) | 0.25 (0.12) * |
| Gender | YES | YES | YES |
| Age and age squared | YES | YES | YES |
| Occupation (SOC digit 1) | NO | NO | YES |
| | F-statistic: 95.14 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 5.746 on 6 and 1050 DF, p-value: 6.769e-06 | F-statistic: 7.588 on 14 and 1042 DF, p-value: 2.198e-15 |
| | Influence tasks/skills (vpersuad) | | |
| | Total population | HTE | HTE |
| Intercept | 0.48 (0.13) *** | 0.74 (0.53) | 1.53 (0.51) ** |
| Year2006 | 0.19 (0.024) *** | 0.00 (0.086) | 0.07 (0.08) |
| Year2012 | 0.23 (0.029) *** | -0.09 (0.1) | 0.03 (0.09) |
| Year2017 | 0.26 (0.28) *** | 0.03 (0.1) | 0.12 (0.10) |

| | | | |
|---|---|---|---|
| Gender | YES | YES | YES |
| Age and age squared | YES | YES | YES |
| Occupation (SOC digit 1) | NO | NO | YES |
| | F-statistic: 52.3 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 3.245 on 6 and 1050 DF, p-value: 0.003642 | F-statistic: 14.51 on 14 and 1042 DF, p-value: < 2.2e-16 |
| | Using a computer, 'PC', or other types of computerised equipment (cusepc) | | |
| | Total population | HTE | HTE |
| Intercept | 0.94 (0.17) *** | 2.09 (0.61) *** | 3.04 (0.51) *** |
| Year2006 | 0.24 (0.03) *** | -0.03 (0.1) | 0.06 (0.09) |
| Year2012 | 0.38 (0.04) *** | 0.04 (0.1) | 0.27 (0.10) * |
| Year2017 | 0.50 (0.03) *** | -0.04 (0.1) | 0.22 (0.11). |
| Gender | YES | YES | YES |
| Age and age squared | YES | YES | YES |
| Occupation (SOC digit 1) | NO | NO | YES |
| | F-statistic: 62.49 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 0.8354 on 6 and 1050 DF, p-value: 0.5425 | F-statistic: 25.7 on 14 and 1042 DF, p-value: < 2.2e-16 |

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'

Source: SES, author's calculations.

An analysis of the intensity of tasks with the strongest association with wages, such as influencing others (vpersuad) and applying specialist knowledge (cspecial), show that there was relatively little increase in these skills over time among the HTE-qualified. This contrasts with an overall tendency across the labour market for these skills to grow in significance in time. Tasks, as well as HTE-qualified, are not distributed evenly across occupations, and these between-occupation differences seem to explain variations in the use of the tasks on the job by HTE workers. Models explaining the change in the use of special knowledge by HTE-qualified become significant only after controlling for occupations[24]. (see the associated results in columns 3 and 4). Among tasks positively associated with wages analytical tasks (canalyse) were found to grow in intensity among HTE-qualified. The growth was more pronounced when differences in the distribution of analytical tasks between occupations were accounted for (column 4). Similarly, when differences across occupations were considered, computer tasks performed by HTE-qualified were increasing. This may suggest that there was some increase in the use of analytical and computer skills by HTE-qualified within occupations, independently of HTE-qualified moving over time to less task intensive

[24] When a model is statistically significant a null hypothesis, whereby the model performs not better than the model with intercept only, can be rejected.

jobs. Overall, the analysis of changes in individual tasks among workers with HTE qualifications over time does not allow to draw clear conclusions on their potential impact on the HTE wage over time. Growing intensity of physical tasks may have pushed HTE wages down but this effect may have been compensated by employees with HTE carrying out more analytical tasks.

An analysis of the use of individual on-the-job tasks separately does not provide a full picture of the 'task profile' of the job. This is because jobs are composed of a variety of tasks, and a wage would depend on a combination of skills applied on the job, and because tasks are differently priced. A sales engineer in the automotive industry should have commercial skills and have a thorough understanding of automotive substance, as sales activities have to be supported by substantive knowledge. The engineer thus is responsible for 'selling', which in aggregate tends to be negatively associated with wages but he/she also performs many other tasks. A salesman selling car parts in a local shop is also busy with automotive sales. But in total, tasks performed by the salesman on the job are probably less diverse than tasks performed by the automotive engineer. So, while the two jobs involve selling, the total package of skills required in these two jobs is very different. Tasks also have different values on the labour market. For example, a job that involves a lot of analytical tasks will be assigned a lower value than a job that involves a lot of persuading and influencing others. This is because analytical tasks show a weaker association with wages than activities of persuading and influencing others. To account for the fact that jobs are composed of a range of differently priced tasks and to estimate the effect of all the job-related skills used on the job by the HTE-qualified (rather than of individual tasks), a new variable was constructed to reflect the combined effect of job-related skills on wages.

The new variable is constructed in the following way:

Wage explained by individual's skill i (WSi) = coefficient ($\beta$3 of skill i )* Skill i

Coefficients $\beta$3 are provided by the following model

$$\ln(wi) = \alpha + \beta_1 Y + \beta_2\ Gi + \beta_3 Xi + e\mathrm{i} \quad (6)$$

Where, ln(w) – log wage

$\alpha$ - intercept

Y –a vector of year dummies: 2006, 2012, 2017 (2001 reference year)

Gi – gender of an individual i (dummy variable, male – reference group),

Xi – vector of the selected skill variables

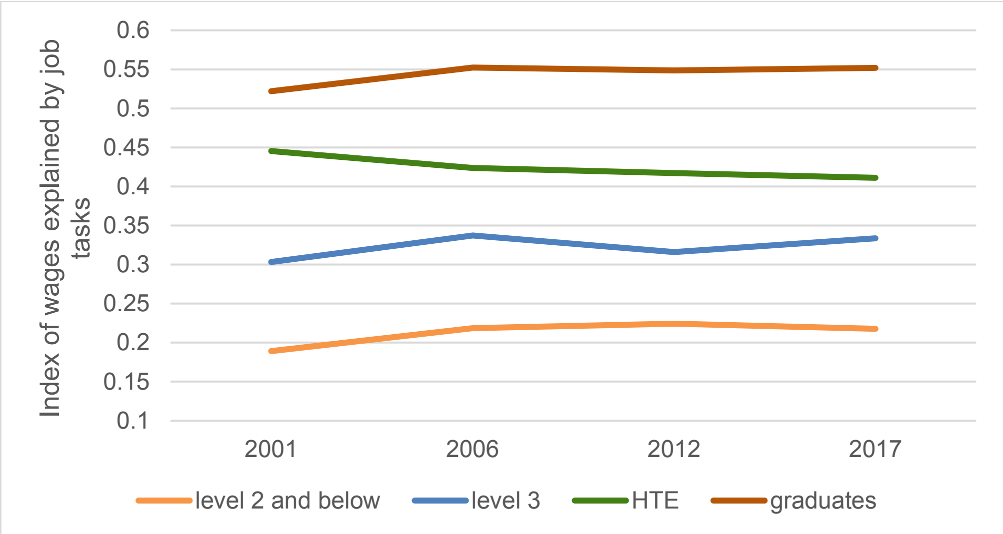
ei – residuals

$\beta$3 coefficients should in principle be stripped off the inflation effect, which is accounted for by year dummies)

Adding up WSi : $\sum_{i=1}^{n} Wsi$ (it is the variation in wages as explained by the sum of all the skills used on the job by an individual i)

The Figure below (Figure 2.2) shows the mean value of the created variable by qualification and by year. It shows that the part of wages associated with skills applied on the job may have marginally declined among the HTE-qualified. This contrasts with the results for graduates where no decline in skills was observed.

### Figure 2.2. Index of wages explained by skills applied on the job over time, 16-60 year olds




Source: SES data, author's calculations

The previous results for HTE holders are confirmed with the model in which the dependent variable is the index of wages explained by job tasks (Model 7). When the effect of gender and age is accounted for, the year coefficients for the HTE-qualified are negative but not significant (Table 2.9, column 4). The performance of the model improves when occupation dummies are included (Table 2.9 column 5). In contrast to the trends observed among HTE-qualified, the intensity of tasks yielding positive wage premium increased during the same period in the total population (Table 2.9, columns 2 and 3).

$$\sum_{i=1}^{n} Wsi = \alpha + \beta_1 Y + \beta_2 Gi + \beta_3 Ai + \beta_4 A_i^2 + ei \text{ (7)}$$

### Table 2.9. Wage index (wages as explained by tasks performed on the job).

16-60 year olds with HTE qualifications

Men with HTE are the reference group. 2001 is the year of reference.

| | (2) | (3) | (4) | (5) |
|---|---|---|---|---|
| | Total population | Total population | HTE | HTE |
| Intercept | -0.09 (0.03)** | 0.42 (0.02)*** | 0.07 (0.11) | 0.33 (0.097) *** |
| female | -0.016(0.004)*** | -0.044 (0.003)*** | -0.02 (0.014) | -0.037 (0.014) ** |
| Age | 0.022 (0.001)*** | 0.01 (0.003)*** | 0.002 (0.005) *** | 0.01 (0.005)* |

| | | | | |
|---|---|---|---|---|
| Age squared | -0.0003 (0.0000)*** | -0.0001 (0.0000)*** | -0.0002 (0.0000) ** | -0.0001 (0.0000)* |
| Year2006 | 0.05 (0.005)*** | 0.05 (0.004)*** | -0.021 (0.017) | -0.003 (0.015) |
| Year2012 | 0.06 (0.006)*** | 0.06 (0.005)*** | -0.033 (0.021) | 0.01 (0.018) |
| Year2017 | 0.07 (0.006)*** | 0.07 (0.005)*** | -0.04 (0.022) | 0.012 (0.019) |
| Occupations | NO | YES | NO | YES |
| | F-statistic: 66.99 on 6 and 16851 DF, p-value: < 2.2e-16 | F-statistic: 1015 on 14 and 16843 DF, p-value: < 2.2e-16 | F-statistic: 3.351 on 6 and 1050 DF, p-value: 0.002823 | F-statistic: 28.5 on 14 and 1042 DF, p-value: < 2.2e-16 |

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'

Source: SES, author's calculations

An advantage of the index wage variable as explained by on the job tasks is that it provides one estimate of the value of all the skills applied on the job. The index accounts for the intensity of the tasks performed on the job and for their price. The index wage variable assumes a constant effect of on-the job skills across years and qualifications. But this assumption may not always hold. As demonstrated, there are small variations in how tasks are associated with wages depending on year and qualifications; for example, specialist knowledge seems to yield higher wage returns for HTE than for other levels of qualification. However, the association between selected on-the-job tasks and wages is consistent across years and qualifications, and potential imprecisions in the value of tasks should not affect the overall conclusions from our analysis.

Overall, the analysis of time trends in job-related skills among the HTE-qualified as compared to changes observed in the total population suggests that the HTE-qualified suffered from a downgrade in terms of skills applied on-the-job. While task intensity in the labour force rose on average in the HTE population it remained unchanged. The match of HTE skills ($S_j$) to skills required in well paid jobs ($S_{jt}$) seems to deteriorate over time ($S_j/S_{jt}$ <1 and decreasing). One cannot however conclude that this skills downgrade is driven by changes in the supply of skills typically found among the HTE-qualified or by demand for such skills, or indeed selection issues. For example, the observed changes may convey information on HTE programmes and how well they prepare for jobs in demand. Perhaps these programmes are producing workers with skills that are not so highly valued in the labour market. Equally, the trends may just reflect a decline in the number of jobs that require HTE type skills. A further explanation however, is that the trends are consistent with sample selection effects whereby the composition of the HTE group is changing over time, if for example, some of the (more able) individuals who in the past opted for a HTE programme now choose a degree programme instead.

### *2.6.6. Over time, HTE may have become associated with occupations involving less complex tasks and lower earnings*

Previous analysis showed that the share of unskilled tasks (such as use of physical strengths) performed by HTE holders increased over time, and argued that this might have happened because of a shift of HTE-qualified workers into less skilled employment. To test this hypothesis, this section focuses on changes in terms of qualifications held by employees and the tasks they perform on the job at the occupation level (SOC digit 1)[25]. The Standard Occupational Classification (SOC) classifies jobs in terms of the required knowledge, experience and complexity of tasks. On this basis it is possible to compare occupations and order them by their tasks complexity and level of skills required (ONS, 2016). For example, among the nine major occupational groups associate professional and technical occupations (SOC digit 1, Major group 3) involve more complex tasks and require a higher level of knowledge and education than skilled trades occupations (SOC digit 1, Major group 5).

To increase the sample size and robustness of estimates we aggregate major occupational group that show similar patterns in terms of over time employment and wages, as explained by tasks on the job, across occupations. We aggregate the major groups 1,2,3, and the major groups 5,8. We associate the first group with cognitive skilled employment, and the second group with manual semi-skilled occupations. Our grouping is similar to that found in Cortes and Salvatori (2016) who analyse changes in job tasks at the firm level. They define cognitive skilled occupations (SOC major groups 1,2,3) as non-routine cognitive jobs, and our second category (SOC major groups 5,8) as routine manual jobs. We also group major occupational groups 6 and 7 that combine semi-skilled employment in service sector. Major group 4 and 9 are unaltered. We refer to the major group 4 as cognitive semi-skilled administrative occupations, and the major group 9 as elementary occupations. Cortes and Salvatori (2016) proceed with a slightly different grouping of the major categories 4,6,7 and 9. They associate SOC major group 7 with SOC major group 4 and classify this new category as routine cognitive occupations. Another group includes SOC major categories 6 with 9 and is referred to as non-routine manual occupations. (see Table 2.10 below).

**Table 2.10. Occupational categories as defined in this research and their relationship to nine SOC major occupational groups**

| |
|---|
| Cognitive skilled occupations:<br>1. managers, directors and senior officials,<br>2. professional occupations<br>3. associate professional and technical occupations |

[25] The Standard Occupational Classification (SOC) digit 1 distinguished following major groups of occupations: 1. managers, directors and senior officials, 2. professional occupations, 3. associate professional and technical occupations, 4. administrative and secretarial occupations, 5. skilled trades occupations, 6. caring, leisure and other service occupations, 7. sales and customer service occupations, 8. process, plant and machine operatives, 9. elementary occupations.

Insufficient sample size precludes a focus on occupations at a more disaggregated level, which we would be our first choice.

| |
|---|
| Manual semi-skilled occupations:<br>5. skilled trades occupations<br>8. process, plant and machine operatives |
| Semi-and low-skilled service occupations:<br>6. caring, leisure and other service occupations<br>7. sales and customer service occupations |
| Cognitive semi-skilled administrative occupations:<br>4. administrative and secretarial occupations |
| Elementary occupations:<br>9. elementary occupations |

In 2017, as compared to 2001, employment increased in occupations requiring complex cognitive skills and associated with high earnings (SOC 1,2,3), and in the service sector (SOC 6,7). Conversely, employment in semi-skilled cognitive occupations (SOC 4) declined. A modest drop was also observed in manual semi-skilled occupations (SOC 5, 8) and there was no change in elementary occupations (SOC 9). According to labour market theories the observed changes can be explained by automation of work places, whereby workers in jobs relying on repetitive tasks, such as jobs at the production chain in the manufacturing industry and office clerks have often been replaced by machines. At the same time, new jobs are created in areas that are complementary to automation, such as in fields relying on complex cognitive tasks[26]. An increase in complex cognitive jobs in the UK may also have been triggered by the quickly rising supply of graduates on the labour market as graduates on average have higher levels of complex cognitive skills. In the service sector and elementary occupations, the scope for automation is more limited, and so these occupations tend to be less dependent on technologies. The observed employment growth in these sectors can be associated with other factors such as a massive entry of women on the labour market and an increase in average household income. These resulted in a reduction of time spent by individuals on nonmarket household activities (e.g. cleaning, cooking, childcare) that were traded for leisure (i.e. reading, going to cinema, restaurant) and work. These changes therefore increased the demand for services substituting nonmarket household activities and for services that are leisure-related (Mincer, 2003).

The employment trend observed among those with HTE qualifications should be considered in the context of a rapidly rising supply of graduates. One of our hypotheses is that graduates have increasingly entered technical jobs previously undertaken by the HTE-qualified, pushing them into less skilled employment. SES data confirm that over time the share of HTE-qualified in cognitive skilled occupations (SOC 1,2,3) declined while there has been an increase of HTE employment in manual semi-skilled (SOC 5,8) and elementary (SOC 9) occupations. There was no change in HTE employment in administrative (SOC 4) and in service (SOC 6,7) occupations. The hypothesis of HTE-qualified moving over time to less skilled

[26] Some authors argue that in the future computers may be able to replace humans in cognitive complex tasks due to a rapid development of computer technologies (Frey & Osborne, 2013). A victory of a machine over a human being in chess, considered for a long time as inconceivable, is a striking example of this process.

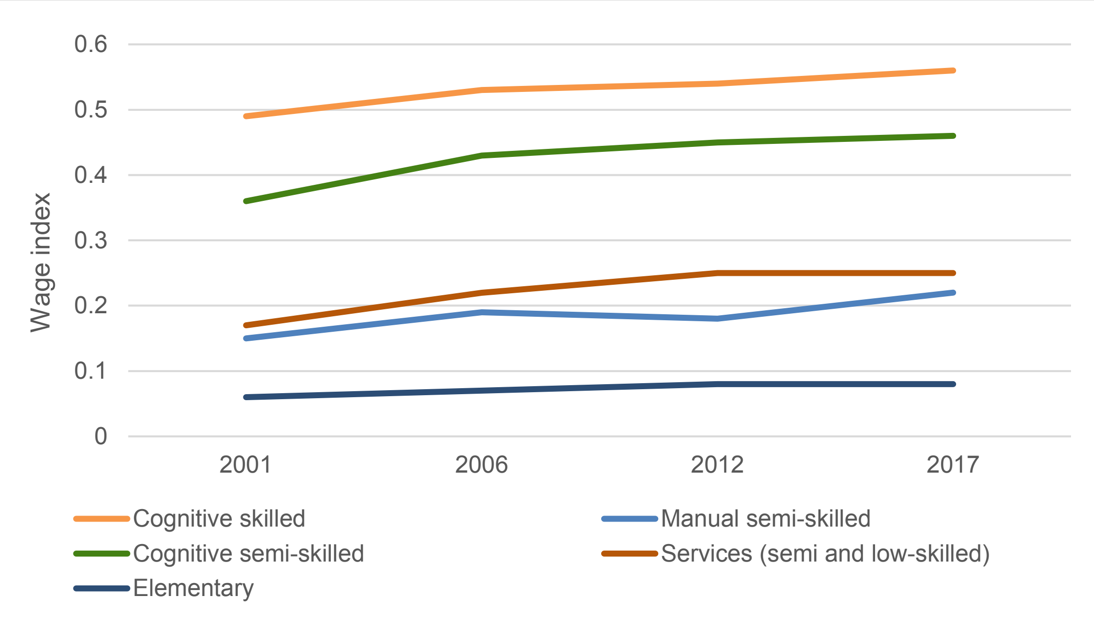
employment therefore seems plausible. However, these results should be treated with caution because of a small cell size.

### *2.6.7. The average level of tasks performed by HTE-qualified is relatively high, but their labour market situation has deteriorated over time despite an upskilling of all occupations*

This section investigates the intensity of tasks across occupations and how it has changed over time. Spread of computer and automation technologies in workplaces may have increased the demand for workers who are familiar with computers and can manipulate new machines across all occupations, including occupations that were relatively unskilled. It could therefore be that there was a task upgrading in jobs HTE workers were transiting too. But even if there was a task upgrading, it may have been too modest to compensate for the lost tasks, as experienced by HTE workers. So, even if jobs HTE-qualified were moving to required more computer knowledge than in the past, these tasks were less complex than computer tasks performed by HTE employees in their previous employment. To observe changes in tasks and associated skills over time across occupations we estimate changes in wages as explained by the sum of tasks performed on the job, and changes in individual tasks that show the strongest association with wages at the occupation level.

An analysis of wages as explained by tasks performed on the job (index wage variable) shows that there was indeed a task upgrading between 2001 and 2017 across all the occupational categories. It also shows that that distances in wages as explained by skills used on the job across occupations increased in some cases (Figure 2.3).

### Figure 2.3. Wages as explained by tasks on-the-job, by occupation and over time (16-60 year-olds)




Source: SES data, author's calculations

An analysis of individual tasks by occupation, confirms, as expected, that employees in cognitively skilled occupations (SOC 1,2,3) report the highest intensity of tasks associated with high earnings and high levels of education such as influencing others, analytical and computer tasks, tasks requiring specialist knowledge. These tasks are relatively less common in jobs requiring less education and even lower in elementary occupations. But tasks showing the strongest positive associations with wages increased in all occupational groups, including in jobs in the middle and the bottom of the earning distribution. The movement of HTE-qualified between occupations was indeed accompanied by a rise in more productive tasks across all occupations, including in manual semi-skilled and elementary occupations. Growing task complexity may explain a rising demand for labour with higher levels of education in these occupations. It is also possible that the observed upskilling at the occupation level was endogenously driven, whereby a relative increase of the HTE-qualified (and graduates) in less skilled jobs allowed companies to introduce more complex production processes. Most likely the two happened simultaneously.

Regardless of whether occupational upskilling was endogenous or exogenous, it remains that the HTE-qualified were on average moving over time from occupations with a higher level of well-paid tasks to occupations that were less intensive in these types of tasks. Since we observe an average task intensity among HTE-qualified there could be a lot of variation in the use of tasks in this group across occupations. It is possible that in a specific occupation, the HTE-qualified were in job roles composed of more diversified tasks than the average worker with HTE qualifications. For example, it could be that while the share of HTE-qualified in cognitive skilled occupations declined over time those who remained in these occupations were in highly skilled and well-paid job roles, in which tasks difficulty rose over time. To observe if patterns of task allocation in the HTE population varied across occupations we estimate changes in wages as explained by a total sum of tasks (index wage variable) by occupation and qualification. Because of a small sample size the analysis cannot be performed separately for each educational and occupational group. Instead, it is carried out in two time periods (2001-2006 and 2012-2017) by occupational groups and with educational dummies.

## Table 2.11. Association between wages explained by tasks performed on the job (index wage variable) and qualifications, in two time periods and by occupational groups

16-60 year-olds

Employees with HTE are the reference group in the model shown in columns 2 and 4; male employees with HTE are the reference group in the model shown in columns 3 and 5.

Qualification coefficients show how the wage index of a specific qualification compares to the wage index of the reference group. E.g. in 2001-2006 the tasks related wage of graduates in cognitive skilled occupations was around 0.57, which is 0.06 point higher than that of HTE employees (column 2, cognitive skilled occupations).

| | 2001-2006 | | 2012-2017 | |
|---|---|---|---|---|
| | Cognitive skilled occupations (SOC major groups :1,2,3) | | | |
| | (2) | (3) | (4) | (5) |
| Intercept | 0.51 (0.01)*** | 0.55 (0.01)*** | 0.51(0.01)*** | 0.49 (0.02)*** |
| Qualif. level 2 and below | -0.13 (0.01)*** | -0.12 (0.01)*** | -0.08(0.016)*** | -0.08 (0.02)*** |
| Qualif. level 3 | -0.04 (0.01)*** | -0.04 (0.01)** | -0.03 (0.016). | -0.03 (0.02) |
| Graduates | 0,06 (0.01)*** | 0.07 (0.01)*** | 0.09 (0.01)*** | 0.10 (0.01)*** |
| Gender and age | NO | YES | NO | YES |
| | Semi-skilled manual occupations (SOC major groups 5,8) | | | |
| Intercept | 0.24(0.01)*** | 0.27 (0.02)*** | 0.24(0.016)*** | 0.27 (0.03)*** |
| Qualif. level 2 and below | -0.10(0.01)*** | -0.10 (0.01)*** | -0.07(0.02)*** | -0.07(0.02)*** |
| Qualif level 3 | -0.02(0.01) | -0.03 (0.02). | -0.02(0.02) | -0.02 (0.02) |
| Graduates | 0.07 (0.02)*** | 0.08 (0.02)*** | 0.09(0.027)*** | 0.09 (0.026)*** |
| Gender and age | NO | YES | NO | YES |
| | Semi-skilled occupations in services (SOC major groups: 6, 7) | | | |
| Intercept | 0.27(0.02)*** | 0.34 (0.03)*** | 0.27(0.03)*** | 0.25 (0.03)*** |
| Qualif. level 2 and below | -0.11(0.02)*** | -0.10 (0.02)*** | -0.08(0.026)** | -0.08 (0.026)** |
| Qualif level 3 | -0.03 (0.02) | -0.03 (0.02) | -0.00(0.02) | -0.01 (0.04) |
| Graduates | 0.02 (0.02) | 0.02 (0.03) | 0.05(0.03). | 0.05 (0.03). |
| Gender and age | NO | YES | NO | YES |
| | Cognitive semi-skilled administrative occupations (SOC major group 4) | | | |
| Intercept | 0.44(***) | 0.51 (0.03)*** | 0.49 (0.02)*** | 0.51(0.04)*** |
| Qualif. level 2 and below | -0.09(0.02)*** | -0.08 (0.02)*** | -0.09(0.03)** | -0.09(0.03)** |
| Qualif level 3 | -0.04 (0.02)* | -0.04(0.02)* | -0.05(0.03). | -0.06(0.03)* |
| Graduates | 0.06 (0.02)** | 0.06 (0.02)** | 0.02 (0.03) | 0.02 (0.03) |

| | | | | |
|---|---|---|---|---|
| Gender and age | NO | YES | NO | YES |
| | Elementary occupations | | | |
| Intercept | 0.07(0.02)** | 0.12 (0.03)*** | 0.16 (0.02)*** | 0.20 (0.03)*** |
| Qualif. level 2 and below | -0.02 (0.02) | -0.01 (0.025) | -0.1(0.02)*** | -0.09 (0.02)*** |
| Qualif level 3 | 0.02(0.03) | 0.02 (0.03) | -0.07 (0.03)* | -0.07(0.03)* |
| Graduates | 0.1(0.04)** | 0.1 (0.04)* | -0.04 (0.03) | -0.04 (0.04) |
| Gender and age | NO | YES | NO | YES |

Note: The results are not shown for the elementary occupations (SOC major group) because of a small sample size. Signif. codes: 0 '***' 0.001 '**' 0.01 '*'

Source: SES data, author's calculations.

The analysis of the value of the total amount of tasks done on the job (as measured with wages) in the two time periods by employees with different qualifications shows that the relative value of tasks carried out by HTE-qualified decreased in cognitive skilled occupations, manual semi-skilled occupations, as well as in services (see Table 2.11). In these occupations the comparative advantage of HTE as compared to graduates and workers with the lowest level of education decreased, i.e. the gap in on-the-job skills between graduates and HTE employees widened while the skill distance between HTE-qualified and workers with low education shrunk. Over time, skills used on the job ($S_j$) by HTE holders in cognitive skilled occupations declined as compared to an optimal set of skills to be applied on the job ($S_{jt}$). This is explained by a growth in $S_{tj}$ rather than a decline in $S_j$. This may imply that in cognitively skilled employment the productivity of individuals with HTE qualifications, and so the demand for these qualifications, fell over time. Deskilling of workforce with HTE qualifications in cognitive skilled occupations is particularly telling, as this category includes professional and technical jobs, jobs HTE programmes traditionally prepared for.

In manual semi-skilled occupations and in services the HTE-qualified were in job roles involving more highly paid tasks than the average employee at the beginning of the studied period. But as these occupations become more complex over time the distance between HTE tasks and tasks performed by an average employee declined.

Conversely, in cognitive semi-skilled administrative occupations and in elementary employment, intensity of well-paid tasks performed by workers with HTE, as compared to workers with other qualifications, increased. Growing relative tasks intensity among employees with HTE qualifications in elementary occupations may result from HTE employees being substituted by graduates in more skilled jobs and being forced into less skilled employment. Whilst upskilling of elementary occupations may collectively yield positive spill overs, channelling individuals with HTE into the least skilled employment is highly inefficient. A wage that a worker with HTE can expect in elementary occupations may not be enough to guarantee a positive return on his/her investment in education.

To conclude, while on average the level of tasks performed by the HTE-qualified is relatively high, it seems that the advantage of HTE holders as compared to other groups, and in particular graduates, diminished in jobs that were traditionally targeted by HTE provision. In these occupations the labour market situation of HTE-qualified seems to deteriorate. It is not clear if this situation is related to the quality of HTE provision and how well it matches labour market requirements or to changes at the cohort level and the previously discussed decline in the ability of a marginal HTE student.

## 2.7. Conclusions

Enrolment in degree programmes has been booming in the UK in recent years, but take up of HTE qualifications, on the contrary, remained modest. Typically, supply of workforce with specific qualifications closely reflects the labour market demand for these qualifications. In a perfect market, the rapidly increasing graduate enrolment simply reflects a rising labour market demand for graduates and the associated skills. By the same token, the stagnating enrolment in HTE signals a modest demand for these qualifications from employers. But markets are hardly ever perfect and mismatches between the supply and demand for labour are common. This research aimed to investigate how the demand for HTE (relative to its supply), and so for skills that are typically associated with HTE programmes has changed over time. To this end the research explored labour market performance of HTE holders over the last twenty years in the context of a rapidly rising supply of degree holders and the spread of new technology in workplaces. It explored whether, and to what extent, changing job requirements explained some of the observed shifts in the HTE wage premium and so the relative demand for HTE. Separately, it looked at changes in specific occupations over time, in terms of their task composition, and expected qualifications of jobholders.

Consistently with existing literature, the study found that jobholders with HTE qualifications earned more than those with lower qualifications, but they also earn less than graduates. These wage differences could be partly attributed to individuals with different qualifications choosing jobs involving different sets of tasks.

The study suggested that the value of tasks performed on the job could depend on the qualification of the worker. During the period of interest, HTE-qualified workers benefited more than other educational groups from using specialist knowledge and understanding on the job. HTE-qualified employees also benefited from intensively using analytical skills in the workplace. This may be related to the selection of HTE-qualified into jobs where these skills are particularly valued. Given that specialist knowledge and understanding are associated with large premium when used by HTE-qualified on the job, these skills and knowledge should be effectively developed and thought in HTE programmes. Inclusion of good quality work-based learning in HTE programmes connecting them directly to the world of work would be one way of achieving this objective.

An analysis of trends overtime revealed that the employees with HTE suffered from a downgrade in terms of skills applied on-the-job. While the share of highly paid and complex tasks preformed on the job steadily increased in the total population, it remained constant among HTE-qualified jobholders. The match of HTE skills to skills required in well paid jobs seems to deteriorate over time. This relative deskilling of employees with HTE qualifications might have happened because of a shift of HTE-qualified workers into less skilled employment.

The analysis suggests that the position of HTE holders as compared to other groups, and in particular graduates, diminished over time in some occupations. This trend is observed in cognitive skilled occupations including professional and technical occupations, thus occupations HTE programmes have been traditionally preparing for. This may imply that in these occupations, the relative productivity of individuals with HTE qualifications and so the demand for these qualifications fell over time.

Drawing on the analysis of tasks performed on the job as reported by individuals this study points to a worsening labour market situation of HTE-qualified, without identifying underlying causes of this deterioration. Further research would be required to determine if it was driven by changes in the supply of skills typically found among the HTE-qualified, by changing demand for such skills, or indeed selection issues (as different types of people select into HTE over time). Depending on the exact causes different policy solutions would apply.

# 3 How have wages and employment opportunities of HTE-qualified been changing over time?

## 3.1. Introduction

This chapter is the part of the research that explores how employer demand for higher technical education (HTE) has changed over time in different occupations and industry sectors. The research defines HTE as postsecondary programmes leading to qualifications at level 4 and 5 in the UK that prepare individuals for a specific occupation and are therefore considered technical. Around 12% of level 4 and 5 students are in general rather than technical routes (Boniface, et al., 2018). HTE programmes typically last 1-2 years (full-time equivalents). HTE therefore normally leads to jobs requiring some post-secondary education but not necessarily a full bachelor's degree.

The research looks at whether employment opportunities of individuals with HTE have worsened over time, a trend which may, setting aside other potential factors, imply falling employer demand for these qualifications relative to its supply[27]; or whether the reverse is true.

The research draws on three data sources: the Skills Employment Survey (SES), the Labour Force Survey (LFS) and job vacancy data. The analysis of the three datasets is reported in separate chapters. This third chapter exploits LFS data to explore the demand for skills associated with HTE qualifications.

This chapter evaluates the labour market performance of HTE-qualified individuals across occupations and identifies how the comparative advantage of the HTE-qualified has been changing over time across occupations with different 'tasks complexity'. The Standard Occupational Classification (SOC) dividing occupations by complexity of tasks performed, the level of education and work experience required to perform these tasks, allows us to observe the labour market performance of HTE-qualified workers in occupations requiring a varying level of skills. In particular, it should allow us to demonstrate if, over time, employees with HTE qualifications became more productive (as proxied with wages) in complex and skilled occupations or on the contrary their comparative advantage in these occupations has declined. And if the

[27] Throughout the thesis, unless otherwise specified, the demand of HTE refers to the demand for HTE qualifications from employers, and the supply of HTE refers to the individuals with HTE qualications in the labour force.

former is true what are the occupations in which workers with HTE qualifications are more likely to be employed in.

The chapter first introduces research questions to be addressed with this LFS data analysis. It then discusses the relevant literature by pointing how this study complements the existing body of evidence. Next, it presents theoretical foundations of this work, and discusses in detail the LFS data. The following sections presents the LFS data analysis by discussing specific research hypotheses to be tested, an empirical model developed to address them, and results of the performed analyses. The final section concludes.

### *3.1.1. Research questions addressed by the LFS analysis*

The second chapter of this research drew on SES data to explore the range of tasks performed on the job, and how the associations between these tasks and wages changed over time. To identify skills applied in the workplace by HTE employees, job specific tasks and the associated wage returns from those skills were analysed in the context of educational qualifications. This third chapter focuses on the demand for skills associated with HTE qualifications by interrogating the Labour Force Survey (LFS) data. The objective is to observe how wage premia and employment opportunities associated with HTE (as compared to individuals with degrees, and those with lower level qualifications have changed over time by occupation and area of specialisation in the UK.

This LFS analysis aims to confirm (or reject) some of the tentative conclusions formulated with the SES data, mainly that employees with HTE qualifications become less likely over time to work in highly skilled occupations as measured with SOC. LFS should provide more robust estimates in this respect than the SES since the LFS includes a much larger number of observations and time points than the SES. The LFS data also enable us to go beyond the research questions addressed by the SES analysis. In comparison to the SES that covers those in employment only, the LFS provides information on unemployed and inactive as well as those who are employed. The LFS therefore allows us to explore not only changes over time in wages in a much wider population but also in employment opportunities, in relation to different qualifications.

The LFS study gives particular attention to how the demand for HTE qualifications has changed over time by exploring the match between the skills associated with HTE qualifications and those required on the job. LFS provides a limited opportunity to study how changing job content drives the demand for individuals with specific qualifications. Except for managerial and supervision tasks reported by respondents, LFS does not include information on the job tasks undertaken by individuals and the skills required to perform them. However the LFS provides a tool that can be used to identify the skills required in the workplace in the form of the Standard Occupational Classification (SOC) of jobs. Job specific 'tasks' and 'skills' that are used to describe the complexity of the content of the occupation can be defined drawing on the SOC classification and previous empirical studies of SOC occupations. Tasks performed on the job and the skills required to perform them situate occupations on the complexity scale. In this LFS analysis we use 'tasks performed on the jobs' and 'skills applied to perform them' interchangeably ('tasks' equal 'skills'). By analysing labour market outcomes within SOC occupations, this research aims to explore how the match of HTE holders to occupations with different skills complexity has changed over time. This enables consideration of whether over time the HTE-qualified were more or less likely to work in occupations requiring high levels of skills.

Our analysis of LFS data aims to contribute to the existing stock of evidence on labour market outcomes to HTE by establishing a relationship between the type of employment in terms of the job task complexity and the relative HTE wage, i.e. do the HTE-qualified earn relatively more in skilled rather than less skilled employment? How the relative HTE wage has changed over time in different types of employment? This analysis also aims to provide an up-to-data analysis of labour market outcomes from HTE qualifications by the area of specialisation, and how they have changed over time. Whenever possible and relevant we combine information on the level of skills (based on SOC) with information on the area of study. Comparison of labour market outcomes by area of study (specialisation) of the qualification, and how they have changed over time, casts light on how the demand for HTE qualifications varies depending on the technical skills targeted by the qualification.

The economic benefits arising from vocational qualifications in the UK have been relatively well researched. Research studies on this issue draw on survey data such as Labour Force Survey (LFS) datasets and data from administrative sources, such as Individualised Learner Record (ILR), data on the population of learners in Further Education, and more recently the Longitudinal Education Outcomes (LEO) data. These administrative datasets provide detailed information on various aspects of individuals' lives and their characteristics, offering researchers new tools to evaluate the impact of qualifications on labour market outcomes. Despite these undeniable advantages of administrative datasets, we opted for the LFS data, primarily because information on occupations is absent from the relevant datasets, and this information is necessary to make the detailed connections between labour market outcomes from HTE and specific job characteristics. This LFS analysis aims to update results obtained by previous LFS research studies, and to bring a new dimension to HTE labour market analysis by looking at changes over time in wage premia and employment benefits within occupations.

This chapter is structured as follows, section 2 describes relevant literature. Section 3 introduces a theoretical model that explains the relationship between labour market performance and education. Section 3 discusses aspects of Skills Biased Technical Change (SBTC) theory that provides a useful theoretical framework for interpretation of findings from our analysis. Section 4 is devoted to data measurement issues, and finally section 5 presents research questions, specific models to address them and discusses the empirical results.

## 3.2. Review of literature

Chapter 1 discussed the wider literature on labour market outcomes associated with vocational qualifications. While some level of duplication is unavoidable, this section focuses on research studies that are particularly relevant to issues addressed in this chapter. First, it discusses research studies exploring how the wages of individuals with vocational qualifications in the UK differ by industry sector and area of specialisation (area of study). Second, it discusses estimation methods applied by other research studies using LFS data and compares them to the approach adopted in our analysis. Finally, it reviews literature comparing wage premium estimates obtained with LFS and other types of data to demonstrate that LFS remains a valid instrument in evaluation of labour market outcomes by education, despite other sources of information being available.

Definitions of vocational qualifications differ slightly across research studies. Some studies look at wage returns to individual qualifications, while others classify qualifications by level and type of qualification (e.g. Level 4 vocational qualifications). Unless otherwise specified, for convenience, in this literature review we will be referring to any qualification at level 4 and 5 as HTE.

### *3.2.1. Wage returns to HTE qualifications by industry sector and field of study*

While evidence on outcomes from HTE by occupation is scarce, a few research studies explored how the HTE wage varied by industry sector in which the person was employed, and the subject area of the HTE qualification. These studies explored associations between the HTE wage and skills required on the job from a slightly different angle than this current study, as the industry sector and the subject area provide some indication of technical skills matching the sector of activity, rather than classifying skills on the complexity scale. For example, if, other things being equal, the wage premium to HTE programmes preparing for jobs in the construction sector exceeds the returns to comparable HTE qualifications associated with other industry sectors, this would suggest the labour market demand for HTE-qualified people specialising in construction exceeds the demand for technical skills associated with other industry sectors. A study by Dickerson and Vignoles (2007) is of particular interest. The authors use LFS data pooled across 2000-2004 to estimate wage returns to a range of qualifications (including vocational ones) within Sector Skills Councils (SSC) each of which corresponds to an industry sector. The authors find that there are large differences in the wage returns to vocational qualifications by industry sector, level of qualification, and gender. For example, wage returns for men with level 5 vocational qualifications are the highest in the health sector (SSC Skills for Health) and in the apparel, footwear and textile industry (SSC Skill-fast UK). These two SSCs are examples of SSCs with, respectively, a relatively high and low share of the workforce with qualifications level 4 and above. This would suggest that the HTE-qualified obtain high wage returns in relatively skilled sectors but also, more surprisingly, in sectors with a low concentration of highly educated labour. However, as the authors mention, these results should be interpreted with caution due to the small sample size.

Other research studies point to a high wage premium to HTE qualifications with specialisation in science, technology, engineering and mathematics (STEM). Greenwood, Harrison and Vignoles (2011) using LFS data found that the HNC/HND-qualified in STEM sectors earned 8% on the top of the average HNC/HND wage premium and that the premium was highest for those HND/HNC-qualified who both studied STEM specialisations and who were working in STEM sectors, where the sector matched their specialisation. Espinoza and Speckesser (2019) use the Longitudinal Education Outcomes (LEO) administrative dataset, which links earnings to individual records from England's central education register covering all stages of education. They analyse earnings of individuals who completed their secondary education in 2003 up to the time they reached the age of 30. The focus is thus on one cohort, which is different from our approach analysing earning patterns in multiple cohorts. The authors demonstrate that men who obtained their higher vocational and technical qualifications in "STEM" areas tend to earn more than those with similar qualifications in other areas, and as much or more than graduates with 'STEM' specialisations. A recent study by Espinoza et al. (2020) provides important insights into the labour market performance of individuals with qualifications level 4 and 5 as compared to those with other qualifications[28] exploiting a range of longitudinal datasets. The authors observe educational and labour market trajectories of cohorts who completed their GCSE's in 2002-2006. They find that men and women with level 4 and 5 qualifications chose different areas of studies, and that wage premia to these qualifications vary greatly by subject. While the authors do not break down wage premia by area of study they note that nearly 40% of those with level 4 vocational qualifications are in engineering, construction and building.

### *3.2.2. Wage returns to HTE as the highest qualification or to HTE as one of the qualifications obtained*

In this LFS chapter we estimate the wage premium associated with an individual's highest qualification. This means that only one, the highest qualification, is associated with each individual, and other qualifications held by the person are ignored. An alternative approach consists of including all the qualifications obtained by the individual in the model (Dearden, et al., 2002; Dickerson & Vignoles, 2007; McIntosh & Morris, 2016; McIntosh, 2004). In this latter approach, the wages of individuals with a given qualification are compared to wages of those who do not have it. In the total population, the wage of those with a HTE qualification would be compared to earnings of those who do not have the HTE qualification, including controls for all the qualifications held by an individual. This approach yields estimates of the average value of an HTE qualification across all those who hold it, rather than for those who hold it as their highest qualification. However it may be argued that what is of greatest interest in determining the demand for HTE qualifications is the wage premia for those for whom HTE qualification is likely to be the most important and visible qualification they have in the labour market, namely their highest qualification.

[28] Level 4 and 5 qualifications discussed in the study overlap with our LFS definition of the HTE but does not match in perfectly. For example, in our analysis foundation degrees are amalgamated with degrees.

Whilst we rely on a model that uses highest qualification held as the explanatory variable, there is one scenario where the model which includes all qualifications held could be usefully applied to explore specific labour market outcomes of the HTE-qualified. Specifically, this approach could be used to evaluate the labour market value of a degree if it was preceded by a HTE qualification, as compared to the value of a degree preceded by other qualifications e.g. A levels (with no HTE). The opportunity of continuing in education to acquire higher level qualifications, the so called “option value” of qualifications, is an important educational benefit that is not accounted for when wage premia are estimated for the highest qualification only, as we do in this chapter. The number of the HTE-qualified continuing in education is not negligible. Espinoza et al. (2020) estimate that around one third of those with level 4 and 5 qualifications obtain a degree by the age of 25. Issues of progression within education and cumulative benefits to qualifications, as important as they are from the individual and policy makers point of view, will not be further developed here, since they are beyond the scope of this research, and more importantly, they have already been addressed in recent research studies (Espinoza, et al., 2020).

### *3.2.3. Comparison of wage premium estimates produced with survey and administrative data*

Depending on the type of data used, estimates of the wage premium for HTE qualifications vary substantially. Espinoza et al., (2020), using administrative data, report that employees with level 4 and 5 qualifications, depending on the gender, earn between 42% and 57% more than workers with qualifications level 3. Wage premium estimates for comparable qualifications obtained with the LFS data are much lower. McIntosh and Morris (2016) estimated the wage premium for higher level vocational qualification to be at most at 13%. Obviously, these differences reflect differences in the model design (such as in the definition of the variables and the population of interest) but they may also reflect a selection bias that we would expect to be larger in estimates drawing on LFS data than in those using administrative datasets. Administrative data contain some information that is not observable in the LFS data, such as detailed academic achievement earlier in the person’s schooling or socio-economic background of the person, and which tends to be correlated with wages and education.

A recent study by Conlon at al. (2017) compares in a rigorous way findings produced with the LFS and administrative datasets, and attempts to reconcile evidence building on these data. The authors identify model specification differences that are responsible for variations in wage premium estimates for vocational qualifications in the studies that use the different datasets. They also carried out wage premium estimations with various wage equations using LFS and Individualised Learner Record Data (ILR) to test if an identical model but run on different datasets would result in identical estimates. Through this procedure they were able to reconcile estimates to a great extent and they concluded that “*either dataset can be used for future research, as availability and the requirements of the researcher vary, and neither dataset should be viewed as necessarily producing unrealistic estimates*” (Conlon, et al., 2017, p. 4).

Conlon et al. (2017) study therefore provides some reassurance in terms of the validity and robustness of outcomes of wage analyses produced with LFS data.

## 3.3. Theoretical background, main model, and concepts

### *3.3.1. Wages are a function of education*

As in the previous chapter, the Mincerian log linear wage function, whereby wage is a function of the worker's human capital proxied by education level (qualifications) and labour market experience, provides a conceptual framework for this analysis. It assumes labour production factors are not homogeneous and their quality depends on the human capital endowment of the worker. Workers with a higher level of human capital are more productive and therefore receive higher wages. Individuals invest directly in education through tuition and other educational expenses and indirectly through foregone earnings to secure better employment opportunities in the future.

Education can be proxied by years of education or by the qualification level and type. In our analysis we use the latter as we are interested in estimating wage premium associated with HTE as compared to other qualifications. The wage premium to HTE, as the highest qualification obtained, is estimated by comparing the wages of those with HTE qualifications to the wages of those with different levels of educational attainment. The analysis therefore examines by how much HTE earnings differ from the earnings of graduates (with qualifications at level 6 and above), and by how much it differs from employees with level 2 and 3 qualifications, and those with qualifications level 1 and below. Depending on the research question, the baseline comparator may differ. Dickerson and Vignoles (2007) report wage differentials between employees with different types of qualification, and those with no education. McIntosh and Morris (2016) estimate the wage premium to vocational qualifications as compared to individuals with no qualification. They also consider a more 'natural' comparison group, whereby qualifications of interest are compared to qualifications at one level below. In the current exercise the baseline category refers to individuals with the HTE qualifications, as the research focuses on the labour market performance of the HTE-qualified and how it compares to labour market outcomes of those with other qualifications.

Labour market outcomes to HTE can be evaluated to HTE as the highest qualification or to HTE as one of the qualifications held by an individual. This LFS analysis gives weight evaluation of the labour market performance of the highest qualification held for two reasons. We assume that among the skills possessed by an individual, the skills attracting the highest return on the labour market are those related to their highest qualification. By examining the wages of employees with a HTE qualification as their highest qualification, we therefore explore the match between skills associated with HTE and the labour market demand for these skills (relative to their supply). Such an exploration would be questionable if the HTE group also included those with a degree, for whom the HTE qualification may be less visible and less important.

### *3.3.2. Analysis of wage premia by qualifications*

The basic relationship between wages (in logs) and the other factors can be written as

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 X_i + e_i$$

Where E is a vector of qualification dummy variables, with qualification = {level 1 qualifications and below, level 2 and 3 qualifications, degree}. To avoid the dummy variable trap (perfect multicollinearity), a dummy variable for HTE is not included and $\alpha$ refers to the wage of the reference group - the HTE-qualified. For example, if the wages of the HTE-qualified (baseline category) are compared to those of graduates, the coefficient $\beta_1$ of the degree dummy would show, ceteris paribus, the wage premium or a percentage increase in wages associated with a degree as compared to the wages of those with HTE, ($\beta_{1degree} = \frac{\partial \ln(wage)}{\partial E_{idegree}}$). Wages are conditional on *Xi* – a vector of exogenous control variables, and $e_i$ is an error term. Depending on the hypothesis tested, the specifications of the model may vary. For example, if data are pooled across years, period dummies will be added to account for changes in circumstance occurring over time, such as economic downturn, that are likely to affect wages. Specific models corresponding to different analysis are discussed throughout the chapter.

Wages are expressed as an hourly wage indexed to 2001 values and transformed into logs. In loglinear models the estimated coefficients roughly represent a proportionate change in wages as a result of a one unit change in the explanatory variable. However, when the percentage difference is large, e.g. when a qualification Eb yields a large wage premium relative to qualification Ea, the log approximation may be inaccurate. To provide an exact magnitude of the effect of a qualification on wages we use the following formula:

$$100\left(\frac{Eb-Ea}{Ea}\right)\% = 100\,(\exp(Eb)-1)\%$$

To conclude, the model measures the effect of HTE on wages relative to the wage associated with other qualifications, and provides an indication if, from an individual point of view, investment in HTE is likely to yield positive wage premium. It also allows us to estimate the demand for HTE relative to its supply and supply of other qualifications by examining changes in the relative wage premium associated with HTE qualifications over time. Increasing wage premia tend to be associated with growing relative demand, while decreasing premia imply the opposite.

### *3.3.3. Analysis of employment opportunities by qualifications*

An analysis of the chances of being employed as opposed to being unemployed or inactive complements the wage analysis. Estimations of employment chances show how shocks in the economy affect the employment opportunities of individuals with different qualifications. For example, it explores if those with

HTE were more or less likely to become redundant or withdraw from the labour market than employees with other qualifications during the Great Recession. When the labour market shrinks, some individuals accept work at a lower wage while others withdraw from the labour market all together. Conversely, when the labour market is tight, fewer individuals of working age are unemployed or inactive and wages increase. The analysis of wages and the chances of being employed across populations with different qualifications should in principle be consistent as both reflect variations in labour market demand. Hence, we would expect an increase both in wages and employment rates of workers in cases where the labour demand rises faster than its supply.

Employment opportunities in populations with different qualifications are estimated with a logistic regression whereby employment, the binary outcome variable, takes values {0,1}, with a probability p of an event occurring and probability (1-p) of the event not happening. The relationship between the outcome variable – odds of being employed in logs, education *Ei*, and the predictor variables *Xi* can be modelled as[29]:

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \alpha + \beta'_1 E_i + \beta_2{}' X_i + e_i$$

As above, $E_i$ is a vector of qualification dummy variables, $X_i$ – vector of exogenous control variables, and $e_i$ is an error term.

### *3.3.4. The risk of a selection bias and control variables*

Wages depend on education (E) but also on many other factors. Models estimating the wage premium to education can be misspecified when factors (V) that influence earnings are omitted. If V have non-zero coefficients when included in the model, and if they are not orthogonal to the qualification variable $\mathrm{E(E'V)} \neq 0$ , the parameter on the education variable will be biased and will not show the true impact of education on wages (Verbeek, 2006). To minimise omitted variable bias, estimates of the wage premium should therefore attempt to account for the exogenous observable variables that affect earnings[30]. They typically include individual characteristics such as age, gender, ethnicity, socio-economic background and ability. Sometimes the models also include employment characteristics. However it can be argued that most of the time it is the choice of education that influences job characteristics and not the other way round.

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[29] The model shows an association between Ei and the outcome variable expressed in log odds points, which is not very meaningful. To transform log-odds into probabilities the following is applied:

$$\frac{p}{1-p} = \exp\left(\alpha + \beta'_1 E_i + \beta_2{}' X_i + e_i\right)$$
$$p = \frac{\exp\left(\alpha + \beta'_1 E_i + \beta_2{}' X_i + e_i\right)}{1 + \exp\left(\alpha + \beta'_1 E_i + \beta_2{}' X_i + e_i\right)}$$

[30] Other techniques, such as instrumental variable, can be used to limit the bias. In this approach an instrumental variable that affects educational choice but not wages is added to the model. The instrument to be valid has to be correlated with the $E_i$, but uncorrelated with the errors $e_i$.

Consequently, job characteristics, alongside wages, would be just another proxy for labour market outcomes.

Lack of data on determinants of educational choices represents a major challenge in wage analyses. From this point of view LFS cross section data represent a weaker tool than some other administrative datasets. Despite this drawback, our preference is for using the LFS data since they are unique in that they combine information on education and employment characteristics at the individual level. To minimise omitted variable bias in our model, we include a range of regressors drawing on information available in the LFS and determinants identified by previous studies as important in wage analysis (Espinoza & Speckesser, 2019). We estimate models where wages are a function of education accounting for age, age squared, gender, ethnicity and GCSE results – our proxy for cognitive ability. In some models we also include selected employment characteristics, following examples from literature. These variables and their impact on wages and education are discussed in more detail below.

We do not pretend that this list is exhaustive and throughout the text we discuss the potential impact of unobserved variables on outcomes of our analysis.

Longer work experience increases wages as individuals become more proficient in their job tasks with time spent on the job. In our analysis, work experience is proxied by the individual's age. To take account of the concavity of wages as a function of age (as wages initially increase in age and fall towards the end of working lives), an age squared term is added as a control variable. We account for gender and ethnicity recognising that there is a gender wage gap. Indeed, wages follow a different pattern in men and women and hence we also estimate separate models by gender. Ethnicity is measured by individuals defining themselves as white versus non-white. Educational and labour market outcomes are far from homogenous in these two groups. For example, the white ethnic group includes white native population and recent migrants from the new EU countries whose earnings are below the earnings observed in the white native population, even after allowing for differences in education (Oxford Economics, 2018). However, more granular analysis on ethnicity is impossible due to data limitations. Given existing evidence we expect being non-white (being from an ethnic minority) to be negatively associated with earnings and employment opportunities in the UK (Dustmann & Fabbri, 2003; Cabinet Office, 2017; Li & Heath, 2020). This may be because some ethnic minority groups have less human, social or cultural capital than the white population or because of labour market discrimination against ethnic minorities (Di Stasio & Heath, 2019).

Choices of educational pathways are not random and depend on prior academic achievement and closely related concept of cognitive ability or individual intelligence. If individuals with poor school records are more likely to opt for education programme A, and those with better results for education programme B, a wage analysis by education with prior school performance not accounted for might suggest that B leads to better outcomes than A. However, these results would be probably upwardly biased as the stronger prior achievement of those who opt for programme B may partly explains higher wages observed in this group. Ideally, we would compare the wage of an individual in programme B to the wage of individual with identical prior achievement but who had chosen programme A. Under these conditions, the difference in wages between B and A, could more reliably be interpreted as a wage premium produced by B. LFS does not provide a direct measure of individual ability but includes information on GCSEs[31] demonstrating academic achievement at the end of the secondary education, which we use as a proxy for individual ability. GCSEs are widely recognized by educational institutions and employers, and often guide and determine students' postsecondary choices. Individuals with at least 5 GCSE grade A-C* (full GCSE) are distinguished from those with fewer full GCSEs and GCSEs below grade C, and those to whom the question on GCSE is irrelevant. We acknowledge that this distinction may not be granular enough to account for variation in academic performance in these two groups, and more broadly, that GCSEs are an imperfect measure of cognitive ability[32].

The LFS data shows that the share of individuals with at least five full GCSEs increases in education. In 2001-2019, 72% of graduates reported having at least five full GCSEs as compared to 58% of HTE holders and 49% of those with just level 3 qualifications. These findings are consistent with many other research studies. Espinoza and Speckesser (2019) for example show that school test performance (English and Mathematics performance at KS2, KS3, and GCSE's outcomes) is highly correlated with subsequent educational attainment[33]. The authors also demonstrate, as expected, that the prior academic performance of the group with level 5 qualifications is higher than among those with qualifications at level 4, but lower than among those with qualifications at level 6. Those with better GCSE outcomes are therefore more likely to opt for, and successfully complete, a degree rather than an HTE qualification. Consequently, we expect that after taking account of prior GCSE results the degree wage premium would drop. This would mean that part of the difference in wages between HTE holders and employees with other higher level qualifications can be explained by the selection of individuals with different cognitive ability (as proxied by GCSEs) into different educational paths, rather than by the education programme itself. In an extreme scenario, with qualifications being only a signal of ability, the qualification coefficient would be close to zero after adding in a proxy for individual ability.

Wages vary by industry sector (Dickerson & Vignoles, 2007). We thus explore the relative HTE wage in a given industry sector. A drop in the wage premium by qualification after accounting for the industry sector would suggest that part of the difference in wages can be attributed to the uneven distribution of employees with different qualifications across industry sectors. One of the potential explanations could be that some qualifications are better than others in helping individuals enter industries where productivity is high (see Annex A.2, Figure A.2.1 for the distribution of HTE-qualified workers among industry sectors).

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[31] In the UK students sit GCSE exams at the end of secondary education when they are 16 year-olds (theoretical age)

[32] According to the American Psychology Association intelligence is defined as: "the ability to derive information, learn from experience, adapt to the environment, understand, and correctly utilize thought and reason." (American Psychology Association, 2021)

[33] See also Kuczera, Field and Windisch (2016) who demonstrated with International Adult Skills Survey data that cognitive skills in young adults in the UK (England and Northern Ireland) increases in education.

Historically, the majority of part-time employees have been women who are combining work with childcare responsibilities. If this remains true, then a gender variable (combined with age) should proxy the effect of part-time employment on wages. However, the share of part-time employment in the UK has been rising gradually, including among men. Office for National Statistics (2019) shows that in 2017, of those who work part-time, 15% were in this type of employment involuntarily because they could not find a full-time job. Individuals in part-time contract may therefore earn less than those who are employed full time and in private sector.

Similarly to Conlon et al., (2017) we also control for the impact of the employer location on wages. We estimate wages accounting for the geographical location, whether the employment is in the private or public sector and whether the person works full or part-time. Geographical areas include 12 regions: North East, North West, Yorkshire & Humberside, East Midlands, West Midlands, East, London, South East, South West, Wales, Scotland and Northern Ireland. We do not account for skill complexity of the jobs (measured with SOC) as a separate analysis is performed on individual SOC categories. Zymek and Jones (2020) points to large differences in productivity across regions in the UK. Areas that are more productive are more attractive to employers and workers. For employers in prosperous regions, firms can easily trade with other companies, benefit from a well-developed transport infrastructure to distribute their products, and take advantage of schools that provide good skills to school-leavers entering the labour market. For workers, in addition to wage benefits, regions with a high concentration of productive and innovative firms provide individuals with better career prospects and higher job mobility, and good schools are attractive to employees for their children. Overall, employees with high levels of education tend to be matched to more productive firms, and to find more secure and attractive employment (Håkanson, et al., 2015; Criscuolo, et al., 2020). Hence accounting for employer features in the wage function is likely to decrease the association between qualifications and wages as the effect of job and employer characteristics on wages is mediated by education, and employment type and employer characteristics can be seen as another outcome of education.

### *3.3.5. A theoretical framework for interpretation of the results*

Chapter 1 discussed in detail the Skills Biased Technical Change (SBTC) theory, which explains the rising demand for complex skills, often associated with degrees. It also briefly discussed empirical evidence supporting the SBTC theory.

As discussed in Chapter 1, the theory suggests some reasons why the relative demand for HTE holders might increase or fall relative to the demand for graduates. It may also explain why the demand for graduates has increased, despite the rising supply of graduates. Technology requiring a high level of skills drives the wage premium of the skilled labour up while the rising relative supply of highly skilled labour suppresses it. Depending on which factor prevails the skill premium will either grow or fall. In this chapter we use the SBTC as one of the potential theoretical frameworks for interpretation of findings from the LFS data analysis.

In occupations with high task complexity (SOC major group 1-3) wages are on average higher than in occupations with less complex tasks as complex tasks yield higher output. It is assumed that other things being equal individuals maximise the present value of income from labour and prefer to work in skilled than unskilled occupations.

An increasing wage premium to a degree encourages individuals to invest in degree programmes and stimulates the supply of graduates into occupations with high earnings. In SOC major occupations 1-3 the relative supply of degree holders as compared to the HTE-qualified individuals has been monotonically increasing in time (Table 3.8. Share of all the employees 16-64 in different occupational groups holding a HTE qualification/degree ($\text{ShareE}_{2e}$). Assuming that HTE and graduates are imperfect substitutes, *ceteris paribus* the rising relative supply of graduates decreases their relative wage unless this trend is offset by the skill biased technology. If we observe a non-decreasing graduate wage premium in skilled occupations over time this would imply that the tasks requirements in jobs altered by new technologies maintain the comparative advantage of graduates over HTE, and so the comparative advantage of the HTE-qualified in these occupations is falling. Falling relative efficiency of HTE-qualified workers in skilled occupations would result in HTE holders moving to occupations where their comparative advantage as compared to those with other qualifications is high.

We are not aware of any research studies looking at the elasticity of substitution between degree holders and employees with HTE (or equivalent). Given that we compare two groups with a relatively high level of educational attainment we assume that the distance in skills between these two groups would be smaller than the distance between graduates and those with qualifications below HTE level (level 3 and below). Drawing on estimates available in the literature and the 'proximity' between HTE and graduates we assume the elasticity of substitution between the two categories to be greater than one – graduates and HTE are imperfect substitutes. But the elasticity of substitution would differ by occupation. In occupations from SOC major group 2 where a degree is often required the elasticity of substitution between graduates and HTE-qualified may be lower than in occupations falling into the SOC major category 3 where some post-secondary education but not necessarily a degree is recommended (see Table 3.1. SOC major occupational groups for a description of SOC major groups). In licensed professions, such as medical doctors and lawyers, where a degree is formally required, the substitution of degree holders by HTE-qualified is legally impossible. Analysis of wage trends in occupations in the SOC major group 3 is particularly telling as in these occupations the elasticity of substitution between the two types of labour should in principle be high. It can be reasonably assumed that a degree holder with a specialisation matching the industry sector of the job should be able to carry out tasks on the job requiring skills below degree level. The share of graduates in occupations SOC major group 3 has been rapidly increasing. In 2017/19 nearly one in two employees in these occupations held a degree. If the HTE and degree holders are nearly perfect substitutes, the non-decreasing graduate wage relative to the HTE wage may imply that graduates have become more efficient over time (per unit of efficient labour). If the two types of labour are not perfect substitutes, changes in task composition resulting from introduction of technology drive the demand for graduates. Obviously, since we do not observe all the wage determinants we cannot exclude the possibility that the observed changes in employment also reflect changes in cohort characteristics.

### *3.3.6. The Standard Occupational Classification (SOC) – a proxy for the tasks performed on the job*

The research explores the demand for HTE relative to the labour market demand for other qualifications within different types of jobs. Jobs are classified depending on the complexity of tasks involved and complexity of skills required to carried out these tasks. In the SES analysis employment was classified according to direct measures of tasks performed in workplaces. LFS data do not provide a direct measure of tasks or skills and to classify employment on complexity scale we use Standard Classification (SOC).The SOC is a taxonomy of occupations, in which occupations are defined in terms of tasks and duties carried out by an employee (Office for National Statistics, 2020). Elias (1995) discusses the origins of the SOC and its connections to the concept of social class and social status conferred by the occupation.

Employment can also be classified by industry sectors (Standard industrial classification of economic activities – SIC). Green et al., (2017) show that the prevalence of skilled employment varies across sectors. They argue that the sectors recording the highest employment growth are those with the largest share of low paid jobs. Goos and Manning (2007) looking at changes in wages over time across occupations, demonstrate that wages differ significantly by industry sectors even after accounting for occupations. At the same time, they demonstrate that occupations (at SOC three-digit level) reflect jobs more accurately than sectors. They note that analysis of wages with a job defined as a particular occupation or as a particular occupation in a particular industry yields very similar results. While our analysis exploring individual labour market outcomes by occupations at SOC one digit level is not fully comparable to that of Goos and Manning (2007) , the evidence suggests that aggregated SOC categories (at one digit level) would still perform better than aggregated SIC categories in term of describing job tasks.

We undertake the analysis using SOC occupations on the grounds that the SOC classification of occupations conveys more information on the tasks performed on the job and required skills than the SIC. The main reason is that jobs that cut across all SOC occupational categories can readily be found in each industry sector. For example, the construction sector provides jobs from all SOC major groups. It employs managers and directors, civil engineers, accountants and human resources specialists to run construction enterprises; skilled workers such as plumbers, electricians, plasters; salesmen dealing with clients; and unskilled labour working on construction sites. While SOC is a better proxy for skills used on the job than SIC, we also test the effect of industry sectors on employment outcomes in our analysis, given the evidence reported above that industry sector has some influence on outcomes.

In this chapter the term ‘occupation’ will hereafter refer to occupations classified at SOC major group digit 1 level. In SOC major group digit 1, occupations are classified into 9 major groups according to their skill levels. Skill levels typically refer to a formal qualification that is theoretically required to enter an occupation. When formal qualification requirements are not specified, reference is made to work experience and/or the duration of training required to be fully proficient in the specific occupation. Office for National Statistics (2020) describes each skill level in terms of knowledge that is associated with specific formal qualifications, period of work-based learning and work experience (See Table 3.1. SOC major occupational groups ). In the SOC classification, occupations in the major group 1 are highly heterogenous and refer to managers, directors but also owners of small business. Some of these occupations require a degree but some others do not. Most of the occupations in the major group 2 require a degree, though in a few occupations in this group short post-secondary education is sufficient. Major group 3 occupations are associated with a high-level vocational education and training. Occupations in major groups 4 and 6 typically require a good standard of general education. Workers in major group 5 need extensive vocational training, typically involving a substantial period of work-based learning. Occupations in major groups 7 and 8 require some general education and some training, respectively, while occupations in major group 9 do not require any formal education although they may require short period of work-related training. Drawing on the description of the major SOC categories, we assume the complexity of tasks performed on the job decreases in SOC. SOC major group occupations 1-3 thus require the highest level of cognitive skills to perform a range of complex tasks. Occupations from the following major groups, 4 and 5, are less skilled than occupations in higher level SOC major groups but probably more skilled than lower level occupations. Major group 4 refers to administrative semi-skilled occupations, and major group 5 includes semi-skilled trade occupations. Occupations from major groups 6 and 7 are related to the service sectors. They include jobs of dental nurses, ambulance staff, porters, janitors, cleaning managers. They are a heterogenous category in a sense they encompass jobs with varying skills requirements. Major group 8 and 9 are relatively unskilled.

## Table 3.1. SOC major occupational groups

| |
|---|
| 1: MANAGERS, DIRECTORS AND SENIOR OFFICIALS<br>Job description:<br>This major group covers occupations whose tasks consist of planning, directing and coordinating resources to achieve the efficient functioning of organisations and businesses. Working proprietors in small businesses are included, although allocated to separate minor groups within the major group.<br><br>Most occupations in this major group will require a significant amount of knowledge and experience of the production processes, administrative procedures or service requirements associated with the efficient functioning of organisations and businesses. |
| 2: PROFESSIONAL OCCUPATIONS<br>Job description:<br>This major group covers occupations whose main tasks require a high level of knowledge and experience in the natural sciences, engineering, life sciences, social sciences, humanities and related fields. The main tasks consist of the practical application of an extensive body of theoretical knowledge, increasing the stock of knowledge by means of research and communicating such knowledge by teaching methods and other means.<br><br>Most occupations in this major group will require a degree or equivalent qualification, with some occupations requiring postgraduate qualifications and/or a formal period of experience-related training. |

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|---|
| 3: ASSOCIATE PROFESSIONAL AND TECHNICAL OCCUPATIONS<br><br>Job description:<br>This major group covers occupations whose main tasks require experience and knowledge of principles and practices necessary to assume operational responsibility and to give technical support to Professionals and to Managers, Directors and Senior Officials.<br><br>The main tasks involve the operation and maintenance of complex equipment; legal, business, financial and design services; the provision of information technology services; providing skilled support to health and social care professionals; serving in protective service occupations; and managing areas of the natural environment. Culture, media and sports occupations are also included in this major group. Most occupations in this major group will have an associated high-level vocational qualification, often involving a substantial period of full-time training or further study. Some additional task-related training is usually provided through a formal period of induction. |
| 4: ADMINISTRATIVE AND SECRETARIAL OCCUPATIONS<br>Job description:<br>Occupations within this major group undertake general administrative, clerical and secretarial work, and perform a variety of specialist client-orientated administrative duties. The main tasks involve retrieving, updating, classifying and distributing documents, correspondence and other records held electronically and in storage files; typing, word-processing and otherwise preparing documents; operating other office and business machinery; receiving and directing telephone calls to an organisation; and routing information through organisations.<br><br>Most job holders in this major group will require a good standard of general education. Certain occupations will require further additional vocational training or professional occupations to a well-defined standard. |
| 5: SKILLED TRADES OCCUPATIONS<br>Job description:<br>This major group covers occupations whose tasks involve the performance of complex physical duties that normally require a degree of initiative, manual dexterity and other practical skills. The main tasks of these occupations require experience with, and understanding of, the work situation, the materials worked with and the requirements of the structures, machinery and other items produced.<br><br>Most occupations in this major group have a level of skill commensurate with a substantial period of training, often provided by means of a work-based training programme. |
| 6: CARING, LEISURE AND OTHER SERVICE OCCUPATIONS<br>Job description:<br>This major group covers occupations whose tasks involve the provision of a service to customers, whether in a public protective or personal care capacity. The main tasks associated with these occupations involve the care of the sick, the elderly and infirm; the care and supervision of children; the care of animals; and the provision of travel, personal care and hygiene services.<br><br>Most occupations in this major group require a good standard of general education and vocational training. To ensure high levels of integrity, some occupations require professional qualifications or registration with professional bodies or relevant background checks. |
| 7: SALES AND CUSTOMER SERVICE OCCUPATIONS<br>Job description:<br>This major group covers occupations whose tasks require the knowledge and experience necessary to sell goods and services, accept payment in respect of sales, replenish stocks of goods in stores, provide information to potential clients and additional services to customers after the point of sale. The main tasks involve knowledge of sales techniques, a degree of knowledge regarding the product or service being sold, familiarity with cash and credit handling procedures and a certain amount of record keeping associated with those tasks. |

| |
|---|
| Most occupations in this major group require a general education and skills in interpersonal communication. Some occupations will require a degree of specific knowledge regarding the product or service being sold, but are included in this major group because the primary task involves selling. |
| 8: PROCESS, PLANT AND MACHINE OPERATIVES<br>Job description:<br>This major group covers occupations whose main tasks require the knowledge and experience necessary to operate and monitor industrial plant and equipment; to assemble products from component parts according to strict rules and procedures and to subject assembled parts to routine tests; and to drive and assist in the operation of various transport vehicles and other mobile machinery.<br><br>Most occupations in this major group do not specify that a particular standard of education should have been achieved but will usually have a period of formal experience-related training. Some occupations require licences issued by statutory or professional bodies. |
| 9: ELEMENTARY OCCUPATIONS<br>Job description:<br>This major group covers occupations which require the knowledge and experience necessary to perform mostly routine tasks, often involving the use of simple hand-held tools and, in some cases, requiring a degree of physical effort.<br><br>Most occupations in this major group do not require formal educational qualifications but will usually have an associated short period of formal experience-related training. |

Source: https://onsdigital.github.io/dp-classification-tools/standard-occupational-classification/ONS_SOC_hierarchy_view.html

Given the description of the educational requirement in SOC major group occupations, we would expect to find the majority of HTE-qualified in major group 3, some in major group 1 and 2 and 5, and a small proportion in the remaining categories.

### *Knowledge and skill requirements in the SOC as reported by empirical studies*

To confirm the validity of our approach, whereby top SOC major group occupations involve more complex tasks and require higher level skills than occupations at the bottom of the classification, we discuss in more detail two empirical research studies, Green and Henseke (2016) and Elias and Purcell (2013) that describe SOC occupations in terms of skills requirements. We also briefly summarise findings from the SES analysis pointing to different level of tasks complexity across SOC major group occupations.

The SES analysis presented in Chapter 2 of this research developed an index of wages as explained by tasks performed on the job, to estimate the complexity and intensity of workplace tasks in different populations and occupations. The index reflects composition of a range of differently priced tasks on the jobs and is expressed as the variation in wages explained by the sum of all the skills used on the job by individuals. Analysis of the wage index showed that, as expected, the intensity of highly priced tasks is the highest in SOC major group 1-3 occupations associated with high level cognitive skill and lowest in the SOC major group 9 elementary occupations, see Figure 2.3 in Chapter 2. Across educational groups, the index takes the highest value among graduates (including those with postgraduate qualifications) followed by the HTE-qualified.

In response to the rapid increase in participation in higher education at degree level, and therefore in the supply of graduates, many research studies explored the match between the demand and supply for graduates. One approach is to identify ‘graduate’ and ‘non-graduate’ employment, and then to estimate the distribution of graduates across graduate and non-graduate jobs. It is assumed that occupations identified as graduate are those involving the most complex tasks and requiring high level skills to perform them effectively.

Green and Henseke (2016) identify the tasks, skills and job characteristics that are the most likely to be observed in jobs where postsecondary qualifications are required. Using skills and educational requirements as reported by individuals in the SES they develop a graduate job indicator. Postsecondary qualifications include degrees and HTE (as defined in the SES) with the overwhelming majority belonging to a degree category. To derive an index of the latent “graduate skills requirement” (GSR) the authors first create a dependent binary variable (D).

D = 1 if an employee reports that a postsecondary qualification of at least level 4 is required to get the job and that this qualification is seen as “essential” or “fairly necessary” to carry out work competently,

D = 0 otherwise.

The authors run a probit model of D on a selection of skills used at work and job characteristics (e.g. use of computers, problem solving, literacy, received training) and on the index of postsecondary qualification requirements in similar jobs. Similar jobs are defined with the Standard Occupational Classification (SOC). Drawing on the estimations from the probit model, a GRS index is computed as a weighted linear combination of the independent variables. Tasks showing the strongest association with jobs defined as graduate employment therefore receive the highest weight. Averaging skill requirements by major SOC groups shows that the skills requirements are the highest (as measured with educational attainment) in the 2nd major SOC group followed by the 1$^{st}$ and the 3$^{rd}$. The lowest skill requirements were found at the bottom of the SOC classifications (Green & Henseke, 2016). This is consistent with the findings according to which the share of graduates and individuals with HTE is the highest in the first three major group SOC occupations.

Elias and Purcell (2013) also look at skills gradation across SOC major group 1 occupations. The authors observe how over time, graduates have ’crowded’ into jobs that traditionally required knowledge and skills associated with lower levels of education. Drawing on the SOC classification they explore the content of jobs to test if there was a skill upgrading in the non-graduate jobs or if graduates are now more likely to work in jobs for which they are nominally overqualified than in the past. In 2002, the authors questioned 220 UK graduates who had obtained a first degree in 1995 about the content of respondents’ current jobs (tasks they carry out on the job, their responsibilities, relationships with other employees and the knowledge and skills required to carry out their jobs effectively). The responses were related to SOC categories. The data show that the 2$^{nd}$ major SOC category required the highest level of expert knowledge associated with higher education. The 1$^{st}$ major SOC category was rated high on managerial tasks but less so on expertise knowledge. Many but not all jobs in this category required a formal degree. Jobs in the 3$^{rd}$

category were still relatively skill intensive but employees reported that in many of these jobs (e.g. estate agent) knowledge and skills typically associated with a 3-year university degree were not required to perform the job tasks effectively. Occupations falling in SOC group 5 required a relatively strong expert knowledge but not at degree level. The content of occupations in other major groups, as reported by interviewed graduates, was much less complex.

The SOC classification and the selected research studies confirm that occupations in the first 3 major groups involve the most complex tasks typically requiring at least some post-secondary education. Tasks found in the occupations in the middle of the classifications (major groups 4,5,6) are less intensive than tasks performed in the top occupations but more intensive than tasks found at the bottom of the classification (7,8,9). Applying the SOC classification with its skills gradation, we estimate the comparative advantage of HTE in skilled occupations (SOC major group occupations 1,2,3) as compared to degree holders over time. Drawing on the previous SES analysis, our hypothesis is that HTE employees will be displaced to occupations with lower skills requirements by degree holders. Our hypothesis is also that the excess of the degree wage premium over the HTE wage premium, has increased over time in skilled employment.

The SOC classification is one indicator of the level of tasks complexity (as measured with education and training) in different occupations but it does not directly reveal the extent of technical (or sector specific) expertise required on the job. For example, both physiotherapists and aerospace engineers need a range of skills typically associated with degree level education to perform a variety of complex skills on the job. But the areas of economic activity where they perform their work-related duties are very different. The engineer should have a deep understanding of mechanics and thermodynamics while the physiotherapist should have a thorough knowledge of anatomy, among many other things. Skills used on the job can therefore be described both in terms of the level of complexity and the area or sector where they are applied. SOC refers mainly to the first aspect, and industry sector or area of specialisation convey information on the second.

### *Drawbacks of the SOC*

A classification of occupations such as SOC allows us to observe the changes in the profile of employees in occupations with different levels of task complexity over time. For such analysis to be meaningful it should be assumed that occupations, in terms of their task requirements, do not change radically over time. However, this assumption is not realistic as many occupations are dynamic and employers have to adapt constantly to changing circumstances such as shifts in technologies, availability and changing cost of labour with given skills (Green, 2012). To prevent the SOC classification itself from becoming obsolete the taxonomy is typically revisited every 10 years. But the revision on a ten year basis may not be sufficient. Djumalieva, Lima and Sleeman (2018) argue that during a period of 10 years jobs may change significantly and that there is a need for a more timely revision. Drawing on job vacancy data the authors propose an alternative taxonomy whereby occupations are classified based on employer skill requirements.

If changes in the content of occupations go undetected, the observed changes in the distribution of the HTE-qualified across SOC groups may be explained by some combination of:

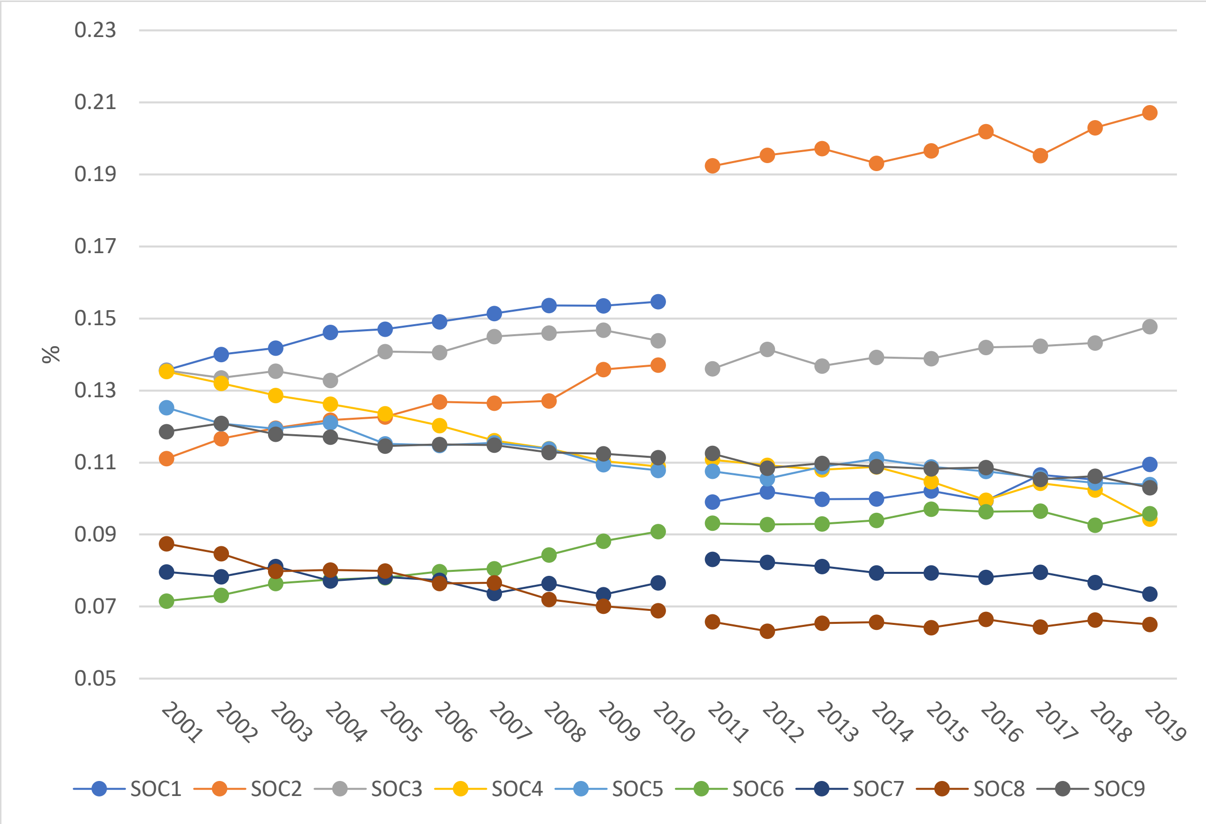
- the changing ability and skills of employees to perform the tasks required in different occupational groups;
- the changing task mix within different occupational groups. In this last scenario, the shift of labour across occupations is explained by upskilling of occupations that has not been captured in the SOC classification, rather than a loss of skills among employees.

The LFS data allow us to observe changing mix of workers in different occupations but not the changes in the occupation content. The SES dataset is more informative in this respect as it conveys information on tasks carried out on the job across occupations and over time. The SES analysis shows that task complexity increased in all occupational groups, including in manual semi-skilled (SOC major group 5) and elementary occupations groups traditionally associated with lower level of skills. Growing task complexity may be due to a rising demand for labour with higher levels of education in nominally less-skilled occupations. It can also be that an inflow of highly educated labour drove the use of complex skills in these occupations. If the HTE-qualified moved from the skilled to less task intensive occupations, as the SES analysis suggested, they were therefore moving from more to less skilled employment on average.

### *Revision of the SOC*

SOC 2000 was revisited in 2010 and the revised classification was introduced in LFS data the following year. Overall, 88,6% of occupations in the classification of Major groups in SOC 2000 are found in the same Major groups in SOC 2010 (Office for National Statistics, 2012). In the reclassification, Major Group 1 has shrunk significantly whereas Major Group 2 expanded. A small drop was also observed in Major Group 3. The revision was undertaken for various reasons. The introduction of a narrower definition of managers resulted in a significant share of occupations previously coded as Major group 1 (Managers and Senior Officials) to be allocated to other groups, notably to Major groups 2 and 3 (Professionals, Associate Professionals and Technicians). For example, occupations of ‘Information Technology and Telecommunications Managers’ classified as Major Group 1 in SOC 2000 were split into: ‘Information Technology and Telecommunications Directors’, ‘IT specialist managers’ and ‘IT project and programme managers ‘. Among these newly created categories, only the first one maintained its place in Major Group 1 with the two remaining being moved to Major Category 2 in SOC 2010. It seems likely that Major Group 1 became more homogenous in terms of its skill profile after the revision, and indeed this was part of the rationale. Revision of occupational categories was also motivated by changing entry requirements, and task composition in certain professions. For example, over time the share of degree-educated nurses has increased rapidly and as a result most nursing occupations were reallocated from Major Group 3 to Major Group 2 (Office for National Statistics, 2012; Elias & Birch, 2010). Figure 3.1 below shows the distribution of employees by SOC major groups. The break in the data in 2010 reflects the introduction of the 2010 SOC.

**Figure 3.1. Distribution of employees by SOC categories between 2001-2019, 16-64 year olds**




Note: weighted data

SOC digit 1 reads as follows: SOC1: Managers, Directors and Senior Officials, SOC2: Professional Occupations, SOC3: Associate Professional and Technical Occupations, SOC4: Administrative and Secretarial Occupations, SOC5: Skilled Trades Occupations, SOC6: Caring, Leisure and Other Service Occupations, SOC7: Sales and Customer Service Occupations, SOC8: Process, Plant and Machine Operatives, SOC9: Elementary Occupations

Source: LFS data, author's calculations

Elias and Birch (2010) propose various methods to deal with discontinuities resulting from the SOC revision, and discuss their advantages and disadvantages. Dickerson and Morris (2017) carry out analysis of the demand for skills in the UK at the SOC 2010 4-digit occupation level. To ensure consistency among occupations over time they convert SOC 2000 data into SOC 2010 equivalences.

In this study we maintain the original 2000 and 2010 coding rather than imposing a mapping of equivalence between the two. The second approach risks increasing heterogeneity in skills composition within the occupational groups that were revised to reflect changes in the complexity of tasks performed on the job. As our occupational data are discontinuous, we carry out analysis in two time periods 2001-2010 and 2011-

2019 separately, with occupations in the first period classified according to the SOC 2000 and occupations in the second defined according to the SOC 2010.

### 3.4. Data and measurement

The Labour Force Survey (LFS) managed by the UK Office for National Statistics is a nationally representative household survey that has been conducted quarterly since 1992. The LFS uses a rotational sampling design, whereby an individual is interviewed in five consecutive quarters (waves) commencing with the quarter when the person was first selected for an interview (Office for National Statistics, 2016). After the fifth interview respondents are replaced by a new cohort. The longitudinal nature of LFS data allows us to capture the seasonal variation in employment, however the period over which individuals are followed (five quarters) is too short to observe changes in the demand for the HTE-qualified. For these reasons we privilege an analysis of cross-sections over time. So as the respondents appear only once in our sample we select participants who are in their first wave of interviews. The choice of the first wave is dictated by the fact that earning questions are only asked in the first and the final wave.

To ensure consistency with the separate SES data analysis reported in this thesis that covers 2001-2017, LFS data from the first quarter of 2001 to the last quarter of 2019 are selected. Data from Q2 2001, and Q2 2004 are removed due to missing information on earnings and education respectively. We pool quarterly data for each year as we do not expect much variation in earnings and in employment (other than seasonal variations) on a quarterly base. In total, this yields 1,070,207 cases.

The sample includes individuals aged 16-64. Older adults are excluded as prior to 2008 information on highest qualifications was not available for those aged 64 and above. Despite the exclusion of adults aged 65 and above, the education data for women are not fully consistent with the data for men. Until 2008 educational information was provided for all those in employment and those of working age, but the working age population was defined differently for men and women. The working age for men was 16-64, and 16-59 for women. Consequently, until 2008 women not in employment aged 59 and above were not covered by the education questions (Office for National Statistics, 2020). LFS documentation situates the change in educational data collection for women at 2010, but the data shows that this information has been available since 2008. It follows that the educational information for women aged 59 and above and not in employment is missing in LFS datasets in the period 2001-2007. While this discontinuity in educational information in the female population has no impact on our wage analysis as the population of interest is composed of those in employment only, it may have a bearing on the outcomes of analysis looking at associations between employment likelihood and qualifications for women over time. Inclusion of older women not in employment since 2008 may contribute to lower employment outcomes for women in the corresponding periods as we expect employment rates of women above the age of 59 to be below those of younger women. To account for the change in the availability of education information among women a dummy variable for women above the age of 59 and not in employment is included in the relevant analysis.

Below we discuss how key variables (such as highest qualifications and wages) and derived variables are defined.

### *3.4.1. Highest educational attainment*

In this study individuals are classified based on their highest qualification. LFS data provide detailed information on the level and type of qualifications held by individuals. The qualifications (highest qualification possessed by an individual) listed in Table 3.2 were identified as HTE. Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate and Level 6 Award, accounting for a small proportion of the HTE qualifications were grouped together with ‘other higher education below degree’ in one category named ‘other HTE qualifications’ (see Table 3.2).

### Table 3.2. HTE qualifications in the UK

Column 2 shows the distribution of different HTE qualifications expressed as a percentage of the HTE holders with a specific HTE qualification (100% - all HTE qualifications).

| | |
|---|---|
| NVQ level 4 | 10% |
| Diploma in higher education [34] | 21% |
| HNC/HND/BTEC higher etc | 53% |
| RSA higher diploma | 1% |
| Other HTE qualifications: other higher education below degree, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award | 15% |
| Total | 100% |

Note: weighted data

Source: LFS data, author’s calculations

In the SES only NVQ level 4 and HNC/HND were defined as HTE. In comparison to qualifications defined as HTE in the SES analysis, the HTE definition adopted in this chapter therefore is more inclusive and more similar to the definition of HTE adopted by Boniface, Whalley and Goodwin (2018) except that it does not include Foundation degrees. In the current study, further to the LFS classification, Foundation degrees are part of the degree category and hence not counted as HTE.

[34] Diploma in Higher Education was created as an academic qualification but over time it developed a more technical profile. A website for students explaining various qualifications compares the Diploma in HE to the HND: "They are both university-based vocational courses (meaning they prepare students for the world of work), and they both carry the same points value"

To compare labour market outcomes from HTE to those from other types of qualifications (i.e. to explore if HTE holders are more likely to work in highly skilled occupation than individuals with other qualifications), qualifications other than HTE are grouped into three categories:

- Degree or equivalent, and qualifications above the degree level;
- Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent;
- Level 1and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills

The classification of qualifications by level adopted here follows closely that proposed in the LFS, with the exception of teaching and nursing qualifications that in the LFS were classified as being below degree level, whereas in this research they are amalgamated with degree type qualifications given that both professions are now widely accepted as all-graduate professions.

While one of the main issues addressed in this chapter is the labour demand for the HTE-qualified in the context of the rising supply of graduates and rising competition for skilled employment between HTE and degree holders, labour market outcomes of the HTE-qualified are also compared to the outcomes of those with lower level qualifications. To make this comparison more meaningful the lower level qualifications are broken down into two categories: level 2 and 3 corresponding to the end of secondary education qualifications, and qualifications level 1 and below.

Before 2011 foreign qualifications were systematically included into the ‘other qualifications’ category. Since 2011, foreign qualifications that can be matched to UK qualifications are allocated accordingly. The change in the way foreign qualifications are counted decreased the share of ‘qualifications’ that were unidentified and by default included in the ‘other’ category. The change in the counting of foreign qualifications resulted in an increase of the share of degrees in the population. The effect on the HTE distribution was negligible. This may be because HTE provision in many countries is much smaller than university provision. It can also be that university qualifications gained outside the UK can be easily matched to UK qualifications while HTE provision tends to vary greatly across countries and finding a direct equivalence to the UK HTE qualifications may be less straightforward. A qualification acquired abroad may have a different value on the UK labour market than its UK equivalent, and the characteristics of holders of qualifications gained abroad (e.g. mastery of English, perseverance) may have an impact on their labour market performance. The effect of foreign qualifications on wages, as compared to qualifications gained in the UK is indirectly accounted for with the GCSE’s variable.

### *3.4.2. GCSE – a measure of academic achievement*

The GCSEs variable is divided into three categories: observations with 5 full GCSEs or more; less than 5 full GCSEs and GCSEs below grade C; and observations to which the GCSEs question does not apply. We derive the GCSE variable drawing on two existing LFS variables that identify: “Number of O level/GCSE passes (above grade C) etc.  already held”, and “Type of GCSE or equivalent held below grade C/1”. These questions were only administered to respondents who had a standard/O grades, GCSE, CSE or

Scottish National qualifications. Among individuals to whom the GCSE question did not apply, 63% had qualifications at level 1 and below (Annex A.2, Table A.2.1). The remaining 37% were individuals who for various reasons obtained qualifications at level 2 and above without going through the GCSE route. This would typically be the case for those who were educated abroad outside the British education system. Indeed, GCSE information is irrelevant for the overwhelming majority of those reporting foreign qualifications. The GCSE question does not apply to 96% of those with degree equivalent foreign qualifications, and 97% of individuals with HTE equivalents. It should therefore be kept in mind that the population to which GCSE question does not apply is highly heterogenous in terms of educational background and potentially labour market outcomes. Observations corresponding to individuals responding 'do not know' to the GCSE questions were coded as missing. The question about the number of full GCSEs was not administered in the first quarter of 2005. 2005 observations that we were not able to associate with the 'do not apply' category were coded as missing too. The total sample of 1,008,297 observations excludes those with missing information on educational attainment and GCSE.

### *3.4.3. Area of specialisation/field of studies*

We also estimate wage premia and employment opportunities among the HTE-qualified by the area of study as we expect the HTE wage to vary depending on the field of specialisation. Business and administration are the most common areas of study among the HTE-qualified individuals with one in four reporting one or other of these specialisations. Engineering and manufacturing trades are the second largest area of specialisation (see Table 3.3). Espinoza et al. (2020) drawing on administrative data with qualifications level 4 and 5, report a similar distribution across areas of specialisations as those described here. To ensure that individual cell sizes are adequate, the areas of study are grouped into 9 categories following the classification proposed in Office for National Statistics (2009). Among the aggregated categories, the third one is dominated by business and administration, which account for 86% of all the qualifications in this category, and engineering and manufacturing trades represent two third of HTE qualifications in the 5$^{th}$ aggregated category.

## Table 3.3. Distribution of HTE graduates 16-64 year-olds across areas of study, 2001-2019

The table also shows allocation of individual specialisations into larger categories. All specialisations add up to 100%.

| Aggregated categories | HTE area of specialisation | (%) |
|---|---|---|
| 1 | Basic programmes | 0.6 |
| | Teacher training | 3.4 |
| 2 | Art | 8.3 |
| | Humanities | 1.3 |
| 3 | Social and behavioural science | 2.0 |
| | Journalism and communication | 0.7 |
| | Business and admin | 25.1 |
| | Law | 0.6 |
| | Life science | 1.0 |

| | | |
|---|---|---|
| 4 | Physical science | 1.5 |
| | Math and stats | 0.5 |
| | Computing | 4.8 |
| 5 | Engineering and manufacturing trades | 18.3 |
| | Manufacturing and production | 1.3 |
| | Architecture and building | 6.1 |
| 6 | Agriculture forestry and fishery | 2.3 |
| | Veterinary | 0.5 |
| 7 | Health, nursing, dentistry | 7.0 |
| | Social services | 5.6 |
| 8 | Literacy and numeracy | 0.2 |
| | Personal services | 6.5 |
| | Transport services | 0.5 |
| | Environment | 0.4 |
| | Security services | 1.0 |
| 9 | Personal skills | 0.5 |
| | Total | 100 |

Note: Number of observations (obs) in each category (cat): cat1- 2569obs, cat2-5552obs, cat3-17946obs, cat4-4808obs, cat5-16194obs, cat6-1725obs, cat7-7799obs, cat8-5107obs, cat9-297obs.

Results are weighted.

Source: LFS, author's calculations

### *3.4.4. Wages and economic activity of the person*

In this study, wages are gross hourly pay derived from gross weekly pay in the main job divided by hours worked including paid overtime. To remove outliers, data points at and below the 0.5$^{th}$, and at or greater than the 99.5$^{th}$ percentile are dropped. In our analysis of wages over time we use wages that are deflated with the Consumer Price Index (CPI) and express in constant 2001 prices (CPI values can be found in Office for National Statistics, 2022). This procedure removes inflation and allows us to observe changes in real wages over time. Wages are expressed in logarithms for ease of interpretation and because a logarithmic function reflects more accurately the wage distribution that tends to be skewed.

Economic activity of the person is based on the ILO definition. It classifies those that are 16 years of age and above as employed, unemployed and inactive. The category of employed includes: employees, self-employed, those in government employment and training programmes and unpaid family workers. Whenever the term employed is used in this chapter it refers to the ILO definition unless otherwise specified.

## 3.5. Hypotheses, models and findings

This section discusses research hypotheses that would be tested, models developed to address them, and results of the performed analyses.

It starts with a comparison of wages and employment opportunities among the HTE-qualified and those with other qualifications. It identifies trends by exploring the rate of change in wages and employment in populations with different qualifications. Next, the analysis focuses down on the relative labour market performance of the HTE-qualified in employment with different levels of task complexity. It culminates with an analysis of labour market performance among individuals with HTE qualifications by the area of specialisation.

### *3.5.1. How wages of the HTE-qualified compare to wages of those with other qualifications*

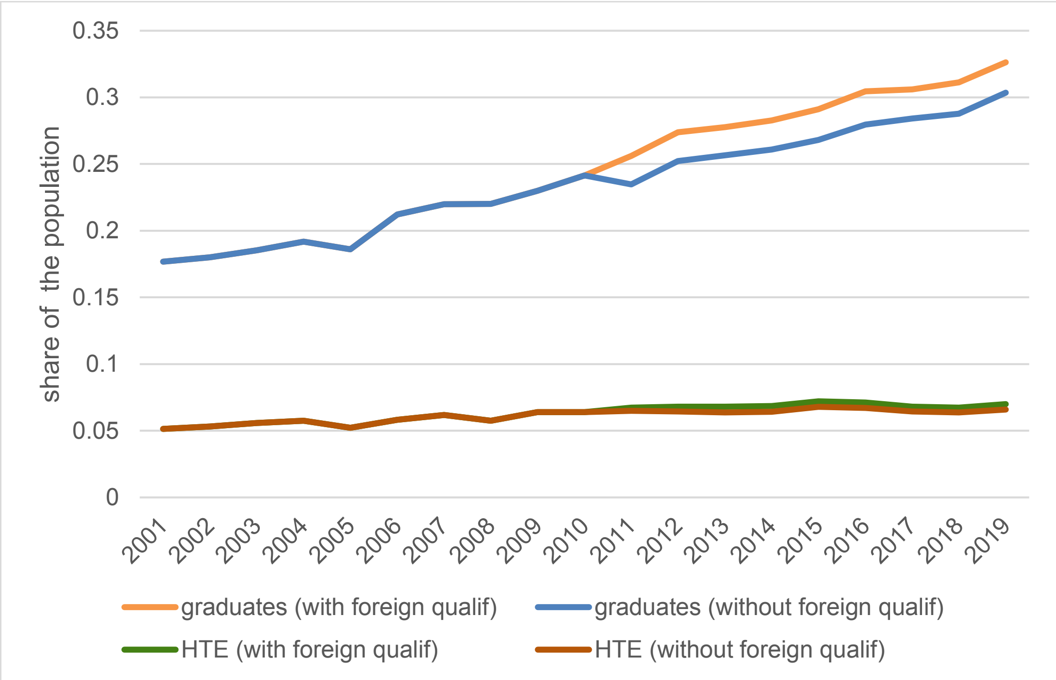
*Hypotheses and descriptive statistics*

The supply of graduates has been steadily rising in the UK in the last two decades (Figure 3.2). In 2019, 30% of the population was educated to a degree level (33% including those who acquired degrees abroad). Conversely, the share of the population with HTE qualifications remained relatively stable over the same period of time. One explanation for this changing mix of qualifiers is that it reflects changing relative demand – in other words an increase in the demand for degrees relative to HTE. We test this hypothesis by exploring wage differences between the HTE-qualified and individuals with degrees, as well as those with lower level qualifications. If the relative demand for HTE-qualified labour is indeed falling, we should observe a decline in the relative HTE wage and worsening employment opportunities among HTE-qualified.

#### Figure 3.2. Share of the 16-64 year-olds with degrees and HTE (as the highest qualification)

Orange and green lines show the shares with qualifications acquired abroad, which since 2011 are not included in "other qualifications" category but are counted together with the UK qualifications of the corresponding level.

How to the read the chart: In 2012 25% of the population held a degree that was acquired in the UK. If degree equivalents acquired abroad are considered, the share of degree holders in the total population rises to 27%.




Notes: HTE qualifications include: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree. Graduates include degree holders and those with qualifications above degree.

Results are weighted.

Source: LFS data, author's calculations

The graduate wage premium relative to HTE wages was maintained over time. In 2001, the HTE-qualified employee earned 79%, and in 2019, 77% of the graduate wage. This may suggest that the demand for graduates exceeded the labour market demand for HTE-qualified between 2001-2019 (see Figure 3.3).

### Figure 3.3. HTE real hourly wage (in 2001 prices) expressed as a percentage of the wage associated with other qualifications

How to read the chart: In 2019, HTE-qualified workers earned on average 23% less than graduates, but 23% more than those with qualifications level 2 and 3, and 42% more than those with qualifications level 1 and below.


Note: Qualifications are classified in 4 groups 1.) Degree or equivalent, and above; 2.) HTE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve1 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills

Results are weighted.

Source: LFS data, author's calculations

The observed differences in wages can partly be attributed to factors other than education, such as individual characteristics and employment features. To test this hypothesis, we estimate wage returns to HTE qualifications after accounting for factors that are associate with wages and education. Since we are interested in how wages change over time we also explore if the HTE wage changed at the same rate and in the same direction as wages of employees with other qualifications.

### *The empirical Model*

We compare the HTE wage to three wage groups: the graduate wage; the wages of employees with qualifications level 3 and 2; and finally, the wages of those with qualifications level 1 and below. We treat the HTE qualifications as baseline qualifications so that the coefficients on qualifications at degree level, level 3 and 2, and level 1 and below show the difference in earnings between the HTE-qualified employees and those with these other types of qualification. We add sequentially to this basic model a range of control variables to observe how they impact the modelled relationship between wages and qualifications.

In this first model, we estimate an association between wages and qualification. $Ei$ is a vector of qualifications held by individual $i$. $Yi$ represents six period dummies (2001-2004, 2005-2007, 2008-2010, 2011-2013, 2014-2016, 2017-2019) accounting for time trends that influence wages and that are not captured by other control variables. For example, the time-period during which the economy grows less rapidly or declines would typically be associated with falling wages. (Results of this analysis are reported in 3.4, column 1)

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + e_i \text{ (1)}$$

In the second model we observe the impact of individual characteristics on wages by adding to the model a vector of control variables *Xi* including: age, age squared and ethnicity (see column 2, Table 3.4

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + e_i \text{ (2)}$$

To account for ability bias, model 1 and 2 may suffer from, we add a control for individual GCSE performance *Gi,* where *Gi* is a vector of GCSE dummy variables (results from the model 3 are discussed in column 3, Table 3.4).

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 G_i + e_i \text{ (3)}$$

In Model 4 we estimate relative wages with the regressors as in model 4 but with additional controls for industry sector (results from the model 4 are discussed in column 4, Table 3.4). *Ii* indicates dummy of industry sectors (SIC) in which individual *i* is employed.

$$\ln(wage_i) = \alpha + \beta'_1 E_{qi} + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 G_i + \beta'_5 I_i + e_i \text{ (4)}$$

Model 5 also controls for geographical area R where the individual *i* works, and type of employment F held (part-time vs full-time and public vs private sector). Geographical areas include 12 regions: North East, North West, Yorkshire & Humberside, East Midlands, West Midlands, Eastern, London, South East, South West, Wales, Scotland and Northern Ireland (results from the model 5 are discussed in column 5, Table 3.4).

$$\ln(wage_i) = \alpha + \beta'_1 E_{qi} + \beta'_2 Y_{it} + \beta'_3 X_i + \beta'_4 G_i + \beta'_5 I_{is} + \beta'_6 R_i + \beta'_7 F_i e_i \text{ (5)}$$

Models 1-5 above provides estimates of the average wages, all levels of qualifications combined, in different time periods. To allow for wages associated with different qualifications to follow different trajectories of growth, interaction terms between time periods and qualifications are added. In addition, to measure the effect of different ability levels across qualifications the model is estimated without (model 6) and with GCSE dummy variables (model 7). Industry and employment characteristics are not accounted for as it can be reasonably assumed that the distribution of employees with different qualifications across sectors and regions remained broadly stable over time, so their inclusion in the model would have no effect on the rate of change of wages over time by qualifications.

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 (E_i * Y_i) + e_i \quad (6)$$

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 (E_i * Y_i) + \beta'_5 G_i + e_i \quad (7)$$

*Results*

Consistent with the existing evidence, the results demonstrate that, from 2001-2004 baseline period, mean real wages increased until the Great Recession, and then stagnated or declined up to 2017. As expected, wages are higher at more advanced education levels, so that HTE-qualified employees earn less than graduates but more than those with lower level qualifications (column 1, Table 3.4). When individual differences are accounted for, the wage premium of graduates over the HTE-qualified workers increases by 4 percentage points, and the wage premium of the HTE-qualified as compared to the holders of level 2 and 3 qualifications drops by 9 percentage points (column 2)[35]. As the inclusion of individual differences in the model reduces the estimated wage premium for the HTE-qualified, the implication is that some of the wage benefits observed among HTE-qualified can be attributed to their individual characteristics, mainly to the fact that they tend to be older and more male-dominated than graduates and level 2 and 3 qualified individuals.

Strong GCSE results are positively associated with wages. Adding an indicator of achieving at least 5 A*-C GCSE's (as compared to less than 5 full GCSE's and GCSE below grade C) to the model reduces the estimated coefficient for the graduate wage premium, relative to HTE, by around 3 percentage points. The estimated difference in earnings between HTE and those with level 2 and 3 qualifications shrinks by the same amount, and the HTE wage as compared to earnings of employees with level 1 and no qualifications decreases by 15 percentage points (compare the results in column 2 and 3, Table 3.4). This suggests that a part of the observed wage differentials as between those with different levels of qualification is due to differences in prior GCSE qualifications. Such GCSE differences may reflect a mix of factors, including deeply entrenched factors, including intelligence and conscientiousness, and strong literacy and numeracy, that then go on to determine job performance. The estimated negative coefficient on the GCSE 'do not apply' dummy suggests that some GCSE (less than 5 full GCSEs and GCSE below grade C), which is the baseline category in the model, is still better than no GCSEs at all. However, it should be born in mind that the group to whom the GCSE question is irrelevant, while composed mainly of those with low level of educational attainment, also includes some highly educated individuals displaying strong labour market performance, including those who received their education abroad. Moreover, even after accounting for GCSEs a significant and large wage gap between qualifications persists: employees with

[35] Please note that the wage premium is not symmetric. For example, a degree coefficient of 0.23 shows that graduates earn 26% more as compared to the HTE-qualified, and that the HTE-qualified earn 21% less as compared to the graduates. This is intuitive and can also be proved mathematically, as (exp(0.23)-1)=0.258, and (exp(-0.23)-1)= 0.205.

the qualifications earn on average 21% less than graduates, 21% more than the level 2 and 3 qualified and 38% more than the workers with the lowest qualification level (column 3, Table 3.4). The wage premium after adjusting for GCSEs could be interpreted as the added value of obtaining a higher-level qualification, reflecting new and more complex skills that are rewarded on the labour market. But it could also be that the remaining wage difference reflects a selection bias i.e. unobservable differences between populations. The number of GCSEs, our measure of academic achievement captures some but not all of the variation in cognitive skills among those taking different qualifications. A more fine-grained measure of ability would depend on the exact number of GCSE's, grades and the subject, features that are not observable in our data. Other individual and family characteristics that we do not observe, such as socio-economic background and unobserved skills of the person, may also bias the association between education and wages. If these characteristics are positively associated with educational attainment the bias would be directed upward. For example, omitting information on socio-economic background that tends to be positively associated with both educational attainment and wages risks inflating the estimated effect of qualifications on earnings.

The relative wage of the HTE-qualified as compared to graduates and those with level 2 and 3 qualifications does not seem to vary much between industry sectors. However, the industry sector does make a difference when the HTE wage is compared to earnings of employees with level 1 qualifications and below. Workers with HTE qualifications appear to be more likely to work in better paid industry sectors as the level 1 qualification coefficient decreases after controlling for industry sector (column 4, Table 3.4). Adding employer and job characteristics (column 5, Table 3.4) further decreases the degree wage premium, and reduces the wage disadvantage of those with lower level qualifications, as compared to the HTE-qualified. This confirms that those with higher levels of educational attainment, presumably employees with higher level skills, are more likely to be matched to more productive firms and sectors.

## Table 3.4. Changes in the relative wage of the HTE-qualified workers (baseline qualification) since 2001-2004 (baseline period)

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
| | Coeff | p-value | Coeff | p-value | Coeff | p-value | Coeff | p-value | Coeff | p-value |
| Intercept | 2.26 | 0.00 | 0.78 | 0.00 | 0.64 | 0.00 | 0.75 | 0.00 | 1.06 | 0.00 |
| Sex (female) | | | -0.23 | 0.00 | -0.23 | 0.00 | -0.20 | 0.00 | -0.16 | 0.00 |
| Age | | | 0.07 | 0.00 | 0.08 | 0.00 | 0.07 | 0.00 | 0.06 | 0.00 |
| Age square | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Ethnicity (non-White) | | | -0.06 | 0.00 | -0.03 | 0.00 | -0.02 | 0.00 | -0.07 | 0.00 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| GCSE's (5 or more full GCSE's) | | | | | 0.14 | 0.00 | 0.13 | 0.00 | 0.13 | 0.00 |
| GCSE (does not apply) | | | | | -0.02 | 0.00 | -0.03 | 0.00 | -0.04 | 0.00 |
| Year 2005-2007 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 |
| Year 2008-2010 | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.06 | 0.00 |
| Year 2011-2013 | 0.00 | 0.43 | -0.01 | 0.00 | -0.01 | 0.00 | -0.01 | 0.00 | 0.00 | 0.04 |
| Year 2014-2016 | -0.01 | 0.00 | -0.02 | 0.00 | -0.02 | 0.00 | -0.02 | 0.00 | -0.01 | 0.00 |
| Year 2017-2019 | 0.01 | 0.00 | 0.00 | 0.14 | 0.00 | 0.92 | 0.01 | 0.02 | 0.02 | 0.00 |
| Level 1 qualif & below | -0.43 | 0.00 | -0.42 | 0.00 | -0.32 | 0.00 | -0.30 | 0.00 | -0.28 | 0.00 |
| Level 2&3 qualifications | -0.28 | 0.00 | -0.21 | 0.00 | -0.19 | 0.00 | -0.18 | 0.00 | -0.17 | 0.00 |
| Degree | 0.23 | 0.00 | 0.26 | 0.00 | 0.24 | 0.00 | 0.23 | 0.00 | 0.21 | 0.00 |
| Part-time | | | | | | | | | -0.10 | 0.00 |
| Public sector | | | | | | | | | -0.16 | 0.00 |
| Industry | NO | | NO | | NO | | YES | | YES | |
| Region | NO | | NO | | NO | | NO | | YES | |
| | Residual standard error: 0.5119 on 489551 degrees of freedom F-statistic: 1.527e+04 on 8 and 489551 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4677 on 489547 degrees of freedom F-statistic: 2.028e+04 on 12 and 489547 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4632 on 489545 degrees of freedom F-statistic: 1.839e+04 on 14 and 489545 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4515 on 488807 degrees of freedom F-statistic: 1.345e+04 on 22 and 488807 DF, p-value: < 2.2e-16 | | Residual standard error: 0.44 on 488107 degrees of freedom F-statistic: 9637 on 35 and 488107 DF, p-value: < 2.2e-16 | |

Note: Baseline category refers to HTE holders, white male, with GCSE below grade C or with fewer than 5 GCSE's grade A-C, employed full-time and in private sector, in 2001-2004.

How to interpret the coefficients: As wages are expressed in logs, the formula (exp(coeff)-1)*100% allow us to transform the coefficients into % wage premium. E.g. a degree coefficient of 0.22 in column 2 shows that the degree holders earn on average 25% more than the HTE-qualified workers, as 100(exp(0.22)-1)= 25

Qualifications are classified in 4 groups 1.) Degree or equivalent and above; 2.) HTE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills.
Source: LFS data, author's calculations

Our estimates are consistent with that obtained in (Conlon *et al.*, 2017). Drawing on LFS data the authors report a wage premium to level 4 qualifications of 16%-17%, as compared to level 3 qualifications. (McIntosh, 2004) reports wage returns to HND/HNC as compared to level 2 and *3* qualifications at between -2% and 20%, depending on the lower level qualification. Notably, HND/HNC qualified workers earn less than holders of 2+A levels. These results are slightly different from ours, which can be explained with a different model specification.

The model with the interaction terms (column 6, Table 3.5) shows that the HTE wage declined faster than the graduate wage between 2011 and 2016. The decline in the HTE wage was also much faster than the wage contraction among those with lower level qualifications since 2011. One possibility is that these changes might be attributed to changing prior academic achievement among those with different qualifications. LFS data confirm that prior academic achievement, as measured by GCSEs, across qualifications was not constant over time. Between 2001 and 2019 the share of graduates in the LFS sample with five or more GCSEs *A-C dropped from 80% to 68%, a striking decline bearing in mind that younger adults in the 2001 sampled population would mostly remain in the 2019 sampled population. This suggests that the rapid expansion in university attainment that took place during this period may have been partly achieved by lowering entry requirements to degree programmes, assuming that GCSE standards did not rise during this time. Major reforms to GCSEs were introduced in 2015 but the new exams only applied in 2017 (Burgess & Thomson, 2019), making it implausible that the effect of this reform would have any significant bearing on the LFS data for the adult population. In 2019, 58% of the HTE-qualified held five or more full GCSEs, a decline of 6 percentage points relative to the 2001 level.

### Table 3.5. Relative HTE wages, allowing for changes in wages to differ across time periods

| | (6) Model 6 | | (7) Model 7 | |
|---|---|---|---|---|
| | coefficient | p-value | coefficient | p-value |
| Intercept | 0.81 | 0.00 | 0.67 | 0.00 |
| Sex | -0.23 | 0.00 | -0.23 | 0.00 |
| Age | 0.07 | 0.00 | 0.08 | 0.00 |
| Age square | 0.00 | 0.00 | 0.00 | 0.00 |
| Ethnicity (non-white) | -0.06 | 0.00 | -0.03 | 0.00 |
| GCSE's (5 or more full GCSE | | | 0.14 | 0.00 |
| GCSE (do not apply) | | | -0.02 | 0.00 |

| | | | | |
|---|---|---|---|---|
| Year 2005-2007 | 0.03 | 0.00 | 0.04 | 0.00 |
| Year 2008-2010 | 0.03 | 0.00 | 0.03 | 0.00 |
| Year 2011-2013 | -0.05 | 0.00 | -0.05 | 0.00 |
| Year 2014-2016 | -0.07 | 0.00 | -0.06 | 0.00 |
| Year 2017-2019 | -0.06 | 0.00 | -0.05 | 0.00 |
| Level 2 qualif & below | -0.47 | 0.00 | -0.37 | 0.00 |
| Level 3 qualifications | -0.24 | 0.00 | -0.22 | 0.00 |
| Degree | 0.25 | 0.00 | 0.22 | 0.00 |
| Yr2005/07*degree | 0.01 | 0.19 | 0.02 | 0.05 |
| Yr2008/10*degree | 0.01 | 0.27 | 0.02 | 0.06 |
| Yr2011/13*degree | 0.03 | 0.01 | 0.04 | 0.00 |
| Yr2014/16*degree | 0.02 | 0.03 | 0.03 | 0.00 |
| Yr2017/19*degree | 0.01 | 0.24 | 0.02 | 0.01 |
| yr2005/07*level 2&3 qualif | 0.02 | 0.01 | 0.02 | 0.01 |
| Yr2008/10*level 2&3 qualif | 0.02 | 0.07 | 0.01 | 0.21 |
| Yr2011/13*level 2&3 qualif | 0.05 | 0.00 | 0.03 | 0.00 |
| Yr2014/16*level 2&3 qualif | 0.06 | 0.00 | 0.04 | 0.00 |
| Yr2017/19*level 2&3 qualif | 0.09 | 0.00 | 0.07 | 0.00 |
| yr2005/07*level 1 qualif | 0.04 | 0.00 | 0.03 | 0.00 |
| Yr2008/10*level 1 qualif | 0.04 | 0.00 | 0.04 | 0.00 |
| Yr2011/13*level 1 qualif | 0.06 | 0.00 | 0.06 | 0.00 |
| Yr2014/16*level 1 qualif | 0.08 | 0.00 | 0.07 | 0.00 |
| Yr2017/19*level 1 qualif | 0.13 | 0.00 | 0.12 | 0.00 |
| | Residual standard error: 0.4674 on 489532 degrees of freedom<br>F-statistic: 9038 on 27 and 489532 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4631 on 489530 degrees of freedom<br>F-statistic: 8892 on 29 and 489530 DF, p-value: < 2.2e-16 | |

Note: Baseline category refers to HTE holders, white male, with GCSE below grade C or with fewer than 5 GCSE's grade A-C, employed full-time and in private sector, in 2001-2004.

Qualifications are classified in 4 groups 1.) Degree or equivalent, and above; 2.) HTE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills.

Source: LFS data, author's calculations

This decline in average academic achievement among more recent graduates could have been triggered by a shift of educational preferences towards degree programmes, i.e. individuals who in the past would had entered a HTE now are more likely to start on a degree programme. Conversely, the share of individuals with level 2 and 3 qualifications with at least 5 full GCSEs *A-C increased during the same period by 9 percentage points and reached 57% in 2019. To explore the impact of academic achievement over time on changes in wages, we account for the type of GCSEs held by individuals. The results displayed in column 7, Table 3.5 show that for a given level of GCSE achievement, the difference in wage growth between HTE-qualified workers and graduates become significant in nearly all time periods and slightly increased in magnitude. This means that in the population with similar GCSE results, graduates experienced a stronger wage growth than HTE-qualified employees before the Great Recession, and that the fall in the graduate wage was less dramatic than in the HTE earnings after 2011. Overall, these findings point to an erosion of labour market demand for HTE, relative to degrees. The main factor here is changes in the economy and the labour market, points further considered in the following section. However, some other possibilities might also be considered. It could be that HTE have experienced declining visibility on the labour market relative to degrees; Dickerson and Vignoles (2007), for example, argue that recent HTE qualifications have a particularly low signaling value on the labour market.

### *3.5.2. How employment outcomes of the HTE-qualified compare to outcomes of those with other qualifications*

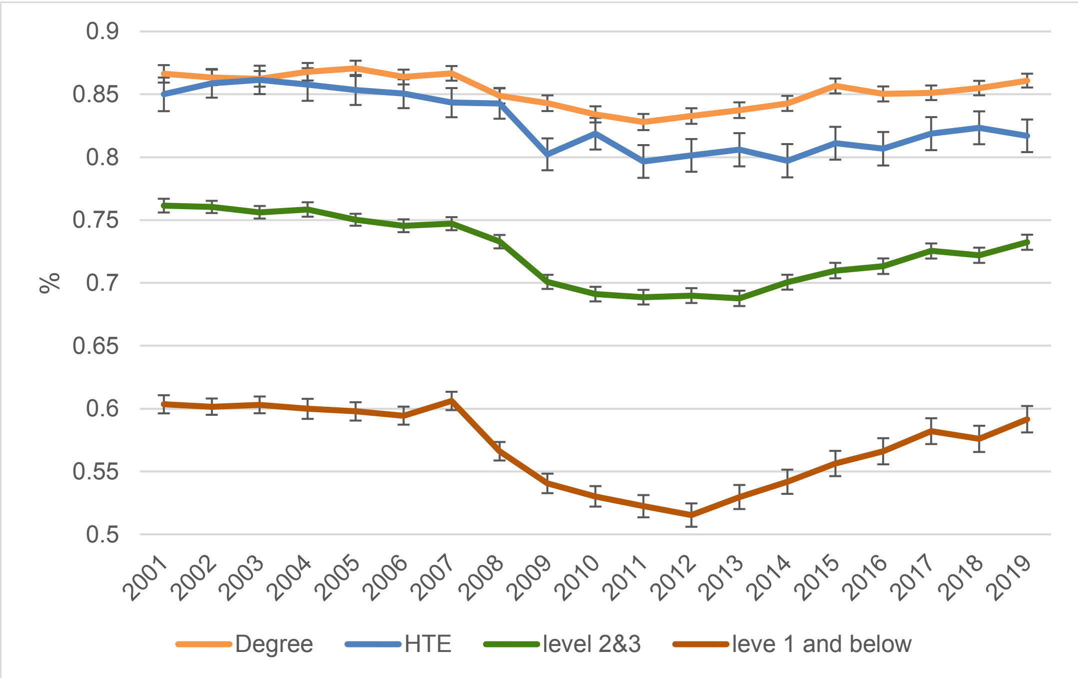
*Hypothesis and descriptive statistics*

Labour markets for specific qualifications may be affected by factors such as the introduction of new technologies in workplaces and by a contracting economy (Acemoglu & Restrepo, 2020). During a recession profits fall and companies reduce employment to cut costs; as a result, unemployment increases and some people leave the labour market. But the impact of a recession varies by level of education. In the UK, the Office of National Statistics (ONS), in its analysis of compositional changes in the labour force shows that workers with the lowest educational attainment saw the largest reduction in working hours during the Great Recession (2008-2009), and that the post-recession growth in hours worked was mainly driven by an increase in graduates' working time. ONS concludes that "this reflects a shift in the UK labour composition towards more highly educated workers" (Office for National Statistics, 2019). To some extent this may also be explained by the rising supply of graduates in the workforce. The ONS observes a modest growth in hours worked among those whose highest qualifications were at level 3 (A level, and some apprenticeships) and level 4. Drawing on these findings it is difficult to identify employment patterns among those with HTE qualifications, as HTE qualifications are amalgamated with other levels of educational attainment. To improve our understanding of employment opportunities of HTE holders during the recession and the recovery, we analyse LFS data.

The data show that the employment rate of the HTE-qualified plummeted during the Great Recession and by 2019 had barely recovered. The effect of the economic downturn on graduate employment was much milder and in 2019 the graduate employment rate was back to the pre-recession level, despite a rapidly increasing supply of graduates to the labour market. The gap in employment rates between the graduate and HTE populations widened during the 2008-2009 economic crisis and has remained large (Figure 3.4). This suggests that relative employment opportunities of those with HTE qualifications have worsened over time as compared to graduate employment opportunities.

### Figure 3.4. Share of 16-64 with different qualifications in employment (as opposed to inactive and unemployed)

How to read the chart: in 2001, 60% of individuals with qualifications level 1 and below, 75% of those with qualifications level 2 and 3, 85% of those with HTE qualifications, and 87% of graduates were in employment.




Note: The vertical bars indicate the confidence interval. Results are weighted.

Qualifications are classified in 4 groups 1.) Degree or equivalent and above; 2.) HTE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills.

According to the definition adopted in this chapter 'employees' refer to those in employment, self-employed, those in government and training programmes and unpaid family workers.

Source: LFS data, author's calculations.

One other possible explanation for the observed decline in the employment rate for the HTE-qualified might be a change in their age profile, given that employment rates among older adults decline with age. (Department for Work & Pensions (DWP), 2018) Health issues among older adults are one factor; individuals in their late 50s, and in particular those in manual jobs, are more prone to health problems making them unable to sustain employment (Parker, et al., 2020). The HTE-qualified are on average older than graduates and more likely to carry out manual tasks if in employment, higher rates of inactivity might be expected in this group.

### *The empirical Model*

To distil the effect of qualifications on employment chances from the effect of other individual characteristics, we estimate models of employment and the effect of qualification accounting for individual characteristics such as age, age squared, gender and ethnicity. As in previous models, accounting for GCSEs adds a control for a measure of prior ability. To eliminate the effect of the change in how education was defined in the female population a dummy for inactive women over 64 is added. The relationship between the probability of being employed, expressed in log odds, and qualifications, while keeping other factors constant, is estimated in models 8 and 11.

As in the wage analysis we start with a basic model (8) where the chances of being employed are conditional on *E* – a vector *of* qualifications held by an individual *i*, keeping difference across time periods *Y* constant.

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + e_i \text{ (8)}$$

Model 9 controls for *Xi*, individual characteristics such as age, age square and ethnicity, and model 10 adds GCSE results to the equation. *G* refers to a vector of GCSE results obtained by an individual *i*.

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + e_i \text{ (9)}$$

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 G_i + e_i \text{ (10)}$$

Finally, interaction terms between qualifications Ei and time periods Yi in model 11 allow employment opportunities among populations with different qualifications to change at different rates over time.

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 (E_i * Y_i) + \beta'_4 G_i + e_i \text{ (11)}$$

### *Results*

The following findings emerge from the regression models 8-11. As compared to the baseline period, employment opportunities in the total population worsened, with the biggest drop in employment observed during and right after the economic downturn: 2008-2010 and 2011-13 (column 8, Table 3.6). Individuals with HTE qualifications were less likely to be employed, as measured with log odds, than graduates, but more likely than those with lower level qualifications. After controlling for individual characteristics, the gap in employment chances between HTE and degree holders increased, while the advantage of the HTE-qualified over those with lower qualifications diminished (column 9, Table 3.6). Cognitive ability, as proxied by GCSE results, is positively associated with the chance of being employed but it explains only a small part of the difference in employment outcomes observed among those with different qualifications. Individuals from minority ethnic groups have a lower chance of being employed than white individuals, even after controlling for GCSE qualifications. The observed differences in employment chances across holders of different level qualifications cannot be solely associated with the individual characteristics and GCSE outcomes (column 10, Table 3.6).

The remaining variability, once the factors above have been reflected, can be explained by education level. This may be because higher level qualifications are better at equipping individuals with skills required on the labour market, or because they signal productive capacity in a manner not reflected in the GCSE measure, or because of institutional factors such as expectations and licensing requirements that link qualifications to labour market outcomes. Other elements that we do not observe and that are unequally distributed across qualifications may also be at work. For example, a high level of socio-economic capital boosts labour market outcomes. If individuals entering degree programmes come from more privileged socio-economic background than those making other educational choices, and the socio-economic background of the person is not observed, the benefits associated with the degree would reflect the cultural and economic endowment of the person independently of the education obtained.

### Table 3.6. Changes in the relative employment opportunities of the HTE-qualified workers (baseline qualification) since 2001-2004 (baseline period), 16-64 year-olds

| | (8) | | (9) | | (10) | | (11) | |
|---|---|---|---|---|---|---|---|---|
| | Model 8 | | Model 9 | | Model 10 | | Model 11 | |
| | Coeff | p-value | Coeff | p-value | Coeff | p-value | Coeff | p-value |
| Intercept | 1.73 | 0.00 | -2.94 | 0.00 | -3.00 | 0.00 | -2.98 | 0.00 |
| Sex (female) | | | -0.47 | 0.00 | -0.48 | 0.00 | -0.48 | 0.00 |
| Age | | | 0.26 | 0.00 | 0.26 | 0.00 | 0.26 | 0.00 |
| Age square | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Ethnicity (non- white) | | | -0.64 | 0.00 | -0.58 | 0.00 | -0.58 | 0.00 |
| GCSE's (5 full GCSE or more or GCSEs below grade C) | | | | | 0.07 | 0.00 | 0.08 | 0.00 |
| GCES (do not apply) | | | | | -0.27 | 0.00 | -0.27 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Year 2005-2007 | -0.03 | 0.00 | 0.00 | 0.88 | 0.01 | 0.34 | -0.01 | 0.82 |
| Year 2008-2010 | -0.26 | 0.00 | -0.09 | 0.00 | -0.09 | 0.00 | -0.12 | 0.00 |
| Year 2011-2013 | -0.34 | 0.00 | -0.12 | 0.00 | -0.12 | 0.00 | -0.13 | 0.00 |
| Year 2014-2016 | -0.25 | 0.00 | -0.07 | 0.00 | -0.07 | 0.00 | -0.12 | 0.00 |
| Year 2017-2019 | -0.15 | 0.00 | 0.04 | 0.00 | 0.03 | 0.00 | 0.00 | 0.98 |
| Level 1 qualif & below | -1.31 | 0.00 | -1.15 | 0.00 | -0.94 | 0.00 | -0.97 | 0.00 |
| Level 2 and 3 qualifications | -0.60 | 0.00 | -0.38 | 0.00 | -0.38 | 0.00 | -0.36 | 0.00 |
| Degree | 0.18 | 0.00 | 0.24 | 0.00 | 0.23 | 0.00 | 0.08 | 0.01 |
| Yr2005/07*degree | | | | | | | 0.10 | 0.02 |
| Yr2008/10*degree | | | | | | | 0.15 | 0.00 |
| Yr2011/13*degree | | | | | | | 0.17 | 0.00 |
| Yr2014/16*degree | | | | | | | 0.26 | 0.00 |
| Yr2017/19*degree | | | | | | | 0.20 | 0.00 |
| yr2005/07*level 2&3 qualif | | | | | | | -0.02 | 0.66 |
| Yr2008/10*level 2&3 qualif | | | | | | | -0.05 | 0.21 |
| Yr2011/13*level 2&3 qualif | | | | | | | -0.06 | 0.13 |
| Yr2014/16*level 2&3 qualif | | | | | | | -0.01 | 0.76 |
| Yr2017/19*level 2&3 qualif | | | | | | | -0.04 | 0.30 |
| yr2005/07*level 1 qualif | | | | | | | 0.03 | 0.44 |
| Yr2008/10*level 1 qualif | | | | | | | 0.08 | 0.05 |
| Yr2011/13*level 1 qualif | | | | | | | 0.00 | 0.91 |
| Yr2014/16*level 1 qualif | | | | | | | 0.04 | 0.29 |
| Yr2017/19*level 1 qualif | | | | | | | 0.07 | 0.11 |
| | Null deviance: 1193966 on 1008296 degrees of freedom Residual deviance: 1089560 on 1008287 degrees of freedom AIC: 1089580 | | Null deviance: 1193966 on 1008296 degrees of freedom Residual deviance: 1015776 on 1008283 degrees of freedom AIC: 1015804 | | Null deviance: 1193966 on 1008296 degrees of freedom Residual deviance: 1013707 on 1008281 degrees of freedom AIC: 1013739 | | Null deviance: 1193966 on 1008296 degrees of freedom Residual deviance: 1013487 on 1008266 degrees of freedom AIC: 1013549 | |

Note: Baseline category refers to I holders, white male, with GCSE below grade C or with fewer than 5 GCSE's grade A-C, in 2001-2004.

Qualifications are classified in 4 groups 1.) Degree or equivalent and above; 2.) THE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills.
Source: LFS data, author's calculations.

We tested whether the rate of change of employment opportunities varied between different qualification levels, taking account of other factors. Interaction terms between qualifications and time periods allow the rate of change in employment chances to differ across qualifications. Given the observed dip in the employment rates from 2010 and the sluggish employment recovery in this group we anticipated that the HTE group's employment prospects would worsen over time as compared to that of graduates. Indeed, the analysis (column 11, Table 3.6) confirms that the employment opportunities of the HTE-qualified deteriorated over time compared to that of graduates. The gap in employment rates between the two groups has been widening in the period since 2001 and until recently. In 2017/19 the employment rate for graduates relative to the changing employment rate for the HTE-qualified decelerated, but still the gap in employment opportunities between degree and HTE holders remained much higher than the gap observed in 2001/2004. Overall, taking account of other factors, while graduates' chances of employment were improving those of the HTE-qualified declined. (The change in graduate employment opportunities by time periods can be calculated by adding the period coefficient to the coefficient of the corresponding interaction term). As compared to other qualifications, the change in HTE employment rates was not different from that observed among those with lower level qualifications. The implication is that, taking account of all other explanatory factors, labour market demand for the HTE-qualified declined relative to graduates over the period, despite a rapid increase in the number of graduates entering the labour market.

### *3.5.3. How HTE employment and wage patterns have changed over time in different types of employment*

*Hypothesis and descriptive statistics*

Previous estimation of the wage premium to HTE qualifications at the mean of the wage distribution revealed that the real wage was falling in 2011-2019 among HTE-qualified employees faster than among degree holders. As compared to lower level qualifications, the wage premium associated with HTE qualifications has been declining over the same period. Regarding HTE employment opportunities, they too have worsened over time as compared to graduate employment rates but remained similar to that of individuals with qualifications level 2 and 3. The wage premium and employment opportunity estimates arising from models 1 to 11 (see: Tables 3.4-3.6) do not discriminate between occupations. However, HTE wages, and wage trends, may also depend on the type of occupation. This section explores if the earnings and employment of those with HTE show different patterns of change depending on the type of employment, and tests the hypothesis advanced in the SES chapter, whereby the match of HTE skills to skills required in highly paid employment deteriorated over time, relative to trends in the total population.

This section starts with a description of distribution of the HTE-qualified in different types of employment. First, it explores if, over time, employees with HTE qualifications became more likely to be found in higher paid jobs, with higher paid employment presumably being more skilled than lower paid jobs. Second, it examines the distribution of the HTE-qualified across occupations (SOC major group), and the composition of each occupation in terms of qualifications of the labour force. Finally, it estimates wage premia to HTE qualifications within individual occupational groups.

**Over time the HTE-qualified have increasingly been found in lower paid jobs**

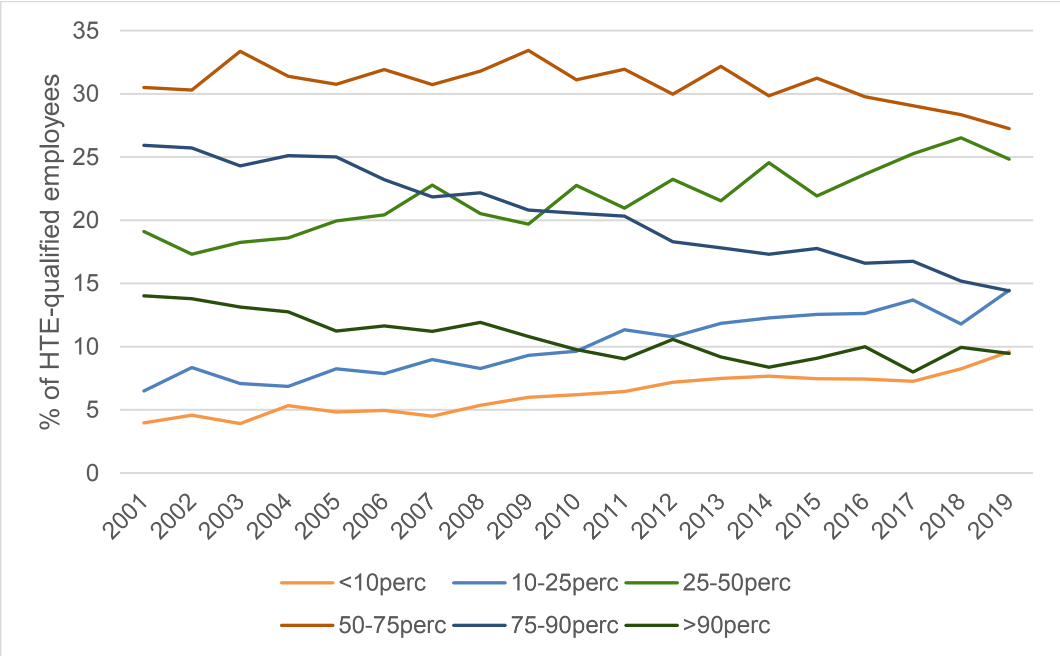
Goos and Manning (2007) evaluated the ‘quality’ of occupations by estimating the share of employment in different percentiles of the wage distribution over time, a more sensitive measurement tool than just mean or median wage, in particular because of its capacity to reflect changing inequality in the wage distribution. In this study, jobs with a large share of low paid workers are considered to be low quality and those with a large share of high earners are seen as high-quality employment. Goos and Manning (2007) observed a positive employment growth for employees situated at the extremes, in terms of occupations of low and high quality according to this measure, and a negative growth for employment in occupations in the middle of the earning distribution over time. Drawing on the occupational quality measure developed by Goos and Manning (2007), we estimate the quality of employment for those with HTE. We compute percentiles (10$^{th}$, 25$^{th}$, 50$^{th}$, 75$^{th}$, 90$^{th}$) of the wage distribution for the total worker population in each year and estimate changes in the share of the HTE employees at each percentile of the wage distribution over time[36]. For example, we estimate a percentage of all the HTE-qualified employees in a given year that were employed in jobs in the lowest decile of wages[37]. Given a relatively stable supply of the HTE-qualified over time a constant share of the HTE workers at different points of the wage distribution could be interpreted as no change in the quality of jobs hold by the HTE employees, relative to the quality of the total employment. An increase in the share of the HTE workers at the bottom of the wage distribution would mean that the relative quality of HTE jobs fell, while the decrease would point to the opposite. Figure 3.5 below shows a sharp fall of the HTE employment between 2001 and 2019 in jobs with earnings above the median and an increase in the share of HTE-qualified workers in jobs situated at the bottom of the wage distribution.

[36] The wage is not adjusted for inflation as the adjustment does not affect the distribution of the HTE employees to different percentiles in individual year.

[37] The share of workers with *HTE* qualifications at each percentile of the wage distribution *w* in the total population, in a year *t* is estimated as: $HTE_{tw}\% = \frac{HTE_{tw}}{\sum_w HTE_{tw}}$

### Figure 3.5. Share of the HTE employees at each percentile of the wage distribution in the total population, 16-64 year olds

How to read the chart: In 2019, 10% of employees with HTE qualifications had wages situated in the lowest 10th percentile of the wage distribution in the total population (orange line), earnings of the further 10% corresponded to the 90th percentile of the wage distribution (black line).




Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree.

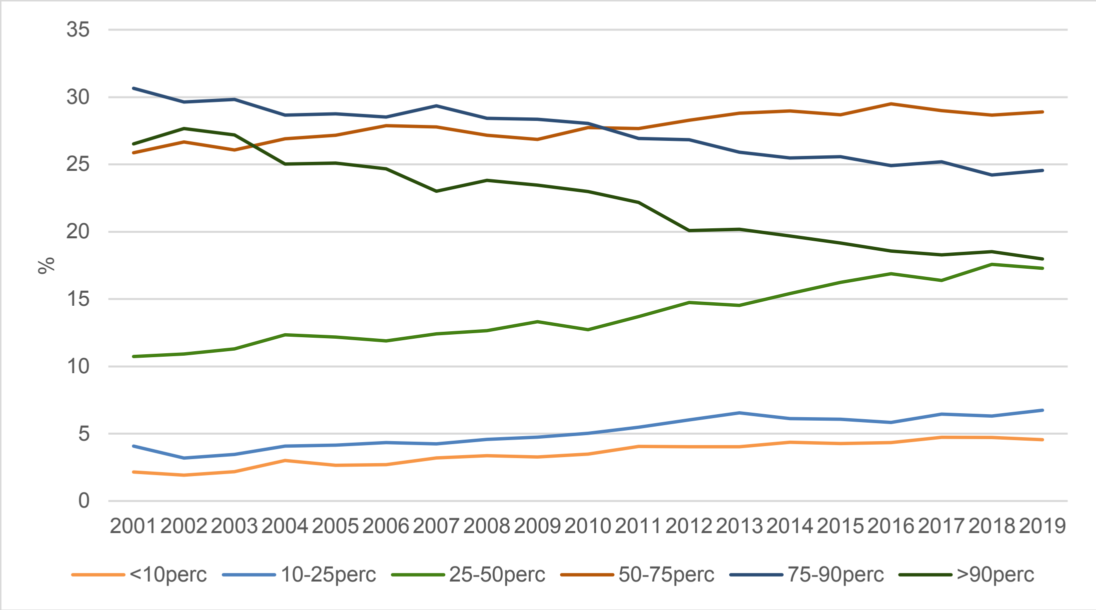
Results are weighted.

Source: LFS data , author's calculations

For both the HTE-qualified, and graduates, the proportion in highly paid employment fell over the studied period (Figure 3.5, Figure 3.6). (As above, the percentage of graduates at each point of the wage distribution is calculated as a share of the total graduate population in employment in individual year.) The proportion of graduates in low paid jobs has been increasing but with the growth following a much flatter trajectory than that observed among workers with HTE qualifications. Contrary to what is observed among the HTE-qualified, there has been an increase in the share of graduates in jobs situated between 50th and the 75th percentile of the wage distribution.

### Figure 3.6. Share of the graduate employees at each percentile of the wage distribution in the total population

How to read the chart: In 2019, 5% of employees with degrees had wages situated in the lowest 10th percentile of the wage distribution in the total population (orange line), earnings of the further 18% corresponded to the 90th percentile of the wage distribution (black line).




Note: 'Degree' refers to degrees and qualifications above the degree level.

Results are weighted.

Source: LFS data, author's calculations

A major difference between the degree and HTE holders is that the supply of graduates rose sharply between 2001-2019, whereas the supply of the HTE qualifications remained constant (Figure 3.2 above). Hence some of the decline in the proportion of graduates in higher deciles of the wage distribution may be a selection effect caused by the average 'ability' of graduates declining as higher education expanded in the UK, a decline indicated by a sharp reduction in the average GCSE results of graduates.

**Over time the HTE-qualified have become less likely to work in skilled occupations (SOC major groups 1-3)**

The SES analysis demonstrated that while an average worker performed more work tasks (typically skilled tasks) that are positively associated with wages over time, the share of such tasks carried out by employees with HTE remained constant or even decreased. The second chapter hypothesised that this might have happened because graduates have increasingly entered technical jobs previously undertaken by the HTE-qualified, pushing the latter into less skilled employment. SES data showed that over time the share of the HTE-qualified individuals in skilled occupations (SOC major group1-3) has declined while there has been an increase in HTE employment in manual semi-skilled (SOC 5) and less-skilled (SOC 8, 9) occupations. There has been no change in the proportion of HTE employment in administrative (SOC 4) and service (SOC 6,7) occupations.

To explore in more detail how HTE employment changed by occupations we estimate 1) the distribution of HTE-qualified employees across occupations, and 2) the share of HTE holders within specific occupations as compared to the workers holding other qualifications. To compare employment trends by occupation among HTE and degree holders a similar analysis is done for graduates. Education E denotes a HTE qualification or a degree, with E= {HTE, degree}

1. Distribution of the HTE/degree qualified employees across occupations, i.e. how likely was a HTE/degree holder to work in a specific occupation. This distribution is calculated using the following equation:

$$ShareE_{1e} = \frac{E_{eo}}{\sum_o E_{eo}}$$

$ShareE_{1e}$ represents the share of the HTE/degree qualified employees in an occupation *o*, $E_{eo}$ represents the number of employees with HTE qualifications/degrees in the occupation *o,* the denominator equals the total number of the employees with HTE qualifications/degrees across all the occupations.

2. The following equation shows the share of HTE/degree holders within a specific occupation as compared to the workers holding other qualifications, i.e. how likely was a person working in these occupations to hold a HTE qualification/degree:

$$ShareE_{2e} = \frac{E_{eo}}{E_o}$$

$ShareE2_e$ represents the share of the employees in an occupation *o* with HTE qualifications/degree, $E_{eo}$ represents the number of employees with HTE qualifications/degree in the occupation as above, *o, Eo* represents the total number of employees in the occupation *o.*

LFS data, due to its design and availability, provide more robust estimates of the distribution of qualifications across occupations over a longer time period than SES data. LFS data also allow a more granular analysis. In the LFS analysis we use 9 major SOC categories rather than 5 aggregated occupational categories as in the SES. Given the introduction of the revised SOC in 2011 in the LFS data, changes over time are observed in two time periods, 2001-2010 and in 2011-2019. Occupations in SOC major groups 1, 2 and 3 are considered as skilled occupations involving complex tasks. We assume that the complexity of tasks on the job declines further down in the SOC major group classification.

The distribution of the HTE-qualified employees across occupations is reflected in ShareE1e. This is a measure of how likely a HTE holder is to work in a specific occupation, and is estimated only among those with HTE with a logistic regression. Being employed in a specific occupational group is the dependent variable. Period dummies on the right-hand side account for the changes over time. Coefficients are expressed in log odds and are transformed into shares[38]. Time period coefficients are shown in Table 3.7 below. For the sake of comparison an identical analysis is carried out for the graduate population.

Results of the analysis show that in 2017/19 HTE holders were as likely as degree holders to work in SOC major group occupations 1 and 3, and less likely to work in major group occupation 2. In the first and second period (before and after 2011) the share of the HTE holders declined in skilled occupations in major group 2 and 3. Conversely, the HTE-qualified became more likely to be found in skilled trade occupations (SOC major group 5) and in service occupations (SOC major group 6 and 7). Overall, the share of the HTE-qualified in occupations with less skilled tasks (SOC major group 4-9) grew faster than the share of the degree holders in the corresponding occupations. Between 2011/13-2017/19 the share of HTE qualifications in these occupations grew by 5 percentage points as compared to 2 percentage point growth among graduates.

### Table 3.7. Share of all the HTE/degree qualified employees 16-64 year-olds in a specific occupation ($ShareE_{1e}$)

How to read the table: e.g., in 2011-13, 20% of the employees with HTE qualifications worked in SOC 3 occupations. The share of the HTE-qualified in these occupations decreased by 2 percentage points to reach 18% in 2017-2019.

| | 2001/04 | 2008/10 | 2011/13 | 2017/19 |
|---|---|---|---|---|
| Degree | | | | |
| SOC1: Managers, Directors and Senior Officials | 19% | 20% | 12% | 13% |
| SOC2: Professional Occupations | 40% | 37% | 46% | 45% |
| SOC3: Associate Professional and Technical Occupations | 24% | 23% | 18% | 18% |
| SOC4: Administrative and Secretarial Occupations | 7% | 7% | 7% | 8% |
| SOC5: Skilled Trades Occupations | 2% | 2% | 2% | 2% |
| SOC6: Caring, Leisure and Other Service Occupations | 4% | 5% | 5% | 6% |

[38] If $\beta_1$ is an intercept referring to the baseline year 2001-2004, and $\beta_t$ stands for coefficients of other time periods t, with t=(2005-2007, 2008-2010, 2011-2013, 2014-201, 2017-2019), the share of employment in the baseline period is calculated as $\exp(\beta_1)/(1+\exp(\beta_1))$. Since $\beta_t$ shows the difference between the baseline time period and the period of interest, the share of employment in time periods other than the baseline year are obtained with: $\exp(\beta_1+\beta_t)/(1+\exp(\beta_1+\beta_t))$.

| | | | | |
|---|---|---|---|---|
| SOC7: Sales and Customer Service Occupations | 2% | 2% | 3% | 3% |
| SOC8: Process, Plant and Machine Operatives | 0% | 0% | 1% | 1% |
| SOC9: Elementary Occupations | 1% | 2% | 3% | 3% |
| All occupations | 100% | 100% | 100% | 100% |
| HTE | | | | |
| SOC1: Managers, Directors and Senior Officials | 23% | 23% | 14% | 13% |
| SOC2: Professional Occupations | 16% | 13% | 20% | 18% |
| SOC3: Associate Professional and Technical Occupations | 23% | 22% | 20% | 18% |
| SOC4: Administrative and Secretarial Occupations | 12% | 12% | 12% | 12% |
| SOC5: Skilled Trades Occupations | 9% | 9% | 9% | 11% |
| SOC6: Caring, Leisure and Other Service Occupations | 6% | 9% | 11% | 11% |
| SOC7: Sales and Customer Service Occupations | 4% | 4% | 6% | 7% |
| SOC8: Process, Plant and Machine Operatives | 3% | 3% | 3% | 4% |
| SOC9: Elementary Occupations | 3% | 4% | 5% | 6% |
| All occupations | 100% | 100% | 100% | 100% |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree. Degree refers to degrees and higher-level qualifications.

Source: LFS data, author's calculations

Since the supply of graduates increased dramatically in the period of interest, we also explore the distribution of qualifications in occupations over time, i.e. how likely a person working in these occupations was to hold a degree or HTE qualification. As above, this is estimated with a logistic regression restricted to employees in the specific SOC major group. Holding a HTE/degree qualification as opposed to holding other qualification is a dependent variable with period dummies on the right-hand side. Coefficients of time dummies transformed into shares are reported in Table 3.8.

Table 3.8 shows that the share of graduates in the SOC major groups 1-3 grew over time while the share of HTE-qualified persons in these same groups declined. In the SOC major group 2 rapid growth in the share of graduates was observed between 2001/04-2008/10. In 2017-2019, nearly one in two of all the employees in the SOC major group 3 occupations had a degree. Occupations from the major group 3 require some post-secondary skills but not necessarily a degree and should therefore represent a good match for HTE holders. However, between 2011 and 2019 the share of employees with HTE qualifications decreased in these occupations. In the remaining occupational SOC groups with lower task complexity, the share of degree holders more than doubled. The share of HTE-qualified employees in these occupational groups also increased, though at a slower pace than among graduates.

### Table 3.8. Share of all the employees 16-64 in different occupational groups holding a HTE qualification/degree ($ShareE_{2e}$)

How to read the table: e.g., in 2001-04, 29% of the employees in SOC 1 occupations had a degree while in 2011-2013, 38% of workers in SOC 1 occupations hold a degree.

Contrary to the table above, the columns do not sum up to 100%, as the 100% refers to all the employees in a given SOC category. For example, in 2001/2004 in SOC 1 occupations there were 29% of employees with a degree, 10% of employees had HTE qualifications, and the remaining 61% (not shown in the table) had other qualifications.

| | 2001/04 | 2008/10 | 2011/13 | 2017/19 |
|---|---|---|---|---|
| Degree | | | | |
| SOC1: Managers, Directors and Senior Officials | 29% | 35% | 38% | 43% |
| SOC2: Professional Occupations | 73% | 76% | 77% | 77% |
| SOC3: Associate Professional and Technical Occupations | 39% | 44% | 41% | 46% |
| SOC4: Administrative and Secretarial Occupations | 11% | 16% | 20% | 26% |
| SOC5: Skilled Trades Occupations | 3% | 5% | 6% | 8% |
| SOC6: Caring, Leisure and Other Service Occupations | 10% | 14% | 17% | 20% |
| SOC7: Sales and Customer Service Occupations | 6% | 9% | 14% | 16% |
| SOC8: Process, Plant and Machine Operatives | 2% | 3% | 5% | 9% |

| | | | | |
|---|---|---|---|---|
| SOC9: Elementary Occupations | 3% | 5% | 7% | 9% |
| HTE | | | | |
| SOC1: Managers, Directors and Senior Officials | 10% | 11% | 11% | 9% |
| SOC2: Professional Occupations | 9% | 7% | 8% | 7% |
| SOC3: Associate Professional and Technical Occupations | 11% | 11% | 12% | 10% |
| SOC4: Administrative and Secretarial Occupations | 6% | 8% | 8% | 9% |
| SOC5: Skilled Trades Occupations | 5% | 6% | 7% | 8% |
| SOC6: Caring, Leisure and Other Service Occupations | 5% | 7% | 9% | 9% |
| SOC7: Sales and Customer Service Occupations | 4% | 4% | 6% | 7% |
| SOC8: Process, Plant and Machine Operatives | 2% | 3% | 4% | 5% |
| SOC9: Elementary Occupations | 2% | 3% | 4% | 5% |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree. 'Degree' refers both to degrees and other higher level qualifications (including Master's degrees and PhD).
Source: LFS data, author's calculations.

Overall, the findings point to a possible displacement of the HTE-qualified in skilled occupations by an influx of degree holders. They also imply that the growth of employment in skilled occupations was mainly driven by an inflow of graduates to the labour market. If we assume that the growth was exogenous (e.g. new technologies increased the demand for individuals equipped with high level skills), it mainly benefited the degree holders. Regardless of the source of growth, these findings may point to a falling demand for HTE, relative to the demand for degrees.

Employees with a HTE qualification earn less on average than degree holders, but the average may hide large variations by occupation and industry sector. We anticipate the HTE-qualified workers as compared to graduates to fare better in occupations requiring strong technical knowledge, a mastery of industry-specific processes and methods but not necessarily at a degree level. These jobs would typically be associated with skilled occupations SOC major group 3 and semi-skilled jobs from SOC major group 5. Conversely, we expect the comparative advantage of the HTE holders to be weaker in jobs relying on strong general knowledge typically associated with degree programmes. To shed more light on this issue we compare the individual HTE wage to the graduate wage, and wages of those with lower level qualifications in a specific occupation and over time. As discussed earlier, a theoretical framework in which a unit of output depends on skills endowment of labour and technology provides a tool for interpretation of results of this analysis.

### *The empirical Model*

To investigate how the relative wage premium for employees with HTE changes over time in jobs with different skills requirements, we estimate wage differentials within SOC major group occupations at the individual level. Recognising the impact of various factors on wages a range of control variables such as sex, age, age squared, ethnicity, region, public versus private sector and type of contract (part-time vs full-time) are included in the estimation.

We also account for the effect of academic achievement, measured with GCSE performance, on wages within SOC major categories. GCSE should have a lesser impact on wages within occupations than in the total population, since individuals are sorted by academic achievement into different types of occupation, resulting in less variation in GCSE outcomes within occupations. In some professions formal entry requirements reinforce uniformity in terms of qualifications and to some degree in terms of skills. For example, medical doctor, nurses, lawyers are required to have at least a degree, de facto preventing individuals without a full GCSE or equivalent to enter to the profession. In skilled occupations (SOC major group 1-3) where at least some post-secondary education is required at least half of the employees have full GCSE's. In unskilled employment (SOC major group 8,9) full GCSEs are less common (see Annex A.2, Table A.2.2 and Table A.2.3).

Academic performance, as measured by GCSEs, has been increasing across all occupations, and in particular in services (SOC major categories 6 and 7). This tends to confirm findings from the SES analysis, whereby the complexity of skills has increased in all occupations, including at the bottom of SOC classifications, assuming the increase in the share of employees with GCSEs reflects rising tasks complexity on the job. Results describing changes over time across SOC groups should be interpreted with caution since the revision of SOC resulted in jobs repositioning. While the SOC major groups 1-3 were subject to major changes, a few small amendments were also introduced in the remaining categories.

The wage premium is estimated by occupation (SOC major groups) and in two time periods separately: 2001-2010, and 2011-2019. First, we estimate the association between qualifications and wages accounting for time periods, individual and employment characteristics (model 14). We then add GCSE results (model 15) and control for industry sector (model 16). Finally, as a robustness check we include interaction terms between qualifications and time periods to explore if wages across qualifications changed at different rates over time (model 17). As in the previous analysis, industry and employment characteristics are not accounted for in the model with interaction terms as their inclusion has no effect on the rate of change in wages over time by qualifications. Qualification coefficients from model 16 are reported in Table 3.9. HTE wage as compared to earnings of those with other qualifications, 16-64 year-olds, 2001-2010 and Table 3.10. HTE wage as compared to earnings of those with other qualifications, 16-64 year-olds, 2011-2019

Qualification coefficients shown in the table are produced by model 16 for the period 2011-2019, whereby hourly wage is explained with qualifications (our variable of interest), and control variables including: year dummies, age, age square, ethnicity, sex, GCSE's, industry sector, whether the employment is in public or private sector, whether it is provided full time or part-time, and geographical regions.

HTE is the baseline category, which means that the other qualification coefficients show the difference in earnings between these qualifications and HTE below while results from all the other models are shown in Annex A.2 (Tables: A.2.4 –A.2.21)

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 F_i + e_i \quad (14)$$

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 F_i + \beta'_5 G_i + e_i \quad (15)$$

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 F_i + \beta'_5 G_i + \beta'_6 I_i + + e_i \quad (16)$$

$$\ln(wage_i) = \alpha + \beta'_1 E_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_5 G_i + \beta'_7 (E_i * Y_i) + e_i \quad (17)$$

Where, w is a deflated hourly wage expressed in logarithms of an individual *i* in a given major SOC occupation

$\alpha$ - intercept

$Y_i$ –vector of time period dummies

$E_i$- vector of qualifications held by the individual *I*

$X_i$ – vector of individual characteristics including: gender, age, age squared, ethnicity, $F_i$ – vector of characteristics of the employment the individual *i* is in, including type of employment (full time versus part time), sector (public versus private), and regions.

$I_i$ – vector of industry (based on SIC) variables.

$e_i$ – residuals

*Results*

**The results show that the degree wage premium, relative to HTE, was higher in skilled occupations than in occupations requiring lower levels of skill, and in some cases increasing between the two time periods (Table 3.9. HTE wage as compared to earnings of those with other qualifications, 16-64**

## year-olds, 2001-2010 and Table 3.10. HTE wage as compared to earnings of those with other qualifications, 16-64 year-olds, 2011-2019

Qualification coefficients shown in the table are  produced by model 16 for the period 2011-2019, whereby hourly wage is explained with qualifications (our variable of interest), and control variables including: year dummies, age, age square, ethnicity, sex, GCSE's, industry sector, whether the employment is in public or private sector, whether it is provided full time or part-time, and geographical regions.

HTE is the baseline category, which means that the other qualification coefficients show the difference in earnings between these qualifications and HTE  below). Alongside the results reported earlier in respect of employment rates these findings suggest that there was no decline in the demand for degree holders, despite the quickly rising supply of graduates. This could be because of the sustained impact of technology on the production process, as suggested by the STBC model. Technology, which increases complexity of tasks requirements in workplaces, would, under this explanation, drive the labour market demand for degree holders who were more productive in the new tasks. But the maintained graduate advantage over the HTE-qualified may also be a sign of a falling productivity of a marginal HTE student as some students who now opt for a university path in the past would have been enrolled in a HTE programme.

## Table 3.9. HTE wage as compared to earnings of those with other qualifications, 16-64 year-olds, 2001-2010

Qualification coefficients shown in the table are produced by model 16 for the period 2001-2010, whereby hourly wage is explained with qualifications (our variable of interest), and control variables including: year dummies, age, age square, ethnicity, sex, GCSE's, industry sector, whether the employment is in public or private sector, whether it is provided full time or part-time, and geographical regions.
HTE is the baseline category, which means that the other qualification coefficients show the difference in earnings between these qualifications and HTE.

| | Degree | Level 2 and 3 | Level 1 and below |
|---|---|---|---|
| SOC1:  Managers, Directors and Senior Officials | 0.18 | -0.11 | -0.20 |
| SOC2: Professional Occupations | 0.15 | -0.09 | -0.01(ns) |
| SOC3: Associate Professional and Technical Occupations | 0.10 | -0.08 | -0.10 |
| SOC4: Administrative and Secretarial Occupations | 0.03 | -0.07 | -0.12 |
| SOC5: Skilled Trades Occupations | 0.03(ns) | -0.13 | -0.26 |

| | | | |
|---|---|---|---|
| SOC6: Caring, Leisure and Other Service Occupations | 0.04 | -0.09 | -0.15 |
| SOC7: Sales and Customer Service Occupations | 0.01(ns) | -0.05 | -0.10 |
| SOC8: Process, Plant and Machine Operatives | 0.02(ns) | -0.08 | -0.14 |
| SOC9: Elementary Occupations | 0.01(ns) | -0.04 | -0.07 |

Qualifications are classified in 4 groups 1.) Degree or equivalent, and above; 2.) THE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree; 3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills

Source: LFS data, author's calculations

## Table 3.10. HTE wage as compared to earnings of those with other qualifications, 16-64 year-olds, 2011-2019

Qualification coefficients shown in the table are  produced by model 16 for the period 2011-2019, whereby hourly wage is explained with qualifications (our variable of interest), and control variables including: year dummies, age, age square, ethnicity, sex, GCSE's, industry sector, whether the employment is in public or private sector, whether it is provided full time or part-time, and geographical regions.

HTE is the baseline category, which means that the other qualification coefficients show the difference in earnings between these qualifications and HTE

| | Degree | Level 2 and 3 | Level 1 and below |
|---|---|---|---|
| SOC1:  Managers, Directors and Senior Officials | 0.20 | -0.10 | -0.18 |
| SOC2: Professional Occupations | 0.16 | -0.08 | -0.08 |
| SOC3: Associate Professional and Technical Occupations | 0.13 | -0.06 | -0.14 |
| SOC4: Administrative and Secretarial Occupations | 0.09 | -0.04 | -0.09 |
| SOC5: Skilled Trades Occupations | 0.00(ns) | -0.15 | -0.26 |
| SOC6: Caring, Leisure and Other Service Occupations | 0.01(ns) | -0.06 | -0.10 |
| SOC7: Sales and Customer Service Occupations | 0.04 | -0.05 | -0.09 |
| SOC8: Process, Plant and Machine Operatives | 0.01(ns) | -0.05 | -0.10 |
| SOC9: Elementary Occupations | 0.02(ns) | -0.03 | -0.06 |

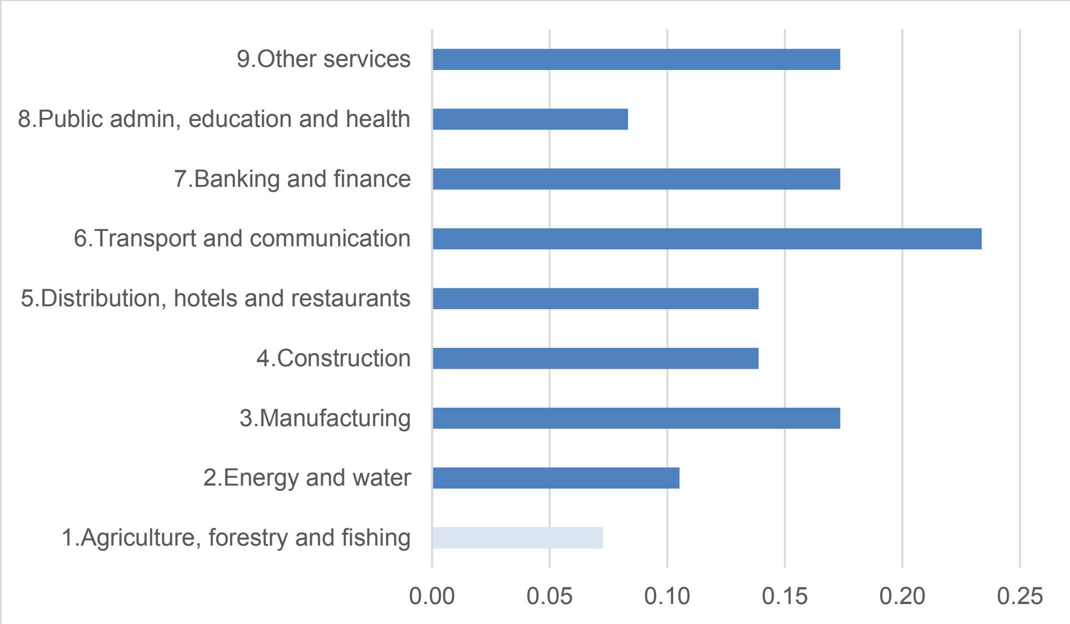
Qualifications are classified in 4 groups 1.) Degree or equivalent, and above; 2.) THE: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree;
3.) Level 2 and 3 qualifications: GCE, A-level, O level, GCSE grade A-C* or equivalent; 4.) Leve 1 and no qualifications: e.g. NVQ level 1, GCSE below grade C, key skills
Source: LFS data, author's calculations

In the two time periods, graduates earned, on average, around 19%-21% more than employees with HTE qualifications in managerial occupations (SOC major group 1), after accounting for individual, employment characteristics, GCSEs and industry sector. In SOC major groups 2, the degree wage premium was respectively 16% and 17% in the two time periods. In technical skilled occupations (SOC major group 3) degree holders earned 11% more than the HTE-qualified in 2001/10, increasing to 14% more in 2011/19. Overall, these findings point to a lower comparative advantage of the HTE-qualified in skilled occupations as compared to graduates, notably in technical skilled occupations (SOC major group 3). They also show that graduates maintained their advantage over time in skilled employment.

A rising degree wage premium in technical skilled occupations may imply that HTE-qualified workers are losing their grip on jobs which historically have often been prepared for through HTE. In early 2000's nearly one in four of HTE-qualified employees was employed in SOC major group occupations. Given the importance of technical skilled employment for the HTE-qualified we explore the relative HTE wages in the relevant occupations in more detail. SOC major group categories are very broad, encompassing jobs in various sectors. It could therefore be that in some sectors, such as manufacturing and construction, where HTE was traditionally providing technical skilled labour, the wage gap between the HTE and degree wage would be lower than in other sectors. Analysis of the relative HTE wage in skilled technical occupations (SOC major group 3) by sector, accounting for individual and employment characteristics, confirms that the wage premium associated with HTE varies by area of specialisation. Depending on the sector, graduates earn between 8% and 23% more than HTE holders, with the lowest premium recorded in public administration, health and education sectors (see Figure 3.7). The relatively low wage premium to a degree in public administration, health and education probably stem from the fact that these are mainly public sectors were wages tend to be more compressed than in some other sectors. Against our expectations, graduates in skilled technical occupations in manufacturing and construction earn 14 and 17% more than those with HTE qualifications. This is similar to the degree wage premium in many other sectors such as banking and services. The highest degree wage premium was recorded in transport and communication. We therefore cannot confirm that employees with HTE qualifications in technical skilled occupations earn relatively more (in comparison with those with degree education) in sectors traditionally associated with HTE provision.

### Figure 3.7. Wage premium of degree holders as compared to the HTE wage (in percentages), in technical skilled occupations (SOC major group 3), by industry sector, 16-64 year-olds, 2001-2019

How to read the chart: among employees in technical skilled occupations, in transport and communication sector, graduates earned 23% more than HTE-qualified workers, accounting for individual and employment characteristics




Note: these results are based on findings from wage regression analysis performed on a sample of employees in SOC 3 major holding a degree or a HTE qualification. Log hourly wage is the dependent variable. The right-hand side of the equation includes: degree dummy – variable of interest, and control variables such time period dummies, age, age square, sex, ethnicity, public versus private sector, part time versus full time employment and geographical region, and an error term. The degree dummy coefficients were transformed to express wage difference between the two qualifications in percentages.

Results in light blue (agriculture, forestry and fishing sector) are not statistically significant.

Number of observations (obs) in each sector : 1. – 44 obs, 2 – 451 obs, 3 – 3742 obs, 4 – 808 obs, 5 – 1914 obs, 6 – 1274 obs, 7 – 8556 obs, 8 – 18943 obs, 9 – 2114 obs.

HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree. Degree refers to degrees and higher-level qualifications.

Source: LFS data, author's calculations

In 2017/19 in semi-skilled trade occupations (SOC major group 5) the HTE wage was on average not different from the graduate wage, and 16 and 32 percent higher than earnings of those with level 3 qualifications and those with qualifications level 2 and below (estimation based on model 16). SOC major group 5 occupations (e.g. boat and ship builder, vehicle painters, welder, plumbers) are less demanding in terms of general knowledge than the skilled occupations (major group 1-3), however they often require technical knowledge and mastery that is typically provided through an extended period of vocational training or work experience. HTE programmes are in principle more applied and practical than degree programmes and often build on existing level 3 vocational qualifications. HTE-qualified employees may therefore have more of the technical expertise required in semi-skilled trade jobs and thus be more productive than individuals with other qualifications in these occupations. In service occupations (SOC major group 6 and 7), the relative wage of HTE holders was lower than in semi-skilled trade occupations, both as compared to graduates and those with lower level qualifications. It could therefore be expected that the HTE workers who have been displaced in skilled jobs by degree holders would privilege trade occupations in which their comparative advantage is the highest. The distribution of the HTE employees by occupation confirms that the share of workers with HTE qualifications choosing skilled trade occupations increased over time. More surprisingly the share of HTE holders also grew in service sector jobs. In 2017/19 18% of the HTE-qualified were in service occupations (SOC major group 6 and 7), as compared to 10% in 2001/04, bearing in mind that some of the change may be attribute to the revision of SOC. It therefore could be that some HTE programmes fail to provide skills that cannot be easily provided by workers with other qualifications, and that graduates push some of the HTE-qualified out of skilled employment into service sector jobs where employment has been rising.

GCSEs, our proxy for ability, are positively associated with wages, but their impact is much higher in skilled occupations. In these occupations productivity gains from academic achievement (as measured with GCSEs) are the highest. These are also occupations where returns to GCSE outcomes are the highest. (see Annex A.2, Tables: A.2.4- A.2.21, models 15-17)

Model 17 allows wages associated with different qualification levels to change at different rates. As compared to graduates in most occupations the rate of change in the HTE wage is not different from that observed among graduates. In a few cases, lower level of qualifications and notably qualifications level 1 and below show a more positive rate of change in wages than HTE-qualified. As discussed in the previous chapter, more favourable wage trends among those with low levels of education may be related to the introduction in 2016 of a National Living Wage (NLW), which between 2016-2018 grew much faster than median and mean earnings (The Low Pay Commission, 2017).

### *3.5.4. Which technical skills yield the highest wages and lead to the best employment outcomes among HTE-qualified*

#### *Hypothesis and descriptive statistics*

Previously discussed models 14-17 focused on the match between the HTE-qualified and employment at different levels of task complexity. We gave particular attention to the performance of those with HTE qualifications in skilled occupations, and how they responded to the pressure from the increasing number of graduates entering the labour market. However, this analysis did not discriminate between different technical (or sector specific) skills required on the job, for example whether HTE-qualified workers with an HTE specialisation in manufacturing were more in demand than those with other specialisations. To address these questions, we explore how wages and employment opportunities vary in the HTE population by area of specialisation and how they have changed over time. To ensure adequate cell sizes for the analysis, the areas of specialisation among those with HTE qualifications are grouped in 9 categories (see Table 3.3)[39].

HTE students opt for a specialisation to develop the knowledge and skills in the chosen area and to secure employment upon graduation in the related industry. Those studying in civil engineering programmes for example, learn about geotechnics, civil engineering contracts and project management, construction site surveying, and construction technology (substructure and structural mechanics) preparing them for jobs in the construction, construction engineering, structural and civil engineering fields. An evaluation of HTE labour market outcomes by field of study therefore should allow us to identify the areas and associated skills that yield the largest benefits on the labour market among the HTE-qualified. In principle these results provide an indication of HTE skills that are most sought by employers, relative to their supply in the labour market. However, the findings should be treated with caution since we do not control for all the factors affecting both choice of area of specialisation and labour market outcomes of HTE holders. It can be that those choosing the most rewarding HTE areas of studies share characteristics that are unobservable and that improve their earnings and chances of employment independently of the chosen HTE programme.

### Descriptive statistics confirm that both wages and employment chances vary by area of specialisation among the HTE-qualified. Figure 3.8. Real hourly wage of the HTE-qualified by the area of specialisation in two time periods, 16-64 year olds and Figure 3.9. Employment rates (as opposed to unemployed and inactive) of the HTE-qualified by area of specialisation in two time periods, 16-64 year-olds

below show that among the HTE-qualified individuals, those who studied engineering and manufacturing, production, architecture and building record the best labour market outcomes, both in terms of earnings and employment opportunities. Relatively low employment rates of those who studied life science, mathematics and statistics, and computing come as a surprise, given relatively high earnings in this group. In principle this finding might be explained by the composition of this population, if for example among those with this specialisation there were more women and adults approaching retirement age, as these populations are more likely to be inactive. But adding age, age squared, sex and ethnicity as controls to the employment analysis improves employment opportunities of those with specialisation in science, mathematics, statistics and computing (category 4) only by a small margin, suggesting that other factors are responsible for the relatively low employment rates in this population. It could be that the jobs these specialisations prepared for experienced educational upgrading, whereby graduate-level qualifications become widely expected or even mandatory for particular jobs. This is typically the case of jobs in the

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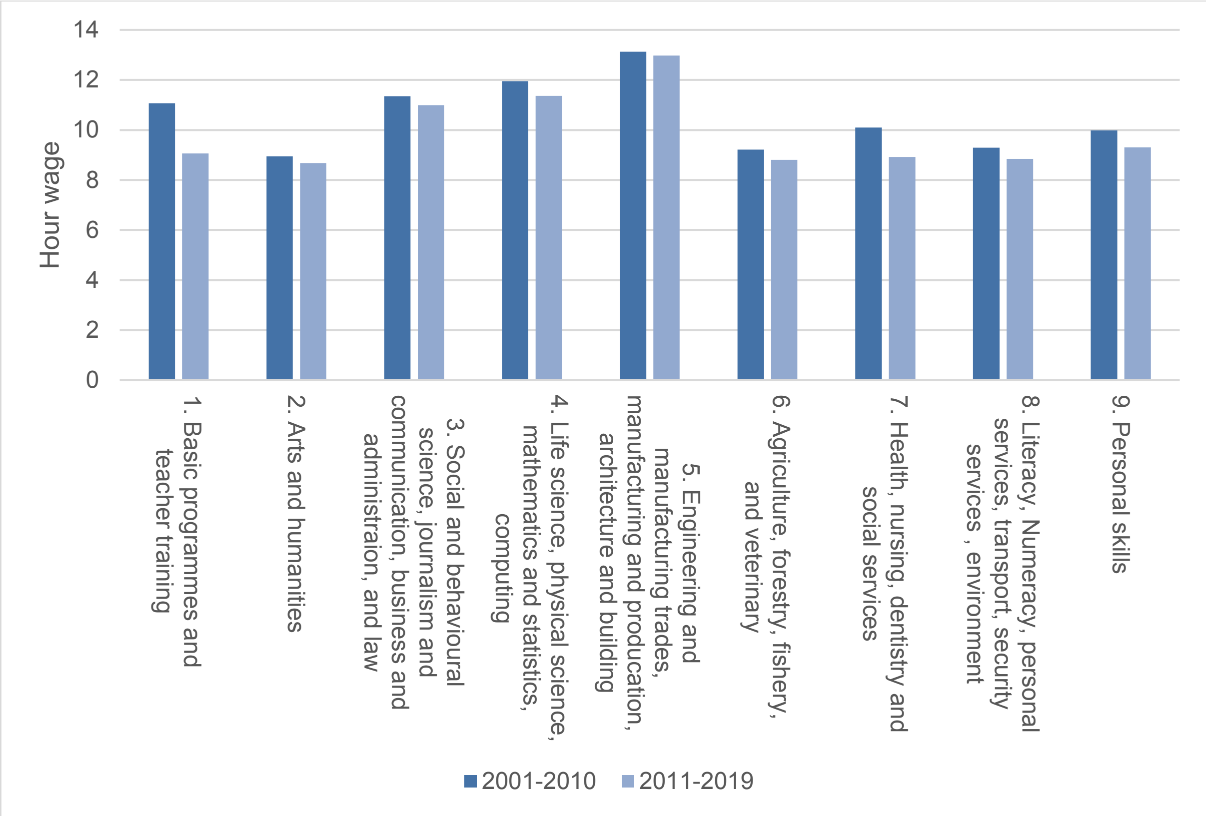
[39] Number of observations (obs) in each category (cat): cat1- 2569 obs, cat2-5552 obs, cat3-17946 obs, cat4-4808 obs, cat5-16194 obs, cat6-1725 obs, cat7-7799 obs, cat8-5107obs, cat9-297 obs.

public sector. LFS data shows that individuals with specialisations in science, mathematics, statistics and computing (category 4) were indeed more likely to work in the public sector than those with specialisations in engineering and manufacturing but less likely than those with specialisation in business and administration (category 3). It could also be that specialisations in science, mathematics, statistics and computing resist less well the competitive pressure from graduates, independently of the sector of employment (public versus private).

Comparison of the wage level in 2001-2010 and in 2011-2019 (Figure 3.8) shows that the earnings of the HTE-qualified declined over time across many areas of specialisation or at best remained constant. This is not different from trends observed in the total population. Some groups, such as those with specialisations in teaching and health saw a sharp drop in earnings, and experienced worsening employment prospects over time. While these negative trends could reflect changing cohort characteristics, more likely they result from the introduction of a degree requirement for entry into teaching and nursing professions. Those HTE-qualified who were unable to upgrade their qualifications were probably blocked in their career progression or left the labour market all together. Educational upgrading in teaching and nursing professions thus curtailed the demand for qualifications below degree level that in past were used as an entry route to the profession. Among all the areas of specialisation, art and humanities specialisations, accounting for one in ten of the HTE qualifications, yielded the weakest labour market outcomes. This may reflect the fact that HTE programmes in humanities and arts are loosely connected to the labour market and do not provide an obvious entry to a specific profession. Individuals with these specialisations may be less well equipped to compete with individuals with other qualifications, where no specific technical expertise is required but where presumably strong cognitive skills and social competencies are valued. It should be noted that earnings also vary significantly among graduates depending on the area of specialisation with no wage premium to degrees in creative arts as compared to the non-university population (Britton, et al., 2016).

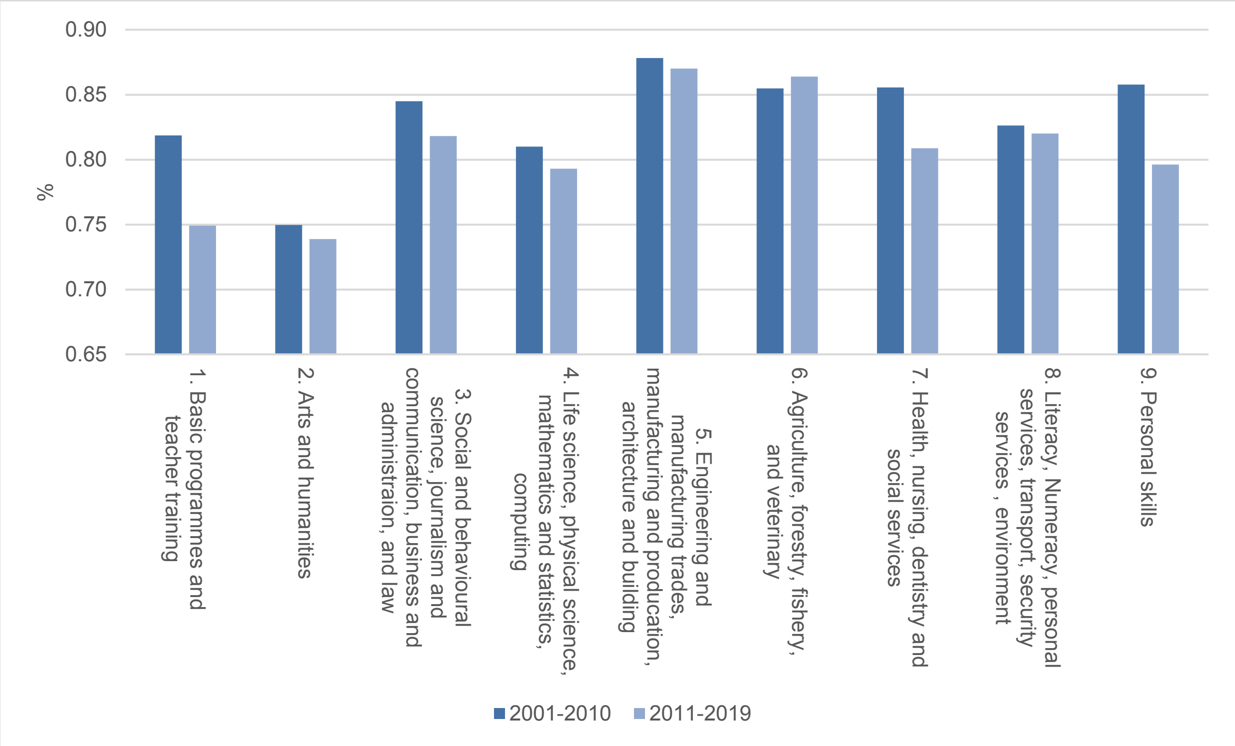
## Figure 3.8. Real hourly wage of the HTE-qualified by the area of specialisation in two time periods, 16-64 year olds




Note: HTE include: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree.
Source: LFS data, author's calculations.

## Figure 3.9. Employment rates (as opposed to unemployed and inactive) of the HTE-qualified by area of specialisation in two time periods, 16-64 year-olds

How to read the figure: In 2001-2010, 82% of the HTE-qualified with specialisation in basic programmes and basic training were employed. In 2011-2019, the share of the HTE-qualified with specialisation in basic programmes and basic training dropped to 75%.




Note: HTE include: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree. According to the definition adopted in this chapter 'employees' refer to those in employment, self-employed, those in government and training programmes, unpaid family workers.

Source: LFS data, author's calculations

### *The empirical model*

To isolate the effect of the area of specialisation on wages, we explore wage premia to areas of specialisation accounting for individual characteristics such as age, age squared, gender and ethnicity. Some specialisations such as in teaching or health prepare mainly for employment in public sector that on average yield lower earnings than jobs in the private sector. To capture this and other effects of employment characteristics on earnings we include controls for the type of employment (public versus private, full-time, part-time) and the geographical region where the employer is located. It should be kept in mind that individuals with specialisations that are more in demand on the labour market are more likely to be matched to employers that offer more attractive employment conditions. Accounting for employment characteristics may therefore conceal part of the impact of area of specialisation on wages. We do not separately control for industry dummies as in principle this feature should be largely captured by the area of specialisation, given the association between area of specialisation and the industry sector a person is employed in.

More formally, this model focuses on the population with HTE qualifications only. $S_i$ is a vector of the areas of specialisation as reported by a HTE-qualified individual *i*, $Y_i$ is a vector of period dummies during which an individual *i* was interviewed, $X_i$ is a vector of individual characteristics including age, age square, sex and ethnicity, and $F_i$ is a vector of characteristics associated with the job held by an individual *i* such public versus private sector, full versus part time employment and a geographical area. Finally, $e_i$ is an error term.

$$\ln(wage_{hte\ i}) = \alpha + \beta'_1 S_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 F_i + e_i \quad (18)$$

Independently, we also add a control $G_i$ for GCSE outcome, to account for the fact that individuals with different prior academic performance opt for different areas of specialisation.

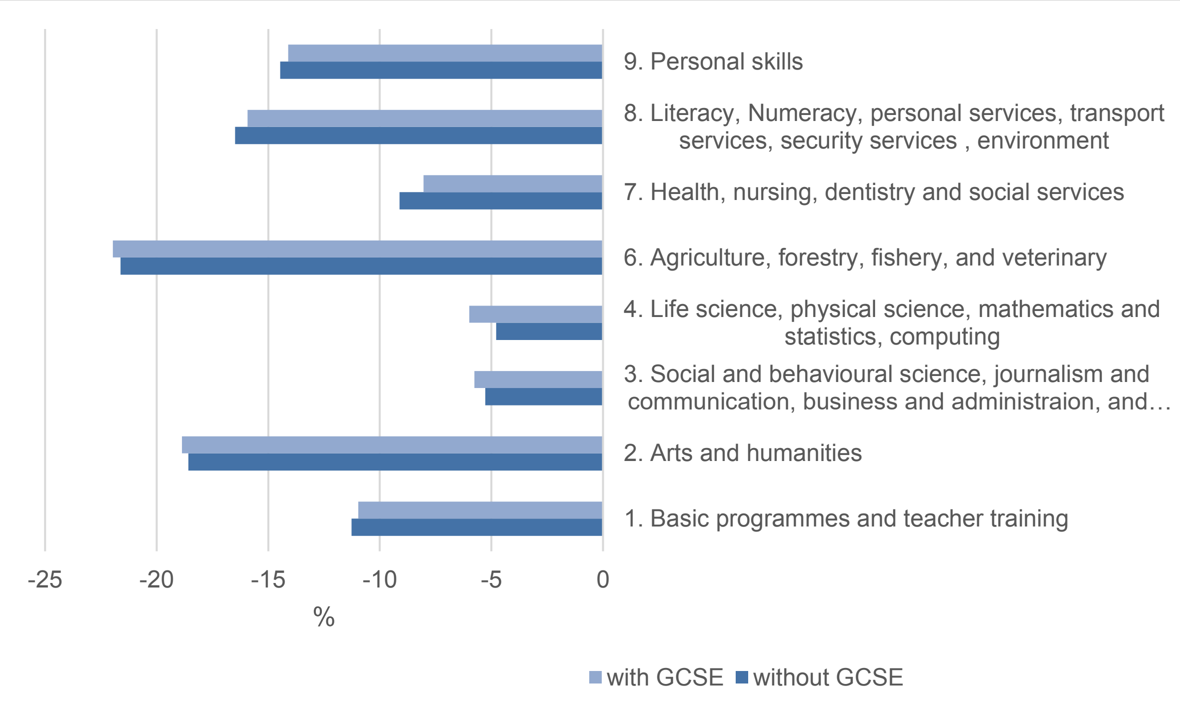
$$\ln(wage_{hte\ i}) = \alpha + \beta'_1 S_i + \beta'_2 Y_i + \beta'_3 X_i + \beta'_4 F_i + \beta'_5 G_i + e_i \quad (19)$$

*Results*

Figure 3.10 below presents the results of the two analyses. Individuals with HTE qualifications in engineering and manufacturing trades, manufacturing and production, architecture and building are the baseline category. For brevity sake this category is called ‘engineering and manufacturing’. The descriptive analysis showed that an engineering and manufacturing specialisation attracted the highest average wage among all areas of specialisation. These findings hold after accounting for individual and employment characteristics. Adding GCSEs has only a small impact on the magnitude of the specialisation coefficients and the associated wage premia. This suggests that among all the HTE skills, skills associated with the baseline specialisation (engineering and manufacturing) are valued the most on the labour market, and independently of prior academic performance measured through GCSEs. These findings should be treated with caution though as we do not observe all factors that can be correlated with the area of specialisation and wages. Surprisingly, accounting for GCSE outcomes widens the gap in earnings between the baseline category and those with the area of specialisation in life and physical science, mathematics, statistics and computing (category 6). This suggests that if there are two people with the same GCSEs results and HTE as the highest educational attainment, the person with an engineering and manufacturing specialisation would be better off in terms of earnings than the individual with an HTE qualification in life science, physics, mathematics, statistics or computing. This may reflect the wage premium for specific technical competencies acquired through engineering and manufacturing programmes that can be immediately applied on the job, over and above cognitive skills of the person. Engineering and manufacturing programmes may thus be better at targeting specific jobs than programmes in life science, physics, mathematics, statistics and computing.

## Figure 3.10. Wages of the HTE-qualified workers with different areas of specialization, as compared to those with the area of specialisation in engineering and manufacturing trades, manufacturing and production, architecture and building (baseline category)

The bars represent the coefficients of the areas of specialization yielded by model 18 (without GCSE) and 19 (with GCSE)




Note: the results are stripped off the effect of individual characteristics (age, age square, sex, ethnicity) and employment characteristics (public versus private sector, full-time versus part-time employment, geographical location).

All the results are statistically significant at 0.1% level.

Source: LFS data, author's calculations

Second, we explore how wages and employment opportunities associated with different areas of specialisation have changed over time. Previous analysis set out in this chapter introduced interaction terms between time periods and qualifications to allow wages associated with different qualifications to change at a different rate over time. In this analysis, instead of adding interaction terms to the main model, wage and employment analysis is performed separately by area of specialisation. Time period coefficients returned by these analyses thus show how wages and employment opportunities changed over time in the population with the particular specialisation. Part of the observed changes may reflect changing cohort characteristics rather than changing demand for the associated skills. For example, falling employment rates over time may capture the effect of more recent cohorts getting older, as labour market inactivity declines among adults approaching retirement age. To take account of potentially confounding factors, individual characteristics, including age, age squared, sex and ethnicity are included as control variables.

An advantage of running the analysis by individual areas of specialisation rather than plugging interaction terms into the main equation is that it also allows the effect of control variables to vary across areas of specialisation. Consistent with the previous analyses discussed in this chapter, employment characteristics are not accounted for as we do not expect to see much change in these factors over time.

Table 3.11 below shows time period coefficients corresponding roughly to percentage changes in the real hourly wage over time as compared to the baseline period 2001-2004 by area of specialisation, keeping age, age square, sex, ethnicity constant. It confirms that since 2011, the wages of employees with HTE qualifications in health and teaching (categories 2 and 7 respectively) have been falling, probably reflecting the educational upgrading in these professions that stifled the demand for such HTE qualifications. Wages associated with social sciences and business specialisations (category 3) grew in 2008-2010 but declined in the post-recession period. This could be because tasks complexity declined in jobs they were in, or because on aggregate they were moving to less skilled employment. The later seems more plausible as there is evidence of employment becoming more tasks and skill intensive in the corresponding period (2011-2016), as demonstrated by the SES analysis discussed in Chapter 2.

### Table 3.11. Change in wages over time, as compared to the wage level in 2001-2004, among the HTE-qualified employees by area of specialisation

| | 2005-07 | 2008-10 | 2011-13 | 2014-16 | 2017-19 |
|---|---|---|---|---|---|
| 1. Basic programmes and teacher training | 0.06. | 0.00 | -0.15*** | -0.20*** | -0.21*** |
| 2. Arts and humanities | 0.02 | 0.02 | -0.08* | -0.03 | 0.00 |
| 3. Social and behavioural science, journalism and communication, business and administration, and law | 0.03. | 0.04** | -0.03* | -0.04** | -0.01 |
| 4. Life science, physical science, mathematics and statistics, computing | 0.08** | 0.00 | -0.05. | -0.04 | -0.05 |
| 5. Engineering and manufacturing trades, manufacturing and production, architecture and building | 0.02 | 0.02 | 0.02 | -0.02 | 0.01 |
| 6. Agriculture, forestry, fishery, and veterinary | 0.08 | 0.07 | 0.02 | 0.00 | 0.03 |
| 7. Health, nursing, dentistry and social services | 0.02 | -0.01 | -0.08*** | -0.14*** | -0.18*** |
| 8. Literacy, Numeracy, personal services, transport services, security services , environment | 0.06* | 0.05 | -0.02 | -0.05 | -0.01 |
| 9. Personal skills | -0.05 | 0.02 | -0.21 . | -0.01 | -0.06 |

Note : Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

2001-2004 is the baseline period. Control variables include: age, age square, sex, ethnicity

Source: LFS data, author's calculations

We also investigate changes in the chances of being employed over time across areas of specialisation, keeping age, gender and ethnicity constant (Table 3.12). Consistent with the observed trends in wages, employment opportunities, expressed in log odds, associated with HTE qualifications in the health and teaching area of specialisation worsened over time. As expected, period coefficients overlapping with the Great Recession (2008-2013) are negative across all the areas of specialisation, though many of them are not statistically significant (at 5% level). In a few areas, such as in social science and business, the downward trend persisted beyond 2013, which points to a sluggish employment recovery in the post-recession period for these areas of specialisation. Since we control for age and sex, this trend cannot be explained by the aging of the population or changes in its gender or ethnic composition. Individuals with engineering and manufacturing specialisation (category 5) show the strongest employment outcomes. The results show that they have been less affected by employment loss than some other categories during the downturn and their employment opportunities in recent years are not different from that observed in the pre-recession period.

## Table 3.12. Change in employment opportunities over time, as compared to the wage level in 2001-2004, among the HTE-qualified employees by area of specialisation

| | 2005-07 | 2008-10 | 2011-13 | 2014-16 | 2017-19 |
|---|---|---|---|---|---|
| 1. Basic programmes and teacher training | 0.07 | -0.27 | -0.40* | -0.46** | -0.42* |
| 2. Arts and humanities | -0.24* | -0.26* | -0.32** | -0.26* | -0.10 |
| 3. Social and behavioural science, journalism and communication, business and administration, and law | 0.01 | -0.19** | -0.11 | -0.13. | -0.11 |
| 4. Life science, physical science, mathematics and statistics, computing | 0.02 | -0.23* | -0.16 | -0.21. | -0.05 |
| 5. Engineering and manufacturing trades, manufacturing and production, architecture and building | 0.08 | -0.06 | -0.01 | 0.14 | 0.06 |
| 6. Agriculture, forestry, fishery, and veterinary | -0.33 | -0.40 | -0.09 | -0.10 | -0.18 |
| 7. Health, nursing, dentistry and social services | 0.03 | -0.37** | -0.32** | -0.58*** | -0.49*** |
| 8. Literacy, Numeracy, personal services, transport services, security services , environment | -0.06 | -0.08 | -0.11 | -0.14 | 0.13 |
| 9. Personal skills | 0.75 | -0.06 | -0.70 | 0.39 | -0.22 |

Note : Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

2001-2004 is the baseline period. Control variables include: age, sex, ethnicity.

Source: LFS data, author's calculations

Time period coefficients representing chances of employment in different periods as compared to the baseline years (2001-2004) are expressed in log odds. They provide an idea of the direction of the change but are difficult to interpret. For this reason we provide regression results for the employment analysis over time across the 9 areas of specialisation in the Annex A.2 Table A.2.22. With the full results at hand it is possible to translate the log odds into more intuitively meaningful results. For example, among 40 year-old white men with a HTE qualification (highest qualification) with a specialisation in life science, physics, mathematics or computing, 85% were employed in 2005-07, 82% in 2008-10, 83% in 2011-13, 82% in 2014-16, and 84% in 2017-19[40]. Employment rates among white women of the same age were respectively: 80%, 75%, 77%, 76%, 79%. However, many of the reported results are not statistically significant.

## 3.6. Conclusions

The LFS analysis points to worsening labour market outcomes associated with HTE qualification when compared to labour market performance of graduates. Degree holders maintained their wage advantage over HTE-qualified and this despite rising supply of graduates to the labour market. More importantly, our analysis shows that the HTE wage declined faster than the graduate wage between 2011 and 2016. The employment opportunities of the HTE-qualified deteriorated over time as compared to that of graduates. The gap in employment rates between the two groups has been widening since 2001 and until recently. The change in HTE employment rates was not different from that observed among those with lower level qualifications.

Exploration of how earnings and employment outcomes of those with HTE qualifications changed over time depending on the type of employment, revealed that the demand for the HTE-qualified in skilled occupations as compared to graduates decreased, notably in technical skilled occupations (SOC major group 3). A rising degree wage premium in technical skilled occupations (SOC major group 3) may imply that HTE-qualified workers are losing their grip on jobs which historically they have often been prepared for through HTE.

HTE workers have the highest comparative advantage in skilled trades (SOC major group 5). It means that in these occupations a gap in productivity and wages between HTE-qualified and graduate employees is the smallest, and the largest when productivity and wages of the HTE holders are compared to those of workers with lower level qualifications. The distribution of the HTE employees by occupation shows that the share of workers with HTE qualifications choosing skilled trade occupations increased over time. Employees with HTE qualifications who have been displaced in skilled jobs by degree holders may have therefore privileged trade occupations. More surprisingly the share of HTE holders also grew in service sector jobs. It therefore could be that some HTE programmes fail to provide skills that cannot be easily

[40] For example, the employment rate M for men 40 year-old in 2005-2007 was calculated as follows:

m = intercept+age coefficient*40+coefficient of the time period 2007-2007.

As m is expressed in log odd, M = exp(m)/(1+exp(m) ) provided by workers with other qualifications, or that graduates push some of the HTE-qualified out of skilled employment into service sector jobs where employment has been rising.

Comparison of labour market outcomes by area of specialisation (area of studies) of the qualification, and how they have changed over time, demonstrates that the demand for HTE qualifications varies depending on the technical skills targeted by the qualification. Among HTE-qualified those with engineering and manufacturing specialisation show the strongest employment outcomes in terms of wage premium and employment rates. Those with these specialisations have been less affected by employment loss than some other specialisations during the downturn and their employment opportunities in recent years are not different from that observed in the pre-recession period.

The discussed LFS analysis demonstrates that labour market outcomes associated with HTE qualifications have worsened as compared to that of graduates. But is does not allow to identify the cause of this decline. Whilst the analysis takes account of various factors, such as age, sex, academic achievement of individuals, to isolate the effect of the qualification on earnings and employment outcomes, we cannot exclude that other factors that we do not observe may be responsible for worsening labour market situation of the HTE holders. It could therefore be that HTE programmes match now less well demand for skills from employers than in the past, but it can also be that recently qualified HTE holders have a different profile from those opting for HTE qualifications in the past.

# 4 What do job vacancies tell us about HTE qualifications?

## 4.1. Introduction

Previous chapters have used conventional data sources to explore the evidence on changing employer demand for technical skills. This chapter uses a completely new source of data – online vacancy data – to look at the same issues, drawing on the granularity of big data. Analysis of Labour Force Survey (LFS) data, as discussed in Chapter 3, shows that the graduate wage premium relative to the wages of those with level 4 and 5 qualifications has been maintained over time despite a steadily increasing supply of graduates. In 2001, the level 4/5-qualified employee earned 79%, and in 2019, 77% of the graduate wage (Figure 3.3 in Chapter 3). Chapter 3 also shows that the employment rate of those with level 4 and 5 qualifications fell during the Great Recession and did not fully recover by 2019. The gap in employment rates between the graduate population and those with lower level qualifications, including relative to those with HTE qualifications, emerged during the 2008-2009 economic crisis and has remained since (Figure 3.4 in Chapter 3). This suggests that the relative employment opportunities of those with HTE qualifications have worsened over the last decade as compared to graduate employment opportunities. However, the outcomes of HTE depend on the study area, with HTE qualifications in engineering and manufacturing yielding the best outcomes. Chapter 2, using Skills Employment Survey (SES) data, showed that HTE holders perform more productive job tasks (as proxied with wages) than employees with lower level qualifications but less productive than graduates. However it also suggests that there may have been a decline in the share of well-paid tasks performed by HTE-qualified employees over time. In summary, according to the analysis in the previous chapters, HTE still prepares for relatively skilled jobs but the productivity of HTE holders, relative to that of graduates, has been falling over time.

Earlier chapters explained how this gradual erosion in the labour market value of many HTE qualifications can be explained by the content of the HTE programmes and growing problems in how well they match skills in demand on the labour market, as well as by the changes in the ability of the HTE-qualified over time. Lindley and McIntosh (2015) attribute the variation in wages among graduates to increasing variance in their ability that was induced by an expansion of universities and enrolment into degree programmes of individuals from the lower parts of ability distributions. This would suggest that some individuals who previously studied in level 4/5 programmes enrol now in universities, which could explain graduates taking jobs previously done by HTE-qualified workers. The issue that remains is the relative contribution of different explanations: the extent to which the observed ‘downgrading’ of HTE-qualified labour is due to falling ability in this group rather than the type of education itself.

In recent years, the majority of job vacancies in the UK have migrated online, replacing traditional hiring methods such as ads in newspapers (Cedefop, 2018). This migration, combined with a growth in computer processing power has provided researchers with new opportunities for collecting and analysing large, naturally occurring online job vacancy datasets. Consequently, evidence on employers’ demands for skills has been growing over time. The volume and the level of detail in online job vacancy data allow for a granular analysis of employer’s demand, across firms, within a specific occupation, and by region.

This chapter aims to supplement the stock of evidence on labour market outcomes to various qualifications, and notably HTE ones, by exploring Burning Glass Technologies (BGT) online job vacancy data. These data supplement other data sources in multiple ways, particularly because they provide a means of directly examining both the tasks and skills associated with particular jobs by employers, as expressed in job advertisements. Such information is not available from more regular data sources.

This study of BGT data aims to explore how familiar employers are with HTE qualifications and how likely they are to ask for HTE qualifications relative to other qualifications. In this analysis we also look at specific skills that employers associate with HTE and other qualifications, even within narrowly defined occupations. This should shed more light on employers’ perception of the productivity of workers with different qualifications and if employers consider graduates as more productive than HTE holders. The study of BGT data demonstrates how online job vacancies can be used to directly inform providers and policy makers in defining their HTE programmes and to guide students in planning their careers.

The chapter starts with research questions to be addressed in this BGT analysis. It then reviews relevant literature, describes the background, in terms of the changing mix of young qualifiers entering the labour market, and how relative wages associated with different qualification levels have also changed. The subsequent sections of the chapter explain the research approach, the strengths and limitations of online vacancies as a data source. Finally, the results of the analysis are presented.

Part of the research for Chapter 4 was carried out in collaboration with Elodie Andrieu, PhD student in Economics at King’s College London. The collaborative work involved analysis of raw text of job ads that culminated in the creation of an educational variable. Other data related work presented in Chapter 4, such as evaluation of the representativeness of BGT data, analysis of data, interpretation and discussion of the findings are the result of my own work.

## 4.2. The research approach

In this study, we analyse over 30 million UK (England only) job vacancies to better understand firms' demand for educational requirements. The data are provided by Burning Glass Technology (BGT), a labour market analytics company. Job vacancy data provide a direct measure of employers' needs. A large number of observations in online job vacancies allows us to carry out analysis of the labour demand at a high level of granularity. We examine a number of research issues:

- *The relative demand for different education levels within occupations and geographical areas.* We can observe the demand for level 4/5 qualifications relative to the demand for degrees and lower-level qualifications in the whole sample, by occupation and by geographical area. Breaking down information by region allows us to observe if areas with a high demand for graduates also record a high demand for HTE qualifications, or, alternatively, if demand for degrees is inversely correlated with the demand for HTE-qualified.
- *Implications of education level requirements for employer job task expectations.* Exploiting the very detailed information on job tasks available in the BGT, we can identify differences in the task requirements between ads asking for different qualifications. We also explore whether in nominally similar jobs tasks differ depending on the level of education required. E.g. if the distribution of skills within specific occupations differs between ads asking for a degree and those requiring HTE qualifications, and so if employers tend to vest graduates with different responsibilities than employees with HTE qualifications. Jobs traditionally associated with level 4/5 qualifications such as engineering jobs are of particular interest. For that reason a case study of engineering jobs was undertaken.
- *Using wages to indicate productivity.* To grade various job activities we look at the associated wages[41], and thus the importance of the tasks in the production of the output. We explore if employers see graduates as more productive than workers with HTE qualifications, with wages being a proxy for productivity. This analysis eventually intends to inform the vocational policy in England by pointing to skills that are sought by employers in occupations where those with HTE qualifications were traditionally channelled.

## 4.3. Previous research using BGT data and how our study compares

Previous chapters discussed in more detail the literature on skills and labour market outcomes associated with HTE qualifications. Here we review literature looking at employer demand for education and skills drawing on online job vacancy data. Online jobs vacancies have been extensively analysed in the context of real time changes in the stock of vacancies and their content. As far as we know, employer demand for

[41] These are wages offered by employers and not the achieved wages.

education has attracted less research attention in this context. This may be because information on the educational attainment of the labour force is available in other data sources such as the LFS, and because only some job openings (around one ad in five in BGT data) include information on education qualification requirements.

Burke et al., (2019) interrogated BGT US job vacancy data in combination with other data sources over 2007-2017 to explore the impact of business cycles on education and skills requirements in workplaces. To classify skills, the authors used the skills taxonomy proposed by BGT, whereby 17,000 unique skills are aggregated into 3 broad groups: specialised, baseline and software skills (Cournoyer, 2019). Burke and colleagues define educational requirements in job vacancies following the classification of educational requirements developed by the BGT. The authors report an upward shift in the demand for people with more education during the economic downturn, as measured with an increase in the share of ads asking for at least a four-year college degree, across all occupations. However, following the recovery of the economy, the increased demand for college degrees (bachelor equivalent) only persisted in skilled occupations, whereas in middle and low skilled employment[42] the share of ads where a degree is preferred declined. The authors suggest that software skills may drive the demand for college degrees in high-skilled employment. After an initial increase in the demand for software skills in all types of employment during the downturn, it only continued to grow in highly skilled jobs. They argue that continued growth in the demand for college degree education led to a lower matching efficiency between skills demand and supply in highly skilled occupations. Conversely, the mismatch observed in low and middle skilled jobs during the recession faded when the economy recovered. In brief, the study suggests that employer demand for higher level of educational attainment depends on business cycles.

A US study by Wardrip et al. (2017) raises similar questions to those addressed by our research. The authors explore job and regional characteristics that might explain observed variations in employers' educational preferences. They select four large 'opportunity occupations'[43], which are defined as "occupations that pay at least the national annual median wage adjusted for differences in local consumption prices, and that are generally considered accessible to a worker without a four-year college degree" (Wardrip, et al., 2017, p. 1). These occupations also exhibit large geographical differences in employer preferences for education. The authors find that in three out of four occupations, jobs asking for longer work experience are also more likely to require a college degree. Geographical location has a strong bearing on the required education. Other things being equal, college graduates are more in demand in areas with a larger number of college graduates and higher wages. Differences in skills do not seem to explain variation in the demand for qualifications. This suggests that, regardless of the actual skills required

[42] The authors classified jobs into three categories: low, middle, and high-skilled depending on the share of college holders among the incumbent workers in the prerecession period.

[43] The four occupations include: computer user support specialists, registered nurses, first-line supervisors of retail sales workers, and executive secretaries/executive administrative assistants.

in jobs, employers increase their educational expectations in areas where well-qualified labour is in abundance.

In this research study, like Wardrip et al., (2017) , we explore if job advertisements for the same occupation but asking for different qualifications differ in terms of skills requirements. We narrow down the focus to jobs in England where higher technical education (qualifications level 4/5) is required as compared to jobs where a degree is the preferred qualification. Where Wardrip and colleagues rely on the BGT educational variable, we create our own qualification variable (Wardrip, et al., 2017).

Research by Deming and Kahn (2017) also shares some parallels with our study. They investigate the relationship between wages (as a proxy for productivity) and the skills required on the job within narrowly defined occupations in the US. They find that within occupations, wages depend on the skills involved, even after accounting for other factors, such as required education. Deming and Kahn (2017) restrict their analysis to jobs of professionals. Within the US BGT dataset, ads for these jobs represent around 60% of all the BGT job ads, including the majority of jobs requiring a degree. To classify ads by skill requirements the authors analyse more than ten thousand unique keywords and phrases in the BGT data and group skills into 10 large categories with cognitive and social skills[44] receiving particular attention in their analyses.

In comparison to Deming and Kahn, our study adds an extra dimension by exploring the distribution of skills and their association with wages within narrowly defined occupations, but also by qualifications. We allow skills and wages to differ across jobs with different educational requirements. For example, engineering jobs for graduates may involve more managerial skills than engineering jobs for which an HND/HNC might be expected. We therefore aim to identify if within apparently similar occupations the mix of differently priced job tasks varies according to qualification requirements.

Finally, a study by Brown and Souto-Otero (2020) describes the demand for different qualifications within very broadly defined occupations (SOC digit 1) in the UK. It draws on the BGT Labour Insights platform that provides access to aggregated vacancy data across various dimensions as defined by BGT, such as the share of ads with a specific qualification by occupations and regions and distribution of skills by qualifications. While the focus of their study is similar to ours, our analysis, conducted at individual ad level, goes beyond analysis of aggregated data and is much more granular. Instead of using the educational variables proposed by BGT we screen free text of job vacancies to classify qualifications.

To conclude, evidence on the employer demand for education, and in particular HTE, drawing on on-line job vacancy data is scare. We aim to shed more light on this issue by pointing to the employer demand for

[44] The authors highlight cognitive and social skills, as they are prominent in professional jobs and because they tend to be favoured by technological change (Autor, Murnane 2003). By focusing on these two types of skills they thus probe some of the hypothesis set up by the proponents of the skills biased technological change theories.

'Social skills' draw on the O*NET skills classification and refer to activities such as: communication, teamwork, presentation, collaboration, and negotiations.

HTE relative to the demand for other levels of qualifications and by exploring skills associated with HTE qualifications in specific occupations.

## 4.4. Methodology and data

### *4.4.1. BGT data*

Burning Glass Technologies is a US labour market analytics company daily web-scraping approximately 40,000 job advertisement sources, of which more than 6,000 are in the UK (Nania, et al., 2019). BGT data are characterised by a high volume of observations and level of detail. Job openings are described according to various dimensions such geographical location and occupation.

BGT robots visit daily multiple websites such as job boards (e.g. Career Builder, Universal Job Match), government job databases, company's websites, websites of agencies specialised in recruitment (Michael Page, Reed England) (Grinis, 2017). Some of the alternative sources of online vacancy data in the UK analysed by researchers include job platforms (Adzuna, Reed and Indeed) targeting employers searching for workers and individuals looking for jobs[45]. We opt for BGT vacancy data since they are provided in two formats: as free vacancy text (html) and as already coded data including variables developed by BGT. These data permit both analysis of raw vacancy text and the use of variables created by BGT. We parse job vacancy text and job titles to create qualification variables and use BGT variables in other areas of interest, so as to classify occupations by SOC and to identify skills applied on the job.

In the UK, BGT has collected data since 2012 and covered around 60 million UK job adverts over the period 2012-2019. Changes in search and data classification algorithms are applied retroactively to the existing dataset to ensure comparability of the data over time. However, up to 2014 the number of websites visited by BGT was increasing rapidly. Similarly to Smarzynska Javorcik et al., (2019), to ensure comparability of the data over time we restrict our analysis to the period 2014-2019 to avoid the distortions potentially created by a rapid change in the number and composition of websites covered prior to 2014. A vacancy can be posted on multiple platforms or multiple times, such as on the employer website and on job boards, and around 80% of postings collected by BGT are duplicates. To avoid one vacancy being counted several times, BGT removes duplicates appearing within a period of two months.

Both education systems and labour market conditions vary across the four UK countries. To ensure consistency of the data we restrict the sample to ads posted in England, amounting to 32 million observations in 2014-2019. (English job openings accounted for 67% of all the UK vacancy postings in the same period).

[45] See for example Turrell et al. (2018) and Rudy (2021) for the analyse of the UK labour market with Reed data.

### *4.4.2. Comparing BGT with other data sources as measures of labour market demand*

Survey data sources, such as the SES and LFS, discussed in the previous chapters, collect information from the point of view of workers and other individuals in the population. Online job vacancy data sources, such as BGT, permit the exploration of labour market demand from the perspective of the employer. This facilitates the identification of the qualifications and skills that employers would like to see in new recruits. In addition, vacancy data provides a picture of recruitment, or inflow to the workforce, rather than about the stock of persons in the labour force, measured by surveys of the labour force. The two types of data source are therefore quite different, and can only cautiously be compared.

Online job advertisements typically set out the characteristics of an 'ideal' candidate for the job as defined by the employer, and not the (usually lesser qualities) of the person who eventually gets the job. The education match depends on the availability of the specific qualification in the labour force. Employers are likely to accept lower level education in recruits if the qualifications they are looking for are not readily available, either because there is a shortage of these qualifications among the current workers (supply side), or because the job is not attractive enough to the target population (demand side) (Gambin, et al., 2016). When high level qualifications are abundant, profit maximizing employers may want to recruit workers who are overqualified and presumably more productive than those with lower-level qualifications. Burke et al. (2019) demonstrate that when labour markets are slack, employers are in a position to prefer recruits with a level of education higher than that observed among the incumbent workers. 'Academic queue theory' advanced by Brown and Souto-Otero (2018), seeks to explain a rising share of degree holders in the workforce through employers' preferences for a more educated workforce during recruitment, with employers nearly always preferring more educated workers to those with less education (Brown & Souto-Otero, 2020). Finally, during the recruitment process both employers and future employees adjust their expectations. Adams-Prassl et al.(2020) observe that employment conditions can be negotiated, and the final job terms may differ from those described in the vacancy.

Independently of the quality of the match between workers and the job, employees and employers are likely to describe the same job in different terms. When surveyed, individuals tend to downplay any gaps in their skills, whereas employers tend to overstate the skill requirements of particular jobs (Gambin, et al., 2016). Job descriptions provided by employers for recruitment advertisements will have other biases: employers will naturally highlight the most attractive and positive aspects of the job (Turrell, et al., 2018). For several reasons therefore, employer descriptions of both jobs and desired skills and qualifications in online job advertisements will differ from both actual jobs, and the skills and qualifications of those who are actually recruited.

Current recruitment practice will also be at variance with the current workforce. Skills and educational requirements in workplaces change over time, and employers may face different educational needs in different periods. For example, employers who intend to introduce new technologies and cannot find the relevant skills in the current workforce may want to recruit new workers who are able to use the new technology. If employers succeed in matching job openings with the desired candidates, the educational attainment of the freshly recruited are likely to be different (in terms of the level and area of specialisation) from that found among the current employees.

As individuals advance in their careers, their skills and knowledge change too, recognising that the learning curve would depend on the job and individual characteristics. The skills and knowledge of a person with extensive labour market experience would thus reflect not only her qualifications but also the amount of training received while on the job.

### *4.4.3. Limitations of online vacancy data*

BGT data, like other on-line jobs vacancy datasets, are not without limitations. They are a snapshot of recruitment intentions, rather than being representative of the labour force. BGT data reflect gross rather than net recruitment demand, meaning that jobs subject to a high level of labour turnover will be over-represented in BGT data. BGT data are also not fully representative of all job openings as they only capture online vacancies and ignore ads posted through other channels. Traditional channels of recruitment such as newspaper ads, signs on shop doors and word of mouth have declined but are still in use. Low skilled jobs are more likely to be advertised through traditional routes. BGT estimates that around 85% of ads are posted online (Lancaster, et al., 2019). Some other jobs are also filled through personal contacts or specialised head-hunter companies, without any publicly advertised vacancy. Some online vacancies are not included in BGT data. As Adams-Prassl et al. (2020) note, websites can evade screening. Portals, such the Civil Service portal, block scraping their websites, and unless the same vacancy is posted elsewhere it will not be scraped by BGT. The authors note that BGT may miss websites of small employers and start-up companies too. Consequently, among the BGT ads, there might be a disproportionate representation of some occupations, industries, companies by different size, and locations. Djumalieva, Lima and Sleeman (2018) further argue that the quality of online vacancy data is weakened because of misspellings and use of abbreviation in vacancy text. Interpretation of the results needs to take account of these limitations.

#### *Representativeness*

To evaluate the representativeness of the BGT data we draw on the analyses conducted in previous research studies and compare BGT to LFS data.

In the US, various studies carry out a robustness check by comparing BGT data to state and national job vacancy reports that survey a representative sample of employers. Carnevale, Jayasundera and Repnikov (2014) compared BGT jobs vacancy text to the wording of actual job ads and conclude that 80% of BGT ads were coded accurately on occupation, education, experience.

Also in the US, Burke et al*.* (2019) find that BGT data are over-represented in industries such as finance, but under-represented in others (e.g. food services). They note that overall, most of the observed differences are small in magnitude. Similarly, Hershbein and Kahn (2017) show that at the occupation level, highly skilled employment such as computer and management occupations are over-represented in BGT. Conversely, less skilled occupations such as in food preparation and construction are under-represented. More importantly, Hershbein and Kahn (2017) and Burke *et al.*, (2019) find that the relationships between the BGT data and the other data series are consistent and that the distributions of BGT postings by industries and occupations are stable over time. This implies that BGT data analysis by occupations and sectors should produce reliable findings in the US.

In the UK, Smarzynska Javorcik et al., (2019) compare BGT vacancy data to the UK Vacancy Survey, which is administered monthly to a representative sample of employers (Office for National Statistics (ONS), 2012). Information on vacancies in the UK Vacancy Survey is provided by industry (SIC) and by region, but information on occupation and education is not available, which makes these data less relevant for our purposes. The authors show that between 2012 and 2019 the job adverts included in BGT's data accounted for approximately 86 percent of the total number of vacancies in the UK as reported by the UK Vacancy Survey. Grinis (2017) is more cautious, arguing that ads collected by BGT can be counted more than once in the UK Vacancy Survey, as the headline series of the ONS vacancy data are based on 3 month rolling averages whereas BGT applies a two-month de-duplication window. According to Grinis (2017), this difference in ads counting may explain fewer ads being reported in BGT as compared to the ONS Vacancy Survey data. But the difference may also stem from the fact that BGT does not capture job ads that are reported by employers in the ONS survey but not posted on-line.

Further to Nania et al. (2019), Grinis (2017) compares BGT vacancy data to the employment data from the Annual Survey of Hours and Earnings (ASHE) from the Office of National Statistics (ONS). ASHE provides comprehensive information on employees' earnings across all industries and occupations (Office for National Statistics, 2022). Occupational distributions of 2014 UK vacancies from the two sources show a correlation of 0.94. Consistently with the US studies, it also reveals a disproportionate share of occupations requiring higher levels of educational attainment (occupations SOC major groups 1-3), and underrepresentation of occupations with lower educational requirements such as elementary occupations and services in the BGT data (Grinis, 2017).

We compare SOC digit 1 distribution in our BGT dataset to that in the LFS. Unlike the information on qualification available for 30% of ads, SOC is provided for 99% of postings in BGT. To improve the comparability between the two, we restrict the LFS sample to recent hires in England, i.e. those who have been with the current employer for 12 months at most. The results displayed in the table below (Table 4.1) shows that BGT data contain a higher share of ads targeting skilled jobs (SOC major categories 1-3) than LFS data. This confirms findings from previous studies whereby occupations requiring higher education and presumably higher skills such as occupations in SOC major categories 1-3 are overrepresented and low-education/low-skilled occupations are underrepresented in BGT. Differences in the two datasets may also result from higher turnover in some occupations. For example, occupations with a high turnover would see a relatively large number of job openings as compared to the employment figure.

### Table 4.1. Distributions of occupational groups in BGT and LFS (2014-2019)

| | BG (%) | LFS (%) |
|---|---|---|
| SOC1 | 11 | 6 |
| SOC2 | 34 | 16 |
| SOC3 | 17 | 13 |
| SOC4 | 9 | 10 |
| SOC5 | 6 | 9 |
| SOC6 | 6 | 11 |
| SOC7 | 9 | 11 |
| SOC8 | 3 | 7 |
| SOC9 | 5 | 17 |

Source: BGT and LFS data, author's calculations

To test the representativeness of BGT data over time we compare the distribution by year and by occupation (SOC digit 1) in BGT and LFS (Annex A.3 Table A.3.1). The distribution of jobs/ads across SOC categories is relatively stable over time in both datasets, except for professional occupations - SOC major group 2. Job vacancies in this category dropped by 4 percentage points between 2017 and 2019 in the BGT dataset. A similar trend was not observed in the LFS data. Cammeraat & Squicciarini (2021) in their analysis of representativeness of BGT data over time in the UK conclude that in occupations classified at SOC6, SOC7, SOC8 and SOC9 there are some representativeness concerns. It could be that over time more ads associated with these occupations went online, increasing their share of the total number of jobs vacancies. The use of BGT data to analyse time trends across occupations thus requires caution.

### *4.4.4. Constructing an educational variable using BGT data*

BGT provides an educational variable based on the educational requirements defined by employers, allowing a range of English qualifications to be identified. To have more transparency and control over how individual qualifications are identified, we parsed job vacancy text with the aim of creating our own qualification variable.

We proceed in two steps.  First, we identify vacancies where required qualifications are mentioned. We classify qualifications as follows:

- GCSE : academic level 2
- A levels: academic level 3
- NVQ 1: vocational level 1
- NVQ 2, diploma level 2 : vocational level 2
- NVQ 3, diploma level 3, BTEC, City & Guilds  : vocational level 3

- NVQ 2 and 3 (this includes NVQs that cannot be matched to a specific level): vocational level 2 and 3
- HNC, HND, diploma level 4, diploma level 5, foundation degree: higher technical education (HTE)
- Bachelor, Master degree, PhD : level 6 and above

Second, we identify jobs where a degree (or higher) is legally required, independently of the qualification being mentioned in the job text.

For the purpose of this analysis we aggregate the identified qualifications into three groups: level 3 and below, HTE, bachelor degree and above.

Before matching key words in job text and jobs titles we made an initial preparation of the vacancy text and that of job titles. We changed all capital letters to lower, ensured all the numbers are in Arabic numerals, changed all the characters other than letters and numbers (e.g. punctuations) into white spaces, and finally shrank multiple white spaces into single spaces.

We are interested in ads with different educational requirements including higher technical qualifications (qualifications level 4/5). We therefore identified keywords corresponding to qualification names in England and match them in the text of job adverts. It is the first keyword encountered that counts, as after the first match the search stops. Our educational variable is thus binary. We assign '1' to the ad if the qualification is matched and '0' otherwise. Vacancies with qualifications such as "HNC", and "national certificate" are relatively easy to identify as the key word corresponds to a specific qualification and level, it is not commonly used in other contexts, and rarely appears as part of other words. Other keywords such as "NVQ", "degree", "master" are more problematic. While NVQ clearly refers to vocational qualifications, it does not allow the level of qualification to be identified. "Degree" and "master" may well designate a university qualification at level 6 and above, but they can appear in other contexts too (e.g. "applicants are required to demonstrate a high degree of integrity"). The word "master" is a commonly used word and a component of other words such as "mastery". For these and other ambiguous keywords, we extract not only the keyword from the text of the ad, but also the 4 words before and 4 words after the keyword. This allows us to have contextual information which we then use in cleaning and filtering strategy. By manually checking hundreds of ads in two different time periods (years) we identify combinations of words that allow us to classify qualifications with more precision. For example, ads matched with: "a master", "master in", "master\s of science" etc., are coded as requiring a master's degree and all the other ads with the word 'master' are considered as not relevant. To identify the level of qualifications, such as 'NVQ' or diploma, we search for a number among the four surrounding words. If for example, we match a number '3' in the four words around the keyword 'NVQ' we code the ad as NVQ level 3. Ads matched with 'NVQ' and no numerical values among the four surrounding words are assumed to be at level 2 and 3. This is a separate category as we cannot distinguish qualifications level 2 from 3 with certainty. This does not matter in our analysis as we aggregate all qualifications level 3 and below into one category.

A qualification mentioned in an ad usually refers to the type of education the employer would like to see in a potential recruit, but sometimes it refers to the qualification the person can obtain after completing training while on the job – for example in a job advertised as an apprenticeship. Scrutiny of the job ads reveals that vacancies with a training option are, for example, common in the area of social care, where employers are ready to recruit and train unqualified workers, most likely because of skills shortages in this sector. The issue of training opportunities and skills shortages in BGT data could usefully be explored further but is not examined in this study as it is not relevant to the issues addressed in this research. We identify apprenticeship vacancies through the word 'apprenticeship/traineeship' in the job title. We identify other postings with opportunities for training by matching expressions such as "opportunity to", "trained", "training", "towards" in the four words surrounding selected keywords. Ads where qualifications mentioned are associated with training following recruitment rather than a requirement for recruitment are excluded from the analysis involving educational variables.

Table below (Table 4.2) provides a summary of the strategy that was used to match qualifications in BGT data. The ad is matched with a specific qualification IF it is matched with the key word in the job text AND if there are no exclusion words in the four words surrounding the key word.

### Table 4.2. A summary of matching strategy applied to identify qualifications in BGT data (main key terms)

| | Key terms matched in the job text | Exclusion words in the four words surrounding the key term |
|---|---|---|
| NVQ 1 | NVQ 1, diploma 1, diploma level 1 | Towards, fully, funded, attain, achieve, offer, training, undertake, study for |
| NVQ 2 | NVQ 2, diploma 2, diploma level 2 | Towards, fully, funded, attain, achieve, offer, training, undertake, study for |
| NVQ 3 | NVQ 3, diploma 3, diploma level 3 | Towards, fully, funded, attain, achieve, offer, training, undertake, study for |
| NVQ 2 and 3 | NVQ | |
| City&Guilds | Guild/s | |
| BTEC | BTEC | |
| A LEVELS | A LEVEL\S | a level of, experience, year, visa, a level that, a level to, teach., taught, a level where, student., learner., gain a level, strain, work, towards |
| | | |
| HNC | HNC, NATIONAL CERTIFICATE | |
| HND | HND, NATIONAL DIPLOMA | |
| DIPLOMA LEVEL 4 | DIPLOMA 4, DIPLOMA LEVEL 4 | towards, fully, funded, attain, achieve, offer, training, undertake, study for |
| DIPLOMA LEVEL 5 | DIPLOMA 5, DIPLOMA LEVEL 5 | towards, fully, funded, attain, achieve, offer, training, undertake, study for |
| GSCE | GSCE, HIGH SCHOOL DIPLOMA, HS DIPLOMA | |
| FOUNDATION DEGREE | FOUNDATION DEGREE | |
| BACHELOR | BACHELOR, BS IN, A BS, BSC, DIPLOMA 6, DIPLOMA LEVEL 6 | |
| GRADUATE | Graduate, under grad | apprenticeship, recruitment consultant, graduate programmes, graduate programs, graduate courses, high school graduate |
| DEGREE | | degree/s of, 360 degree, 90 degree, 180 degree, some degree |
| MASTER | a masters, masters in, degree masters, master\s degree, | |

| | | |
|---|---|---|
| | master\s level, master's, master of finance, master of arts, master of science, master of business, master of engineering, mba, master qualification, masters graduate, economics master, master equivalent, ceng, ms, msc, mb, post grad, | |
| PHD | PHD Doctora., | |

In some occupations educational requirements are self-explanatory. This is the case of many occupations in the health sector, teaching, and some other areas such as law where a qualification (typically a degree) is legally required. Professional organisations can also voluntarily adhere to educational standards to improve the status of the profession. For example, the Engineering Council, the regulatory body for the engineering profession in the UK defines standards of professional competence, and assesses and awards professional titles against these standards. Chartered engineer, one of the certifications conferred by the organisation, is awarded to those holding a bachelor's or master's degree in engineering (Engineering Council, 2022).

We identified jobs where a bachelor's level or higher is a licensing requirement for the job, and match them with the job titles[46]. For example, an ad with a word 'teacher' or 'chartered engineer' in the job title is classified as a vacancy requiring a degree. Our approach is conservative as unless the job formally requires a qualification it will not be classified as such. For example, a translation degree is not obligatory for those wishing to work as translators in the UK and even though many translators do have a degree in translation we do not code the translation occupation as a degree one. Ads where the required qualification is based on occupation are matched with one qualification only, the one that is formally required to enter the profession. This qualification prevails over all the others identified through job text search.

Job openings can also mention qualifications in relation to employers. This would typically be the case of ads posted by teaching institutions. For example, if a school is looking for an English teacher, the ad may say that the successful candidate will teach Key Stage 3, Key Stage 4, and Key Stage 5, and that the school offers AQA GCSE, AQA 'A' Level courses. Applying our matching strategy this ad would then be coded as academic level 2 and level 3 by matching keywords with the ad text[47], which would be wrong as these qualifications refer to the employer and not to the hire. The same ad will also be identified as a degree job as there is a word 'teacher' in the job title. In the end, we will code this job opening as degree level only since we let qualifications based on occupations prevail over other qualifications. By applying this procedure, we ensure that jobs for teachers are properly classified. However, we do not eliminate the risk of misclassification of all vacancies posted by teaching institutions if the degree is not formally required.

[46] We draw on information provided on the EU website: https://ec.europa.eu/growth/tools-databases/regprof/index.cfm?action=regprofs , and UK websites such as https://www.healthcareers.nhs.uk/working-health

[47] Ads for teachers often do not mention the required qualification as in this profession in state schools the degree is formally required, and so the educational requirements are self-explanatory.

For example, if a school is looking for a janitor, the ad will be matched with GCSE and A levels, if they are mentioned in the ad, overestimating the amount of education required for the janitor job.

Among vacancies in England appearing over the period 2014-2019, we identify nearly 9 million or 28% of ads with qualification requirements. If we exclude ads where education is deduced from occupations the share of ads with qualifications is 19%.

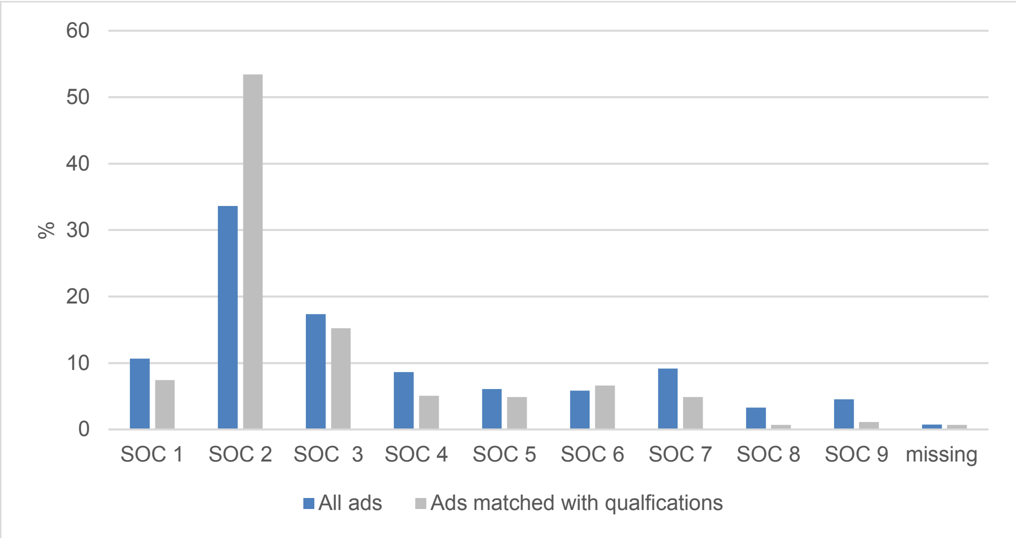
To increase the pool of applicants employers sometimes ask for a range of qualifications. The ad may say that the candidate should have an HND or a degree. It may also say that a degree with A levels in mathematics would be desirable. We identify all qualifications in the ad and allow one ad to be matched to more than one qualification (except for the ads in which education is identified based on the occupation as stated above). We also create variables with minimum and maximum qualifications required, by identifying the lowest and highest qualification respectively among the qualifications appearing in the ad.

### *4.4.5. Validating our educational variable: comparison with the LFS*

We check the performance of the created education variable by comparing the qualification distribution in our dataset to that in the LFS. In line with the literature discussed in previous sections we expect to find an overrepresentation of highly skilled jobs in ads with educational requirements in BGT data. It should be kept in mind that the comparison of BGT and LFS data has some limitations as BGT provide information on the educational requirements stated in job openings, but not on the educational background of the person who gets the job.

The figure below confirms that ads matched with qualifications report a higher share of jobs of professionals (SOC major 2 occupations) than ads where education is missing (see Figure 4.1).

**Figure 4.1. Distribution by SOC digit 1 among all ads regardless of education, and among ads with educational variable, all years combined (2014-2019)**




Notes: Adding shares across SOC categories, by availability of educational information, totals 100%.

Source: BGT, author's calculations

To improve comparability between the LFS and BGT data we restrict the LFS sample to employees in England who have been with the current employer for 12 months at most, so that this LFS subset effectively samples recent recruits. It should also be noted that while the major level 4 and 5 qualifications are identified both in BGT and LFS the overlap is not perfect. Furthermore, BGT reflects the demand at the moment of job vacancy appearances, whereas LFS data signals the demand for education (relative to the supply) in the last 12 months.

In line with the existing evidence, comparison of the two datasets confirms the overrepresentation of qualifications at level 6 and above in BGT (Tables 4.3-4.5). When ads with qualification requirements based on occupations are removed (Table 4.5) the proportion of ads where a degree is preferred shrinks but still remains more than twice as high as in the LFS.

The LFS data show that the share of degree holders among recent employees has increased steadily over the period 2014-2019; there was no change in the share with level 4 and 5 qualifications; and the share of those with lesser qualifications fell (Tables 4.3-4.5). However, in BGT data the share of ads requiring a degree and above was relatively stable over the same period of time. If we set aside ads with qualifications based on occupations (for example teachers where degree-level education is a requirement), the relative demand for degrees has been falling since 2015 in BGT. This may mean that the overall demand for degrees in BGT data was maintained by more vacancies being created in formally regulated occupations such as teachers and nurses. BGT thus tells a slightly different story than LFS data, even after taking into account of the lag in the LFS data as compared to the BGT data. The difference between LFS and BGT data could be explained by degree holders going into jobs where employers ask for lower-level qualifications, with the trend accelerating in recent years. It is also possible that the observed discrepancies are due to differences in BGT data coverage over time, i.e. an increase of low skills / low education ads being posted on line. Whatever the reason and bearing in mind the limits of the comparison, dissonance between LFS and BGT data suggests that any comparison over time with BGT data should be carried out and interpreted cautiously. For that reason, we refrain from an analysis over time in favour of an examination of the pooled sample for the period 2014-2019.

### Table 4.3. Share of workers recruited in the last 12 months, by qualifications, LFS data

| | level 3 and below | level 4/5 | level 6 and above |
|---|---|---|---|
| 2014 | 0.72 | 0.05 | 0.23 |
| 2015 | 0.71 | 0.05 | 0.24 |
| 2016 | 0.70 | 0.05 | 0.25 |
| 2017 | 0.70 | 0.05 | 0.25 |
| 2018 | 0.69 | 0.05 | 0.26 |
| 2019 | 0.67 | 0.05 | 0.27 |

Note: Values in rows add to 100%

Source: LFS data, author's calculations.

### Table 4.4. Share of BGT ads by qualifications

| | level 3 and below | level 4/5 | level 6 and above |
|---|---|---|---|
| 2014 | 0.26 | 0.06 | 0.69 |
| 2015 | 0.22 | 0.06 | 0.71 |
| 2016 | 0.25 | 0.06 | 0.69 |
| 2017 | 0.22 | 0.06 | 0.72 |
| 2018 | 0.23 | 0.05 | 0.71 |
| 2019 | 0.26 | 0.06 | 0.68 |

Note: Values in rows add to 100%

Source: BGT data, author's calculations

### Table 4.5. Share of BGT ads by qualifications (minimum qualification required), excluding job ads where degree is formally required

| | level 3 and below | level 4/5 | level 6 and above |
|---|---|---|---|
| 2014 | 0.28 | 0.10 | 0.62 |
| 2015 | 0.29 | 0.10 | 0.62 |

| | | | |
|---|---|---|---|
| 2016 | 0.30 | 0.10 | 0.60 |
| 2017 | 0.30 | 0.10 | 0.61 |
| 2018 | 0.33 | 0.09 | 0.58 |
| 2019 | 0.33 | 0.10 | 0.57 |

Note: Rows add to 100%

Source: BGT data, author's calculations

## 4.5. Findings

### *4.5.1. Skills and Wages*

This subsection reports on the results from an analysis of the task composition of jobs and how these tasks are related to the qualification requirements of the same jobs. In this analysis of BGT data, 'tasks' and 'skills required on the job' are used interchangeably. In job ads employers enumerate skills that are necessary to fulfil tasks on the job. For example, employers require future hires to be proficient in Java as the job involve programming in Java language. Skills are thus in direct correspondence with the tasks.

The analysis identifies how the task mix in jobs where employers seek graduates differs from those in which employers are seeking those with level 4/5 qualification. In part this difference in the mix of tasks can be explained by a selection of workers with different qualifications into different occupations. For example, the use of medical knowledge and the task of relating to patients are more likely to be found in jobs for graduates simply because a degree is required to become a medical doctor or a nurse. To account for differences in skill use across occupations and the fact that the employer appreciation of level 4/5 qualifications can vary depending on the job we opt for an analysis within narrowly defined occupations. The large number of observations in the BGT data allow an analysis at a such a granular level.

Both the research literature (Green, et al., 2016; Autor, et al., 2003; Autor, et al., 2008), and our own previous analysis of SES presented in Chapter 2, describe how different skills are differently priced on the labour market. For example, the SES analysis shows that jobs where analytical and managerial skills are frequently used attract higher wages than jobs relying heavily on physical strength and manual dexterity. The productivity of labour thus depends on its human capital endowment, with workers who perform complex analytical and problem-solving tasks, and displaying a high level of industry related knowledge typically receiving higher wages. Analysis of BGT vacancy data shows that skills are associated with qualifications, i.e. job advertisements ask for a different set of skills depending on educational requirements. This information on its own does not tell us how much employers are ready to pay for these skills. To identify the labour market value of skills we compare salaries in job advertisements, as contained in the BGT data, with different skills requirements. This involves looking at whether ads asking for skill A offer a higher wage than ads demanding skill B.

We also explore if employers expect different skills among workers with a HTE background than those they expect for employees with other qualifications, even within very similar jobs. For example, an engineering job for graduates may involve more managerial and planning tasks than engineering job defined with an HTE holder in mind. We also explore if ads for graduates are composed of more productive tasks (proxied with wages) as compared to ads asking for HTE qualifications.

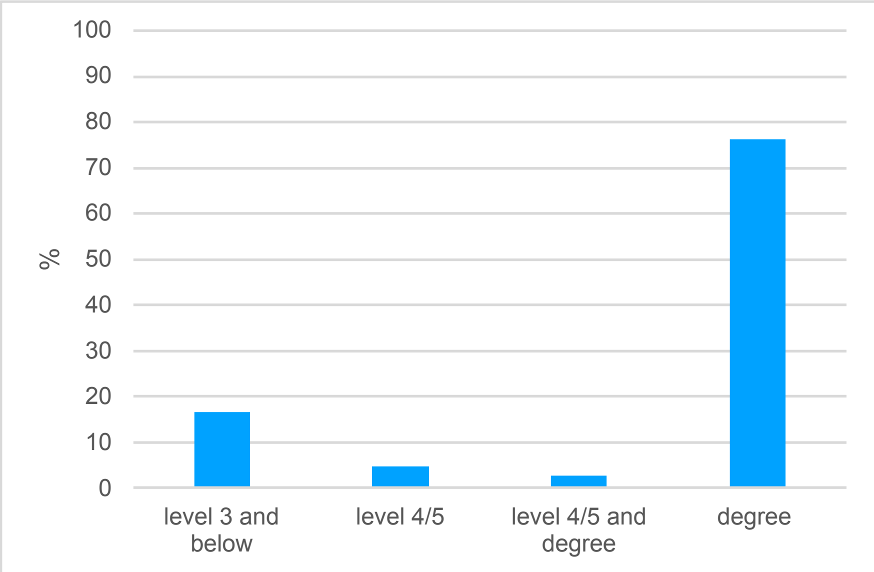
Wages are specified in around 20 million ads in our sample, and just over 5 million contain information both on wages and education. Previous chapters explored the labour market performance of HTE holders as compared to graduates. The comparison with graduates is of a particular interest as HTE programmes typically target skilled technical occupations where the share of university graduates has been rising over time and where HTE holders have been competing for jobs with graduates.

We look at skills and wages across four levels of education as identified by employers:

- HTE is the highest qualification required with no mention of degree
- both HTE and degree are mentioned
- degree is required with no mention of HTE
- and finally a level 1/2/3 qualification is the highest qualification demanded.

The second category above, of vacancies where both HTE and degrees are mentioned as preferred qualifications, are of particular interest. One possibility is that in these jobs employers are indifferent as between employing HTE and degree holders. However, employers may have preferences independently of skills, for example, if they perceive degrees as more prestigious than HTE qualifications, and therefore more desirable in their workforce. BGT data shows that across ads with level 4/5 requirements, more than one third also mention a degree as a preferred qualification (see Figure 4.2 for distribution of educational qualifications in job vacancies). We use the four-level qualification variable to compare skills requirements in narrowly defined occupations, and to differentiate the skills that employers associate with HTE qualifications as opposed to degrees.

### Figure 4.2. Share of qualifications in job vacancies, 2014-2019




Source: BGT data, author's calculations

Analysis of mean and median wages by qualification shows that ads where both level 4/5 and degree are mentioned attract the highest wages, see Table 4.6 below (differences are statistically significant). Controlling for regions does not affect the results, showing that the observed differences in wages are not due to the distribution of ads across regions (Table 4.7).

It could be that the observed difference is due to experience as typically those with HTE qualifications enter the labour market earlier than graduates, and those with longer work experience tends to earn more than workers with shorter work experience keeping other things constant. However, a separate analysis including experience as a control variable is not performed as experience is not provided for a majority of ads.

### Table 4.6. Hourly wage in £ by qualification, all years combined (2014-2019)

| Qualification | Mean hourly wage | Median hourly wage |
|---|---|---|
| Level 3 and below | 11.1 | 9.86 |
| Level 4/5 | 16.1 | 14.4 |
| Degree | 17.2 | 14.7 |
| Level 4/5 and degree | 18.0 | 16.8 |

Source: BGT data, author's calculations

## Table 4.7. Wages by qualifications, 2014-2019, level 4/5 and degree – the qualification of references

| | Estimate | Std. Error |
|---|---|---|
| Intercept | 2.89 *** | 0.0013507 |
| Level 3 and below | -0.463 *** | 0.0012457 |
| HTE | -0.097*** | 0.0014309 |
| Degree | -0.077 *** | 0.0011880 |
| Year | YES | |
| Region | YES | |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4072 on 3463832 degrees of freedom

(1486 observations deleted due to missingness)

Multiple R-squared: 0.1641, Adjusted R-squared: 0.164

F-statistic: 3.999e+04 on 17 and 3463832 DF, p-value: < 2.2e-16

The wage results may reflect the way in which certain occupations are linked to licensing requirements which determine the qualification demanded. In our sample a large share of ads classified as requiring a degree (with no mention of HTE) are in areas such as teaching and nursing. These jobs tend to be provided in the public sector, in teaching and nursing, where wages are more uniformly distributed than in the private sector (Cribb, et al., 2014). To account for the effect of sectors and occupations on wages we narrow down the analysis to specific occupations. As in the previous analysis of LFS we explore wages and skills associated with qualifications in the context of the SOC classification. Given the number of observations in BGT it is possible to carry out analysis at the SOC digit 3 level, thus at a much more detailed level than in LFS. An advantage of this approach is that we compare jobs that are relatively similar. An analysis at a more disaggregated level (SOC digit level 4) is possible in principle with BGT data, however as noted by Turrell, et al. (2018), the risk of SOC misclassification increases with its granularity. We apply an approach similar to that privileged by Turrell, et al. (2018) and chose SOC digit 3 as the occupational unit of analysis.

Within narrowly defined occupations, it is more likely that any variation in wages by qualifications could be attributed to differences in skills endowment among qualification holders, as perceived by employers, rather than to the nature of the occupation. Some occupations are more common in the public sector (e.g. teachers, nurses, doctors). By narrowing down the focus of the analysis to 3 digit SOC occupations we reduce the variation in the sector (public vs private) too. Industry (typically expressed with SIC) may also be associated with wages. As discussed in the LFS chapter, we opt for a wage analysis within SOC rather than SIC as occupational classification seems to explain a larger part of variation in wages than industry.

The following sections of this study focus on one occupation only. Our aim is to demonstrate how BGT data can be used to analyse skill needs *within* occupations. This type of analysis can inform vocational policy in England by pointing to the skills HTE programmes should be developing in students, since they are demonstrably needed by employers and well rewarded in the labour market. Criteria according to which we select an occupation include the number of observations in occupations and the share of ads within occupations asking for HTE qualifications (see Annex A.3 Table A.3.2 and A.3.3). On this basis we select an occupation at three digit SOC level belonging to the SOC 212 category. SOC 212 includes engineering professionals such as civil, mechanical, electrical, electronics, design and development, and production and process engineers. This is an occupational group where we find a large share of ads with HTE being mentioned, as traditionally HNC/HND qualifications provided the skills for engineering employment (Field, 2019). Ideally, further analysis would be carried out on a wider range of occupations to provide a more holistic picture of skill needs by qualification in the economy.

### *4.5.2. Wages and skills in engineering jobs – proof of concept*

This subsection reports on the results of an analysis of wages and skills in engineering jobs using BGT data. It aims to explore how the content of engineering jobs varies by qualification, and if employers see the HTE-qualified as providing complementary job roles to employees with degrees, or as potential substitutes. It also looks at skills employers expect the HTE-qualified to possess in engineering jobs. Finally, it examines skills that are seen as the most productive by employers and that could be provided in HTE programmes to make the qualification more relevant and attractive to employers. This analysis takes engineering jobs as an example, but a similar analysis could be performed for other occupations.

We perform analysis on a narrowly defined occupation (SOC digit 3 level) to observe if employers conceive job tasks differently depending on the qualification of the future employee, and to limit the risk that the observed variation in job tasks reflect differences in occupations. We are interested in exploring if employees are expected to perform different roles within narrowly defined occupations depending on their qualifications. For example, employers might want engineers with degrees to undertake more management and supervision, while those with level 4/5 qualifications might be expected to take more responsibility for hands-on-tasks such as technical maintenance of systems and equipment. Such distinction of roles by qualification will have implications for wages, partly because the different tasks are differently priced in the labour market. It could also be that the expected level of diligence, creativity and adaptability applied to nominally the same task (which may be somewhat open-ended) depends on the qualification. If ads do not explicitly mention these skills, and if workers with qualification A tend to have more of these soft skills, and are therefore more productive than employees with a qualification B in performing a specific task, those with qualifications A may be rewarded with higher wages, independently of skills that are listed in job vacancies. Finally, we should bear in mind that even within a narrowly defined engineering occupation (SOC digit 3), there are different specialisations. Some engineers may specialise in IT while others would be experts in civil engineering or aeronautics. The description of the job and the required knowledge and skills would differ depending on the specialisation, for example a job description for a software engineer would normally include more references to various programming languages and frameworks than a job ad for a civil engineer.

The analysis starts with a description of all job vacancies for engineers, including those with and without education, to identify how ads with educational variables differ from the group of ads lacking this information, and to test if the sample with education is representative of all the engineering ads (SOC digit 3 level). Second, it looks at the different skills involved in engineering jobs and explore how these skills relate to the different educational qualifications expected in future recruits by employers, and also how they relate to wages. The objective of this analysis is to identify the engineering skills employers tend to associate with HTE qualifications and degrees, and to pinpoint the contribution of different skills to the firm's outcomes as measured with wages. Next, we analyse the distribution of skills in engineering ads where HTE qualifications are required. This analysis provides a direct indication of the skills that employers expect HTE-qualified workers to possess. Finally, we analyse the co-occurrence of skills to shed more light on the complexity of job tasks in engineering occupations. This analysis is designed to see whether similar skills clustered together (e.g. Python appear with other programming languages only) or if they tend to appear with very different skills (e.g. if Python co-occurs with skills related to management, design, innovation, core engineering knowledge).

*Comparison of engineering job vacancies with and without educational variable*

During the period under study (2014-2019), employers posted 979,252 ads for jobs classified as SOC 212, with 43% of these containing information on educational requirements. Within the full dataset of SOC 212 ads, we compared advertisements with information on education to those without it, to see if findings from the analysis performed on ads with education can be extrapolated to all the ads in the same occupation. The comparison reveals that the ads mentioning education more often specify required experience but are less likely to indicate the wage on offer (see Table 4.8). There are more high earning positions among ads not mentioning education. It is thus possible that the sample with education includes more entry jobs. Vacancies mentioning required educational qualifications also list on average more desired skills than job postings with educational requirements missing. One explanation for this pattern could be that some recruitment efforts like to be more specific for various reasons, and therefore list more skill requirements as well as specific education requirements; other recruitment efforts are less specific, and therefore do not mention education and indicate relatively few required skills. In engineering occupations, ads for entry jobs can be more explicit in terms of skills and knowledge required, whereas senior positions take some skills and educational attainment for granted.

### Table 4.8. Comparison of ads within SOC 212 group with and without education

| | SOC 212 ads with education | SOC 212 ads without education |
|---|---|---|
| Share with experience | 23% | 11% |
| Share with wages | 62% | 67% |
| Wage: 25$^{th}$ percentile | £12.98 | £13.46 |

| | | |
|---|---|---|
| Wage: 50th percentile | £16.35 | £16.83 |
| Wage: 75th percentile | £19.23 | £21.63 |
| Average number of skills | 5.6 | 3.1 |
| Nb of obs. | 418,609 | 560,916 |

Source: BGT data, author's calculations

To define the skill profile of ads associated with different qualifications we rely on thousands of detailed unique skill names that have already been standardised by BGT. To remove the noise resulting from errors in classifying skills and SOC categories, we reduce the size of the skill vector by removing skills with the lowest occurrence - skills that appear in less than 1 percent of ads in the whole sample of engineering jobs (with or without education), all years combined. Djumalieva, Lima and Sleeman, (2018) classify occupations based on skill requirements as provided by BGT. As in this exercise, they tidy up the skill information by removing skills that appear the least. They also remove skills that are the most often found across occupations (e.g. communication, planning, organisational skills). These 'common' skills tend to inflate the skill level in occupations without helping to discriminate between occupations. As our analysis is carried out within a narrowly defined occupation and since we do not use skills to identify occupations, we keep these 'common' skills in our sample. We anticipate finding an overall high occurrence of these skills in the chosen occupation and that their intensity would vary depending on the qualification. After having eliminated skills with the lowest frequency, the skills vector is composed of 223 skills. It includes a wide range of engineering and technical skills such as civil engineering and robotics, computing, and IT skills inherent to many engineering jobs, but also more generic and transversal skills related to management, administration, and communication. (Table A.3.4 in the Annex A.3 shows the most common skills - representing at least 1% of all the skills in online advertisements for engineering jobs.)

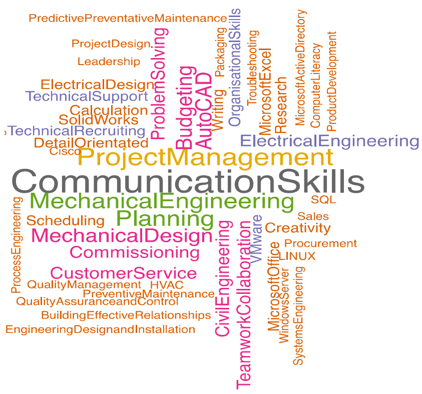
A comparison of the distribution of skills in engineering vacancies with and without educational information reveals that the following skills appear the most often in all the engineering ads, namely: skills such as civil engineering, mechanical engineering and IT skills such as AutoCAD (software used by engineers to draw); managerial skills such as planning and budgeting; and finally the softer skills that help individuals to relate to others and achieve their goals, such as communication skills, teamwork, and organisational skills. As expected, communication skills are very common in ads with and without education (see Figure 4.3). In comparison with ads mentioning education, ads without education seem to involve more management and planning, and advanced programming skills such as SQL and Linux. Knowledge of these IT tools does not necessarily require a formal qualification as these skills can be self-taught or developed through a range of online courses. Both ads that do and do not specify education level set out requirements for industry specific knowledge and soft skills. While there is a lot of overlap in skills between the two groups, differences in the skills distribution should be kept in mind when an attempt is made to extrapolate findings applying to the sample with education to all the ads in the engineering profession.

## Figure 4.3. 50 most common skills in engineering occupations (SOC212) with and without educational requirements (2014-2019)

The size of the text indicates relative prevalence. For example in the sample with education, communication skills, the most commonly mentioned by employers, appears in 26% of ads. The second most common skill – mechanical engineer, is included in 17% and project management in 16% of job vacancies

*With education*


*Without education*




Source: BGT data, author's calculations

### *HTE qualifications and degrees: complements or substitutes in engineering job?*

We explore if employers consider HTE and degree holders as complements or as substitutes. To shed more light on this issue first, we plot a distribution of ads requiring HTE (only) and degree (only) by geographical areas (travel to work distance – TTWA). Second, we analyse the distribution of the two types of qualifications in ads with specific skills to find out which skills employers tend to associate with HTE, and which with degrees.

Of the 418,609 advertisements for engineering positions that mention education requirements, 27% indicate HTE as a desired qualification, including those that mention HTE alongside degrees, (Table 4.9). A glance at the number of skills mentioned on average in ads with different qualification requirements reveals that, as discussed earlier in relation to all vacancies, engineering vacancies where HTE is listed mention, on average, fewer skills than ads with degrees, and also fewer than ads where HTE is listed alongside degrees (Table 4.9).

**Table 4.9. Distribution of qualifications in engineering occupations**

| | Share (%) | Nb of skills on average | Nb of observations |
|---|---|---|---|
| Level 3 and below | 11 | 3.1 | 46184 |
| HTE | 13 | 5.4 | 53386 |
| HTE or degree | 14 | 6.4 | 59769 |
| Degree | 62 | 5.9 | 259254 |

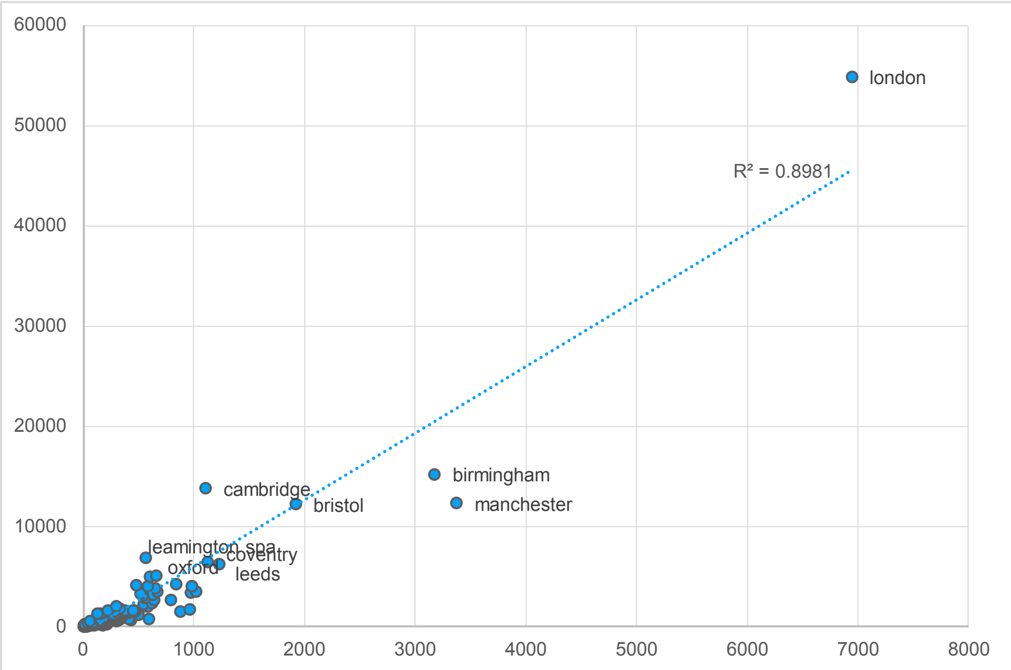
Source: BGT data, author's calculations

To observe the relationship between the demand for degrees and HTE qualifications in engineering ads we plot the distribution of degrees and HTE qualifications (excluding ads that mention both) by travel to work area (TTWA). The plot (Figure 4.4) shows a strong correlation between the two, which may suggest that employers see degrees and HTE qualifications as complementary; but it could also be that in areas where the demand for degrees in engineering occupations is high the demand for degrees exceeds supply. Consequently, employers, in order to meet their needs, are ready to employ HTE-qualified workers in jobs initially targeting degree holders. If the first scenario holds, we should see that jobs targeting HTE-qualified workers involve a different set of tasks than jobs where a degree is required. In the second scenario, whereby firms are ready to employ those with a HTE background in jobs for graduates, we should see an overlap in the job description between ads for graduates and those with HTE qualifications. The two scenarios are not mutually exclusive.

Some TTWAs such as London and Cambridge stand out as having a relatively higher demand for degrees than for HTE qualifications in engineering jobs. These areas probably have more engineering jobs relying on degrees rather than HTE qualifications, and at the same time in these areas there may be enough degree-qualified labour to meet the demand for the corresponding skills. To shed more light on the relationship between engineering jobs targeting graduates and HTE-qualified, we explore which skills employers tend to associate with degrees and which skills with HTE. This analysis involves looking at the distribution of HTE and degrees in ads mentioning specific skills.

## Figure 4.4. Demand for degrees and HTE by travel to work area (TTWA) in engineering jobs, 2014-2019

Vertical axis - engineering ads requiring a degree and above, horizontal axis – engineering ads requiring HTE




Source: BGT data, author's calculations

Next, we are interested in examining the profile of skills posted in engineering jobs. Do employers see specific skills and associated job tasks as requiring a degree or rather a HTE qualification? Which skills are seen as more valuable as measured with wages? In this analysis, we cluster or group skills based on the distribution of qualifications within each skill. The analysis is performed on ads mentioning either HTE only or degrees only. Job vacancies that mention both HTE and degree are excluded. In the selected sample 17% of ads request HTE only, leaving 83% seeking degrees. Most engineering job openings thus target degree holders.

We analyse the distribution of HTE and degree requirements in ads in which a specific skill appears. For example, we select job vacancies that require future hires to perform analytical skills on the job and compute the share of ads asking for HTE qualifications and degrees in this group. We observe that ads mentioning analytical skills mainly seek degree holders, as 91% of ads with analytical skills require a degree and only 9% a HTE qualification. HTE qualifications are even less common in ads mentioning Java skill, as out of all the ads involving Java, nearly 99% of the ads require a degree and 1% HTE qualifications. It should be noted that this analysis does not intend to identify skills that are common in HTE jobs as skills are not weighted depending on their distribution in the whole sample.

To group skills by their education profile – i.e. the comparative shares of HTE qualifications and degrees in ads with a specific skill, we use K means clustering. We opt for this method as it is easy to use, easy to interpret, computationally efficient and offers meaningful insights. A similar approach has been used to identify skills that are associated with STEM jobs in a study of STEM occupations drawing on BGT data (Grinis, 2017).

K-means clustering partitions data points into 'k' groups or clusters drawing on the variables provided. In our case we use only one variable, mainly the share of HTE and degrees in ads mentioning a specific skill. Observations are allocated to groups where other members of the group are most similar to the allocated observations. Each cluster is defined by the mean (centroid) of the data points in the sample. The objective is to minimise the sum of the squared Euclidean distances of each point to its closest centroid, a procedure which minimises the within clusters variance. The number of clusters have to be determined before running the k means clustering algorithm. This determination can be based on prior knowledge. Alternatively, there are various methods of selecting an optimal number of clusters. Grinis (2017) who is interested in the 'STEMness' of the skills, predefine the number of clusters as: STEM skills, non-STEM, and neutral skill. In our k means clustering analysis we use an elbow method to define the number of clusters[48]. In the elbow method the total within clusters sum of squares is a function of the number of clusters. As the number of clusters increases the within cluster variance decreases. We divide the data points into 4 skill clusters as according to our analysis from this point on, adding another cluster decreases the variance only by a small margin (see Figure 4.5).

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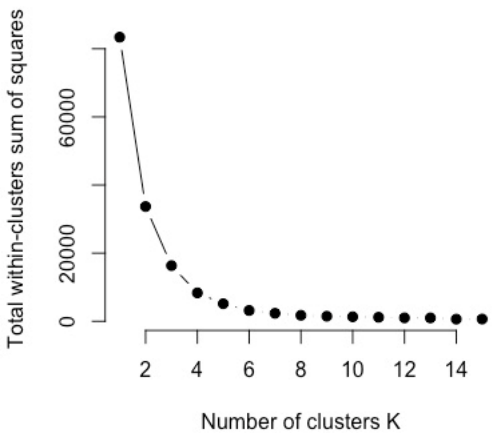
[48] We also run k-means clustering with three predefined number of clusters: HTE, degree and neutral or common skills, similarly to the approach applied by Grinis (2017). However, this approach yields a less nuanced picture of HTE skills than k means clustering with 4 clusters, with very few skills associated with HTE qualifications.

## Figure 4.5. Choosing the number of clusters - Elbow method




Source: BGT data, author's calculations

Table A.3.5 in Annex A.3 shows the distribution of each skill by qualification and the skills clusters they are allocated to.

To interpret the clusters, we look at the average distribution of the qualifications (HTE and degrees) in each cluster. This approach allows four groups of skills to be distinguished by the strength of their association with HTE qualifications: from the skills strongly associated with HTE to skills with hardly any association with HTE, and two intermediary categories. As the association of skills with HTE qualifications decreases, the association with degrees on the contrary rises, i.e. skills that have hardly any association with HTE are strongly associated by employers with degrees. Table 4.10 shows the average distribution of qualifications in each cluster.

## Table 4.10. Skills Clusters and their implications for qualifications

Advertisements mentioning HTE only or degree only. Figures for each cluster show the percentage distributions of all advertisements in the cluster as between those mentioning HTE and those mentioning degrees.

| Cluster | Percentage of ads requiring HTE (only) | Percentage of ads requiring degree (only) |
|---|---|---|
| Skills with hardly any association with HTE | 6.36253 | 93.63747 |
| Skills weakly associated with HTE | 18.32357 | 81.67643 |

| | | |
|---|---|---|
| Skills moderately associated with HTE | 34.49432 | 65.50568 |
| Skills strongly associated with HTE | 69.39387 | 30.60613 |

Source: BGT data, author's calculations

The cluster of skills with hardly any association with HTE includes skills that most of the time are associated with the expectations of a degree qualification. The associated skills will here be called 'degree' skills. Degree skills represent 30% of all the skills appearing in the engineering job vacancies (sample with education variables). Degree skills tend to refer to core engineering elements of knowledge such as knowledge of the electronics industry and civil engineering. In comparison to the three other clusters, 'degree' skills also involve more programming and advanced computing skills (data analysis, Java, Linux, SQL, Python, C). They also have a stronger focus on research and development of new products and ideas. In the group of skills weakly associated with HTE, around one ad in five mention HTE as a required qualification. This group includes occupation specific skills such as electrical engineering and automotive industry knowledge; soft skills referring to personality traits such as attention to detail and the capacity to work with others, knowledge of basic Microsoft programmes (e.g. Excel, Word) as well as more specific engineering software such as CATIA. Skills in this group also refer to managerial tasks such as budgeting, contract review and management of staff. These skills make up more than half (56%) of all the skills in engineering ads. Finally, clusters of skills moderately and strongly associated with HTE correspond to technician skills such as cabling, hydraulics, welding, water treatment and mechanical maintenance, but also to managerial skills such as engineering management and costing. Skills that are strongly and moderately associated with HTE represent 2% and 12% of all the skills (sample with education) in engineering occupations respectively.

The distribution of qualifications by skills shows that employers in engineering occupations consider few skills as purely HTE related. Conversely, they associate many job tasks with degrees and are unlikely to look for HTE-qualified to fill jobs including these job tasks. However, a picture of employers' preferences regarding the number of other engineering skills (weakly and moderately associated with HTE) is more nuanced. While overall, employers are more likely to consider these skills as degree skills some are open to recruitment of the HTE-qualified to fill the corresponding job roles. This difference in preferences may be explained by firms' characteristics such as firm size, geographical location, and industry sector. For example, the supply of graduates varies locally, which affects the chances of filling the position with degree holders.

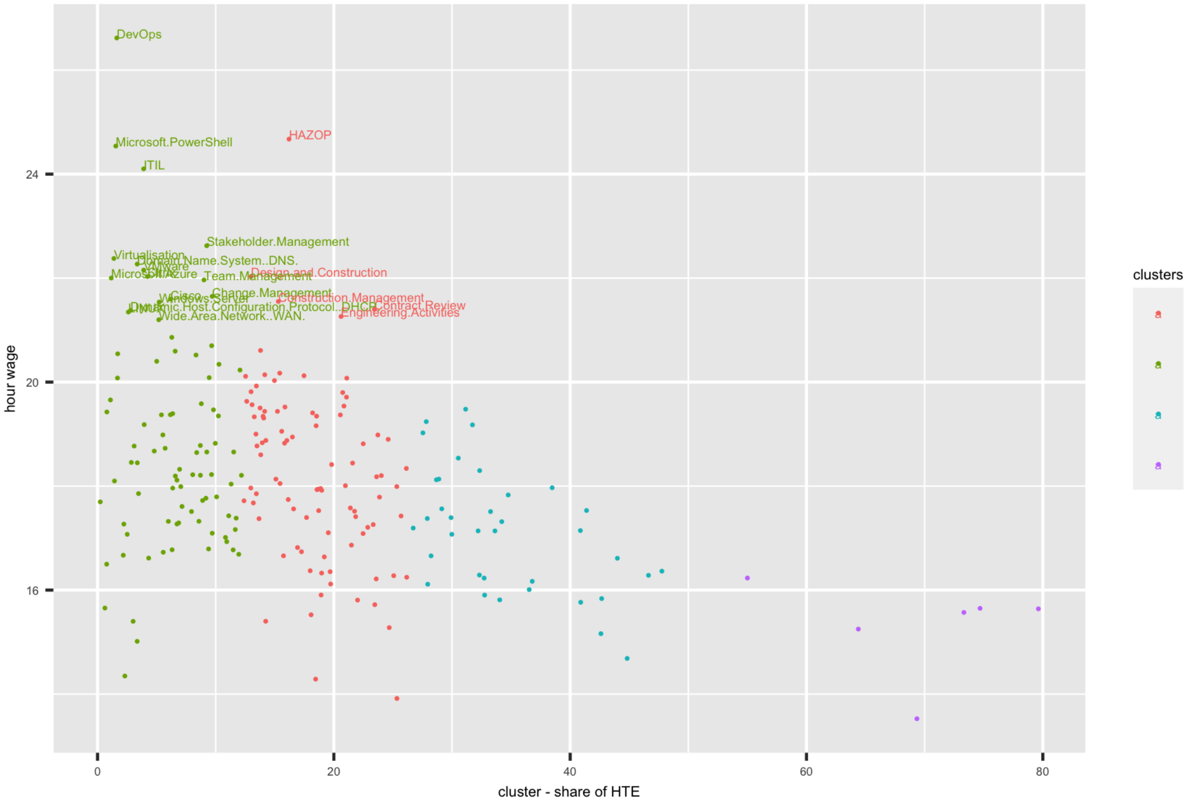
To classify skills according to the value employers attach to them by looking at the association of skills with wages. We may expect that employers will pay more for skills which, in their view, contribute most to the production process, and where the demand for labour exceeds supply. This exercise examines the value of skills in different clusters and explores whether employers consider 'degree' skills as more productive than skills that are strongly or moderately associated with HTE.

The Figure 4.6 below plots hourly wages against the skills in engineering jobs (vertical axis), and the skill clusters - how common the skill is in ads targeting HTE as compared to ads requiring degrees. The colours correspond to clusters, with red standing for skills weakly associated with HTE (cluster 1), green (cluster 2) referring to degree skills (skills with hardly any association with HTE), and blue and violet (cluster 3 and 4) corresponding to skills moderately and strongly associated with HTE. The chart shows that, on average, degree skills pay the most, followed by skills that are weakly associated with HTE. Among top paid skills are those requiring engineering knowledge, programming and advanced IT and programming skills (e.g. Dev Ops, Citrix, ITIL), and managerial skills (stakeholder management, team management). Skills moderately and strongly associated with HTE qualifications attract lower salaries on average.

This analysis of wages in relation to skills provides an indication of which skills are most demanded by employers and yield large returns to individuals. This information may guide the providers of HTE programmes in their choice of programmes to offer, and more importantly, the skills which it would be most useful to teach in these programmes. For example, high returns to programming skills may encourage HTE providers to address programming skills fully in their teaching programmes and qualifications.

### Figure 4.6. Engineering skills, hourly wages, and skills/qualification clusters

In this scattergram each data point represents a skill. Data points are placed in the scattergram in relation to average hourly wages offered in the advertisements citing that skill (vertical axis), and (horizontal axis) the percentage of ads mentioning a requirement for an HTE qualification. The colours indicate the skills cluster.




Note: Skills associated with an hourly wage of at least £20 are named.

Source: BGT

The aim of the above analysis was to examine skills in engineering jobs and explore if employers were more likely to associate specific skills with degrees or HTE qualifications. This analysis revealed that employers associate a number of skills with degrees and many of these degree skills attract the highest salaries. A few skills, typically those associated with relatively low wages, targeted HTE qualifications. These skills may thus be concentrated in less productive jobs. Some other skills appear in ads for graduates and in ads for the HTE-qualified though to a lesser extent. Employers therefore have a preference for degree holders as regards the majority of engineering tasks, but in some circumstances they are open to recruiting the HTE-qualified, because of the employer's geographical location, company characteristics or other reasons.

Another way of analysing HTE skills is to explore the distribution of skills in job vacancies which only specify HTE as a qualification requirement. The aim here is to identify those skills appearing the most often in engineering jobs targeted at the HTE-qualified. The analysis of skills distribution in ads asking for HTE shows that core engineering skills, such as mechanical and electrical engineering, managerial and some soft skills, are at the heart of engineering jobs targeting the HTE-qualified. For example, mechanical engineering skills appear in 22% of ads requiring HTE qualifications. This information can be seen as a check list for providers and individuals with HTE qualifications preparing for careers in engineering of key engineering skills, skills that employers expect the HTE-qualified to be equipped with (Table A.3.6 in Annex A.3)

### *4.5.3. Skills association*

Until now we looked at individual skills in isolation. However, this is not very realistic as typically a job vacancy describes a range of expected skills in potential recruits. Some skills are more likely to appear in combination with others. Observing such co-occurrence of skills helps to identify the skill content of engineering jobs with more precision. For example, programming skills are among the skills attracting the highest wages in engineering job openings. We are interested in exploring further if these skills are required in combination with some other non-programming skills, such as core engineering skills and soft skills, or whether they tend to be accompanied mainly by other programming and IT skills. The first scenario would mean that engineering jobs are more complex in the sense that job roles in engineering require diverse and complex skills. The second scenario points to the concentration of closely related skills in a limited number of job roles. These two scenarios have different implications for the providers of HTE programmes. In the first scenario, the provider would need to ensure that students develop an appropriately broad range of diverse skills. In the second scenario, the provider should focus on equipping students with a limited range of interrelated technical skills, such as programming skills. We do not pretend that this analysis captures all skills that are part of engineering jobs. Some skills may not be mentioned in the ad because employers do not include them in the job description (e.g. these skills may be difficult to verify during the recruitment process) or because they are not captured by the search algorithm.

The study of co-occurring words is used in natural language processing. It is based on an assumption that we can learn about the use of words by looking at its neighbours. Gries & Durrant (2020) distinguish lexical co-occurrence "i.e. the co-occurrence of words with other words such as the strong preference of hermetically to co-occur with, or more specifically, be followed by" (Gries & Durrant, 2020, p. 142), and lexico-gramatical co-occurrence, "i.e. the co-occurrence of words with grammatical patterns or constructions" (Gries & Durrant, 2020, p. 142)

We are interested in the lexical co-occurrence of skills at the job vacancy level. In this analysis we do not match skills ourselves but use the skill variable provided by the BGT. Finding how often different skills occur together in the same ad would be the simplest way to do this.  This would allow us to identify pairs of skills appearing the most often in job ads but does not provide any information on the strength of this relationship, i.e. whether these two skills are more likely to appear together than with other skills? For example, skills that frequently appear in engineering ads, such as communication skills, can be found in association with many skills, without these relationships being necessarily meaningful. Niekler and Wiedemann (2017) in their tutorial of co-occurrence analysis argue that "frequency is a bad indicator of meaning constitution".

Niekler and Wiedemann (2017), alongside others (Gries & Durrant, 2020; Terra & Clarke, 2003) recommend methods such as log-likelihood to examine the link between two words. Log-likelihood is also an approach that we use to examine the co-occurrence of skills in engineering job ads. This approach compares the co-occurrence of skill A and skill B to the co-occurrence of skill A with 'skills -B' (all skills other than B). If probability (A) * probability (B) = probability (A) * probability (-B), the two skills occur independently. If on the other hand, probability(A)*probability(B) ≠ probability(A)*probability(-B) they are not independent (Terra & Clarke, 2003).

Following Schweinberger (2022) we look not only at the significance but also the sign of the association between two skills, i.e. we explore skills that attract and repel each other.

To demonstrate the analysis of skills co-occurrence we chose skills appearing commonly in ads requiring HTE, such as communication skills and the skills required in mechanical engineering. We also examine skills appearing in combination with 'DevOps', the skill that yields the highest wages in the whole sample of engineering ads (degrees and HTE combined). DevOps is a set of practices articulated more than ten years ago to combine software development and IT operations (such as software deployment, maintenance, and updates), which in the past were seen as separate job roles. DevOps is clearly a skill that is related to IT sectors. By looking at co-occurrence of DevOps with other skills we therefore test if high level IT and programming skills are transversal or tend to be concentrated in job roles focusing on programming and IT mainly. In the Annex we report the results for all three selected skills if the associations are significant at least at 0.001 level. (Annex A.3 Tables A3.7-A3.9)

Analysis of the co-occurrence of skills associated with mechanical engineering in HTE ads reveals that mechanical engineering skills are often mentioned alongside technical skills such as mechanical maintenance, hydraulics, and automotive engineering. More general knowledge and skills such as physics and calculation are also positively correlated with mechanical engineering tasks. Familiarity with software such as SolidWorks, CATIA, Autodesk, CAD seems to be required alongside mechanical engineering skills. Ads requiring mechanical engineering skills may also involve contracts and facility management and ask for soft skills such as creativity and attention to detail. These are thus competences that employers expect HTE-qualified workers to demonstrate in jobs involving mechanical engineering. Mechanical engineering skills rarely co-occurs with skills such as civil or electronic engineering skills, probably because civil engineering and electronic engineering refer to different job roles. High level IT and programming skills as well as team management, and leadership are also unlikely to be posted in ads targeting mechanical engineering skills. Overall, jobs with mechanical engineering tasks require a range of technical skills and occasionally some mid-level management skills.

### Table 4.11. Skills co-occurrence with mechanical engineering tasks in engineering ads requiring HTE

Ordered by the strength of the association

| Skills over-proportionally used with mechanical engineering | Skills under-proportionally used with mechanical engineering |
|---|---|
| SolidWorks | Civil Engineering |
| Mechanical.Maintenance | Electrical.Design |
| Teaching | Highway.Design |
| Hydraulics | Electrical.Engineering |
| Welding | Electronics.Design.and.Engineering |
| X3D.Modelling...Design | Human.Machine.Interface..HMI. |
| Boilers | Programmable.Logic.Controller..PLC..Programming |
| Machining | Quality.Management |
| Water.Treatment | Siemens.Nixdorf.Hardware |
| Forklift.Operation | Software.Architecture |
| CATIA | Cabling |
| Autodesk | Electronic.Engineering |
| HVAC | PCB.Layout.and.Design |
| Catia.V5 | SCADA |
| PTC.Creo | Schematic.Diagrams |
| Product.Design | Design.and.Construction |
| Calculation | Quality.Assurance.and.Control |
| Engineering.Drawings | Test.Equipment |
| Manufacturing.Processes | Telecommunications |
| Computer.Numerical.Control..CNC. | Wiring |
| Predictive...Preventative.Maintenance | Electronic.Design |
| Preventive.Maintenance | Civil.3D |
| Ventilation | Drainage.Design |
| Computer.Aided.Draughting.Design..CAD. | Circuit.Design |
| Engineering.Management | Electrical.Diagrams...Schematics |
| Client.Base.Retention | Systems.Engineering |
| Technical.Recruiting | Planning |
| Pro.ENGINEER | Microsoft.Project |
| New.Product.Development | Electrical.Systems |
| Automotive.Engineering | Project.Management |
| Power.Generation | Six.Sigma |
| Plumbing | Microsoft.Office |
| Packaging | Construction.Management |
| Enterprise.Resource.Planning..ERP. | Engineering.Activities |
| Engineering.Support | People.Management |
| Bill.of.Materials | Network.Engineering |
| Product.Development | Embedded.Software |
| Physics | Prioritising.Tasks |
| Purchasing | Site.Investigations |
| Industrial.Engineering.Industry.Expertise | Negotiation.Skills |
| Detail.Orientated | Microsoft.Excel |
| Creativity | C.. |
| Engineering.Design.and.Installation | Software.Development |
| Engineering.Design | Site.Surveys |
| Process.Design | Microsoft.Active.Directory |
| AutoCAD | LINUX |
| Facilities.Maintenance.Industry.Knowledge | Team.Management |
| Contract.Management | Transmission.Control.Protocol...Internet.Protocol..TCP...IP. |
| Sales.Engineering | Stakeholder.Management |
| Project.Engineering | Writing |
| Facility.Management | Budgeting |
| | Software.Engineering |
| | Commissioning |
| | Written.Communication |
| | Microcontrollers |
| | Cisco |
| | Microsoft.C. |
| | Hardware.Experience |
| | VMware |
| | Decision.Making |
| | Teamwork...Collaboration |
| | Verbal...Oral.Communication |
| | Digital.Design |
| | SQL |
| | Python |
| | ITIL |
| | Change.Management |
| | VHSIC.hardware.description.language..VHDL. |
| | Windows.Server |
| | Microsoft.Exchange |
| | Environmental.Engineering |

Mentoring
Scheduling
Building.Effective.Relationships
Microsoft.Powerpoint

The analysis of co-occurrence of communication skills in engineering ads for HTE-qualified, shows that these skills appear in combination with other skills related to interacting with others, either within the work organisation or with actors from outside the workplace (e.g. customers, stakeholders). Conversely, they are much less likely to appear together with technical skills.

Finally, DevOps, the skill associated with the highest wages co-occur with a limited number of skills mainly related to programming. Teamwork and collaboration, and being a self-starter are also mentioned by some employers together with DevOps. DevOps is under-represented in ads requiring technical and core engineering skills. It is also negatively associated with management skills, sales, and customer service and many skills referring to the personal characteristics and capacity to work with others. Analysis of DevOps in relation to other skills demonstrates that programming skills tend to be concentrated in specific job roles and that DevOps cannot be considered as a transversal skill.

The analysis of co-occurrence of selected skills in engineering ads shows how it can inform providers and students in preparing for engineering careers. It points to a combination of skills that students should be taught, including core engineering and IT skills but also other more transversal skills such as creativity, and skills in sales and management.

## 4.6. Conclusions

Analysis of the SES and LFS data aimed to identify trends in labour market outcomes to HTE qualifications and in tasks performed by HTE holders. The analysis of BGT on pooled year data (2014-2019) provides a direct measure of the employers' demand and demonstrates how online job vacancies can be used to inform policy makers, providers, students and companies. A very large number of observations permits an analysis of employers' preferences at a detailed level, within specific occupations and by geographical areas.

The analysis of BGT data shows that a small percentage of job vacancies in England mention HTE qualifications, which is consistent with our previous findings demonstrating that HTE-qualified represent a relatively small share of the labour force in the UK (bearing in mind limitations of such a comparison). BGT data also shows that ads requiring HTE qualifications promise higher wages than ads mentioning lesser qualifications but lower wages than job vacancies targeting graduates, which is again consistent with literature on outcomes to HTE (see Chapters 2 and 3). Interestingly, the highest wages are observed in jobs ads mentioning both HTE and a degree. These ads also mention more skills on average than ads requiring only a degree or a HTE qualification. A combination of skills typically associated with HTE and degrees may thus the most sought after by employers.

To demonstrate how BGT data can be used to explore specific occupations we analyse job specific tasks and qualification requirements, as defined by employers, within an engineering occupation defined at SOC digit 3 level. Engineering occupations have traditionally been targeted by HTE qualifications and HTE qualifications are relatively common in BGT engineering jobs ads. We show that employers associate many skills listed in engineering vacancies with degrees and few tasks are seen as proper to HTE qualifications. Wage exploration demonstrates that 'degree' skills attract the highest wages, which suggests that employers consider these skills as most productive. Conversely, skills that are associated by employers with HTE appear in ads with the lowest wages. Employers thus have a strong preference for degree holders in engineering jobs involving highly paid and presumably the most productive tasks. Employers may require degrees rather than HTE qualifications because there are no HTE programmes targeting these skills. It can also be that the corresponding HTE programmes are available but those who complete them have a poor mastery of the skills as compared to graduates. Depending on the underlying cause, policy makers and providers may aim to develop engineering programmes delivering skills in high demand. If these programmes already exist it can be explored how to ensure completers of these programmes are proficient in the associated skills.

While some skills found in engineering jobs are overall more likely to be matched with degrees, sometimes they appear in combination with HTE qualifications. Some employers are thus open to hiring HTE-qualified to perform the associated tasks. Employers may want to hire HTE-qualified instead of graduates because in their area the supply of graduates is insufficient and a supply of the relevant HTE qualifications is high, for example because the local HTE providers offer the corresponding programmes. There might also be differences across employers. Graduates may prefer to work for big companies, often seen as more attractive to work for (in terms of salary, benefits packages and long-term career opportunities), leaving small companies with fewer candidates for jobs. Further research could explore these issues in more depth to identify factors favouring HTE-qualified labour.

This analysis can also inform companies' recruitment policy, by pointing to skills that are most in demand in the industry and revealing information about latest technologies and methods of working. This information may be particularly helpful to smaller companies that may not be fully aware of the most recent development in the area. Firms that do not have a well-developed human resources policy may also struggle with translating industry needs into recruitment policy and with the analysis of skill needs among the current employees. Furthermore, analysis of job vacancy data also provides an indication of what employers can expect from workers with different qualifications and which qualifications they should target in the recruitment, assuming that an association of qualifications and skills found in job vacancy data provides a fair description of the skills endowment among workers with different qualifications. Finally, analysis by distribution of skills and qualification across geographical areas can support firm's investment decision by pointing to areas with a large pool of labour with the desired characteristics, again assuming that job vacancy data are a good proxy for the geographical distribution of skills.

# 5 Discussion

Degrees (level 6 and above) have become more costly over time, both to individuals and to government, and a worrying proportion of HE graduates end up in jobs which are not normally considered as graduate jobs (GOV.UK, 2022). Since HTE programmes are shorter and so less costly than degrees, an expansion of HTE as a quality alternative to three year degrees might be seen as cost-effective, both from the point of view of the individual and the public purse. HTE qualifications are also often thought to facilitate entry to the labour market as they tend to be more applied and target specific jobs.

However, the demand for degrees shows little sign of faltering. The number of young people in England aiming to enter university in 2022 has hit record levels (UCAS, 2022). In an economic downturn, degrees may often be perceived by young people as the best protection against an uncertain future. This year (2022), although the most selective institutions have cut the number of places available and overall student enrolment has dropped, the 2022 university entry is the second highest on record (Hall, 2022). The demand for HE is expected to be maintained next year, not least because of an increase in the size of the youth cohort.

Entry to HTE programmes in England has increased too, though more slowly than at higher levels. In 2020/21, entry to level 4 and level 5 programmes grew by 3% and 6% respectively as compared to the previous year. But the comparable figure for level 6 was 10%, and 22% for qualifications at level 7 (GOV.UK, 2022).

The UK government envisages an expansion of shorter post-secondary qualifications. The intention is to identify those level 4 and 5 qualifications that match employers' demand for skills and rebranding them as higher technical qualifications (HTQ), approved by the Institute for Apprenticeship and Technical education and open to government funding. Individuals pursuing level 4 and 5 qualifications will be entitle to lifelong loans. Importantly, the reform establishes a parity between level 4 and 5 qualifications and degrees in terms of funding (Foster, 2019). For example, maintenance support will be available to all students taking level 4 to 6 qualifications, whereas in the past such support was only available to some students in programmes leading to level and 5 qualifications (Bolton and Hubble, 2019).

For an increase enrolment in HTE, as envisaged by the government, to make sense, it is important to understand the market value of these qualifications. The comparison with degrees is particularly relevant as HE graduates often seek to enter similar jobs as the HTE-qualified and the rising supply of graduates makes the competition for these jobs even fiercer. Individuals have incentives to prefer degrees to HTE if they perceive degrees as better value for money. This perception might be accurate, or be a misperception, because students are not fully informed about opportunities associated with HTE qualifications. Previous policy reviews argued that public policy in the past has tended to favour degrees and increased their visibility (Wolf, 2015; Augar, 2019). Other research looked at returns to various vocational and academic qualifications and found that overall HTE yields positive returns, though varying depending on the area of study.

This research contributes to this discussion by looking at the outcomes from HTE in different time periods and by identifying trends in the demand for HTE relative to the demand for other qualifications, including degrees. Positive returns to HTE qualifications found at one point in time, as reported by the literature, do not tell us about time trends.  Any negative trend, if identified, would argue for a scrutiny of the quality of HTE provision to ensure continued labour market relevance – a scrutiny which is already in train (Institute for Apprenticeships and Technical Education, 2022) . This research aims to inform this scrutiny by pointing to strengths and weakness of the HTE qualifications and by providing tools showing how the value of HTE qualification on the labour market might be increased.

This research examines labour market outcomes using the indicators of employment opportunities and wages, whereby wages are an expression of individual productivity. The Mincerian wage function, explaining wages through a combination of educational attainment and work experience, provides a theoretical framework for this investigation. The research also looks at job tasks and the skills required to perform those tasks to evaluate the complexity of jobs. The skills that attract the highest wages are associated with occupations 1-3 (1 digit) in the SOC classification, and are considered as more complex and more productive.

The research mobilises three datasets: the SES, LFS and BGT, which are a source of complementary information on the demand for education and skills. In analysing tasks performed by jobholders over time the research exploits the fact that the SES and LFS provide consistent worker-level data in different time periods, while the BGT contains information on millions of job vacancies. The research explores the labour market performance of HTE-qualified workers over the last twenty years in the context of a rapidly rising supply of degree holders and the spread of new technologies in workplaces. In particular, it explores the interplay between qualifications, the tasks performed on the job and the skills necessary to undertake those tasks, and their relationship with wages.

Below we summarise the findings from the three studies as well as describing their limitations. We suggest some possible interpretations of the findings and describe the policy implications. Finally, we propose avenues for further research.

## 5.1. Summary of findings

### *5.1.1. The overall picture: a displacement of workers with HTE qualifications*

The findings point to a gradual displacement of the HTE-qualified from many skilled occupations in response to an influx of degree holders. They also imply that the growth of employment in more skilled occupations is associated with an increase in the number of graduates in the labour market. If we assume that the growth in skilled employment was exogenous (e.g. new technologies increased the demand for individuals equipped with high level skills), this mainly benefited degree holders rather than the HTE-qualified. In other words, newly created jobs with more demanding skills were filled by graduates. Alternatively, the growth in more skilled jobs might not have been driven by technology, or not exclusively, but instead simply by the increasing availability of more skilled labour through an inflow of graduates to the labour market. However, regardless of the source of growth, these findings point to a falling demand for HTE relative to the demand for degrees. Part of the declining demand is due to an upgrade of formal entry requirements from HTE to degree level in occupations such as nursing and teaching.

The changing distribution of tasks performed on the job by the HTE-qualified provides an additional and illuminating perspective on their eroding position in the labour market. In recent years the HTE-qualified have become less and less likely to perform the kind of tasks that are associated with high wages. Within a narrowly defined engineering occupation, employers tend to associate the HTE-qualified with fewer and less paid job tasks. However, the returns to HTE are highly variable; some specialisations such as in engineering and manufacturing have recorded constant labour market outcomes over time.

### *5.1.2. The HTE-qualified have suffered from a downgrade of skills applied on-the-job*

Confirming previous research, this study has shown how some of the tasks performed in the workplace have a stronger association with wages than others, and has described how these tasks are distributed among those with different levels of qualification (including HTE). Tasks involving complex cognitive, managerial and computer skills, and tasks requiring specialist knowledge show the strongest positive association with wages and education level.

The results show that jobholders with HTE qualifications earn more than those with lower qualifications but less than graduates. After accounting for differences in the mix of job tasks performed by those at different levels of qualification, the gap in wages between HTE-qualified workers and those with lower and higher-level qualifications diminishes. Part of the difference in wages between HTE and other educational groups may thus be attributed to the exact nature of the jobs with education mediating selection into different job roles.

However, for those who report having exactly the same job-related skills but different qualifications, HTE holders still earn around 19% less than graduates and 10% more than those with the lowest level of education. Other features associated with the specific qualifications, such as the precise quality or level of skills, therefore drive the wage premium. It could be because education contributes to the development of knowledge and social capital that are not captured in the data but that are used on the job and hence are associated with earnings. It could also be that education is associated with other characteristics that are unobserved such as family background and individual ability.

The research suggests that some job-related skills attract different wage premia depending on the qualification of the worker. During the period of interest, HTE-qualified workers benefited more than any other educational group from using specialist knowledge and understanding on the job. This implies that to make full use of this potential, HTE provision should be strongly connected to the world of work and provide skills that can be directly applied in the workplace. Inclusion of good quality work-based learning in HTE programmes would be one way of achieving this objective. HTE-qualified workers also benefited from 'intensively using analytical skills on the job'.

An exploration of how job-related skills have changed over time among those with HTE qualifications, as compared to the total population, shows that the HTE-qualified suffered from a downgrade in terms of skills applied on-the-job. While an average, workers performed more of the type of complex work tasks that are positively associated with wages over time, the share of these tasks carried out by employees with HTE remained constant. Hence, the match of the skills of those with HTE qualifications to the skills required in well paid jobs seems to deteriorate over time. An increase in the share of less skilled tasks (such as use of physical strengths) performed by HTE holders might have happened because of a shift of HTE-qualified workers into less skilled employment. One cannot however, deduce from this whether this is driven by a) changes in the mix of skills typically found among the HTE-qualified, or b) by changing demand for such skills, or c) the changing way that different types of people select, or are channelled into HTE.

### *5.1.3. The HTE-qualified are less likely to work in skilled technician jobs than in the past*

The analysis shows that, on average, the level of tasks performed by the HTE-qualified has been relatively high. But the findings suggest that, in this respect the position of HTE holders as compared to other groups, and in particular graduates, has weakened over time in some occupations. This trend is observed in skilled professional and technical occupations (SOC major groups 2-3), occupations that HTE programmes traditionally prepared for. This may imply that in these occupations, the relative productivity of individuals with HTE qualifications and therefore the demand for these qualifications fell over time. Any such decline in productivity could be driven by multiple factors. These factors could include variously: an increasing mismatch between the skills offered by HTE programmes and labour market requirements; decline in the quality of HTE provision – for example because of falling teaching quality; and declines in the ability of HTE students on entry to the programmes, and therefore as HTE completers.

Analysis of wage trends in occupations in the SOC major group 3 is particularly telling, as many jobs in this category have traditionally been undertaken by HTE-qualified workers, and workers with HTE qualifications might be substituted by degree-educated workers in many occupations in this sector. It can be reasonably assumed that a degree holder with a specialisation matching the industry sector of the job should be able to carry out tasks on the job requiring skills below degree level. The share of graduates in occupations SOC major group 3 has been rapidly increasing at the expense of the HTE-qualified, implying falling demand for the HTE-qualified in this sector. In contrast, the wages of workers with HTE qualifications relative to degree-holders, was the highest in semi-skilled trade occupations (SOC major group 5) e.g. in jobs of boat and ship builder, vehicle painters, welder, plumbers. Jobs in this group are less demanding in terms of general knowledge than more skilled occupations (SOC major group 1-3), however they often require technical knowledge and mastery that is typically provided through an extended period of vocational training or work experience. HTE programmes are often more applied and practical than degree programmes and often build on existing level 3 vocational qualifications. HTE-qualified employees may therefore have more of the technical expertise required in semi-skilled trade jobs and thus be more productive than individuals with other qualifications in these occupations. In service occupations (SOC major group 6 and 7), the relative wage of HTE holders was lower than in semi-skilled trade occupations, both as compared to graduates and compared to those with lower level qualifications.

The research shows that the HTE workers who have been displaced in skilled jobs by degree holders privileged semi-skilled trade occupations, in which their relative wage was the highest. In these semi-skilled trade occupations the share of workers with HTE qualifications indeed increased over time. More surprisingly, the share of HTE holders also grew in service sector jobs. It therefore could be that some HTE programmes fail to provide skills that cannot be easily provided by workers with other qualifications, and that graduates pushed some of the HTE-qualified out of skilled employment into service sector jobs where employment has been rising.

These findings point to an erosion of labour market demand for HTE, relative to degrees. The main factor here is changes in the economy and the labour market. However, one other possibility is that HTE has experienced declining visibility on the labour market relative to degrees.

### *5.1.4. Labour market outcomes depend heavily on the field of study*

Outcomes to HTE qualifications are not homogenous, but vary according to the area of specialisation. The earnings of the HTE-qualified declined over time across many areas of specialisation or at best remained constant. Specialisations in teaching and health saw a sharp drop in earnings, and experienced worsening employment prospects over time. While these negative trends could reflect changing cohort characteristics, more likely they result from the introduction of a degree requirement for entry into teaching and nursing professions. Individuals with engineering and manufacturing specialisations show the strongest employment outcomes. The results show that their earnings have been constant over time and they have been less affected by employment loss than some other specialisations and during the downturn.

### *5.1.5. In the engineering sector employers associate more productive tasks with degrees, but under some circumstances are open to employing the HTE-qualified*

The research study further explored the skills associated with HTE qualifications by looking at BGT online job vacancy data. These data offer an indicator of the skills and characteristics employers want to see in their recruits. Analysis of a narrowly defined occupation of engineers (at SOC 3 digit level) shows that employers associate many skills listed in engineering vacancies mainly with degree level qualifications. Some skills are mostly mentioned in online vacancies in association with an employer's expectation for both degree-level and HTE-level qualifications. Few skills are seen as specific to HTE qualifications in the sense of appearing mostly in connection with employer expectations that their recruits will have HTE qualifications (without mentioning degrees). Engineering skills linked to graduate status attract the highest wages, which suggests that employers consider these skills as most productive. Conversely, many of the skills that are associated by employers with HTE are mentioned in ads with the lowest wages. Employers thus have a strong preference for degree holders in engineering jobs involving highly paid and presumably the most productive tasks. Various explanations for this finding are possible. Employers may require degrees rather than HTE qualifications because HTE-qualified workers are not equipped with the required skills. There could be a shortage of HTE programmes that develop the required skills. Alternatively, it might be that appropriate HTE programmes are available but those who complete them have a poor mastery of the skills as compared to graduates, so that HTE acts as a signal of lower skills independently of the content of the HTE programmes. One implication is that regardless of the factors involved, engineering programmes at both HTE and degree level need to concentrate their attention on the skills which employers are signalling will attract the highest wages.

While some skills found in advertisements for engineering jobs are overall more likely to be associated with a recruiter's expectation of a degree, sometimes they appear in combination with HTE qualifications. Some employers are thus open to hiring an HTE-qualified person to perform the required tasks. Employers may want to hire HTE-qualified employees instead of graduates because, at least in their location, the supply of graduates is insufficient and a supply of the relevant HTE qualifications is high, for example because local HTE providers offer the corresponding programmes. There will also be differences across employers. Graduates may prefer to work for large companies, often seen as more attractive (in terms of salary, benefits packages and long-term career opportunities), leaving small companies with fewer candidates for jobs. Further research could explore these issues in more depth to identify the factors which may, at least in certain niches of the labour market, favour HTE-qualified labour.

### *5.1.6. Variations in labour market outcomes by qualification persist after accounting for ability*

Wage gaps and differences in employment rates between population groups with different qualifications can be due to selection by ability into different programmes, rather than to differences in the skills acquired during programmes. To control for this factor, the LFS analysis of wages and employment opportunities account for GCSE achievement. The results show that in the population with similar GCSE results, a gap in wages between graduates and HTE-qualified widened over time and the degree wage premium, relative to HTE, was higher in more skilled occupations than in occupations requiring lower levels of skill. There was thus no decline in the demand for degree holders in more skilled employment, despite the quickly rising supply of graduates. After accounting for GCSE results, employees with HTE qualifications earn on average 21% less than graduates, but 21% more than the level 2 and 3 qualified and 38% more than the workers with the lowest qualification level. The wage premium after adjusting for GCSEs could be interpreted as the added value of obtaining a higher-level (degree) qualification, reflecting new and more complex skills that are rewarded on the labour market. This could be because of the sustained impact of technology on the production process, as suggested by the STBC model. Technology, which increases the complexity of task requirements in workplaces, would, under this explanation, drive the labour market demand for degree holders who are more productive in the new tasks. But the sustained wage advantage of graduates over the HTE-qualified may also be a sign of the falling productivity of the marginal HTE student, as some students who now opt for a university path would, in the past, have been enrolled in a HTE programme.

## 5.2. Limitations of this research

The research shows a declining labour market performance of individuals with HTE qualifications, relative to those with degrees, but it does not establish a causal relationship between HTE qualifications and worsening labour market prospects. To prove that HTE qualifications lead to lower wages and employment opportunities than degrees, individuals would need to be allocated randomly into different post-secondary paths. This is obviously not the case as various factors, such as socio-economic and ethnic background of the person, and individual ability, affect educational choices. To reduce omitted-variable bias, ability is proxied with GCSE results in the study drawing on LFS data. However, we cannot establish with certainty that the GCSE variable accounts for all the variation in ability among individuals.

Our research looks at the labour market demand for qualifications over time by analysing labour market performance across different cohorts. While year dummies capture some of the changing labour market conditions such as economic recession that affect wages and employment opportunities, we do not observe changing cohort characteristics by qualifications. For example, if individuals who in the past were choosing HTE now are more likely to opt for degrees, we may see a falling average ability among recent completers of HTE programmes. As ability is correlated with education and labour market outcomes, a drop in average ability among HTE-qualified will very likely be reflected in their labour market outcomes. The BGT analysis may also suffer from the omitted-variable bias as we do not control for the employer characteristics. These limitations do not in any way invalidate the research results, and the similarities between the findings from three analyses of three different datasets are an important point of confirmation. However, the limitations point to the need to look carefully at alternative possible explanations for the observed relative weakening in labour market outcomes to HTE.

### 5.2.1. Future directions on research

Further explorations relying on techniques other than the one privileged in this research would be required to eliminate the omitted variable bias and confirm with certainty that the observed decline in labour market outcomes among HTE qualified is solely due to individuals investing in HTE qualifications rather than degrees. Below we discuss two approaches that could be envisaged to address these shortcomings and to demonstrate a causal relationship between education and the associated labour market outcomes. The first approach consists of a model with an instrumental variable (IV), whereby the IV affects educational choices but not wages or employment likelihood. The instrument to be valid must be correlated with educational choices but uncorrelated with the error terms. A distance to FE colleges (major providers of level 4 and 5 qualifications in England) could be a candidate for an instrument, on the ground that the network of FE colleges is denser than that of universities and a geographical proximity to educational institutions is correlated with educational choices. In this scenario individuals living in vicinity of an FE college and far away from a university would opt for the former rather than the later for the convenience reasons. The second approach would exploit changes in educational policies and an opportunity of comparing the situation before and after the introduction of the policy. To address the rising public cost of HE, the UK government intends to increase financial support for HTE students and decrease the amount of funding channeled to those in degree programmes. This may increase an inflow of more able candidates into HTE, who under the previous scheme would have enrolled into degree programmes. Comparison of outcomes of these two groups:  individuals with similar ability but choosing degree programmes before the introduction of the policy and opting for HTE programmes after the policy has been rolled out would have a potential to capture the effect of the HTE qualification on the labour performance relative to that of degrees.

## 5.3. Policy implications

### 5.3.1. How can HTE be made more relevant?

Falling demand for HTE may reflect a mismatch between skills provided by HTE programmes and skills in demand among employers. Demonstrating this would require a careful evaluation of the mix of HTE qualifications on offer and their content. This is consistent with government plans aiming to identify level 4 and 5 qualifications that are in demand on the labour market and limiting government funding to those qualifications (Department for Education, 2022). In many countries the process of identifying programmes and qualifications that are meant to provide skills for the labour market involves employers. Employers are typically engaged in the technical training system not only by directly providing training (for example through apprenticeships), but also by identifying new and updating existing qualifications (OECD, 2022). Our research shows that employers expect the HTE-qualified to have specialist knowledge, and that use of specialist knowledge on the job is more beneficial to HTE-qualified workers than to employees with other qualifications. Occupation-specific knowledge and skills are often best developed on the job, as in this context students have access to recent technologies and professionals who know how to use them. Training with employers should therefore be systematically provided in HTE programmes. However, to be beneficial, training to students should involve genuine training spells during which students progressively learn new things Kuczera (2017).

Online job vacancies are a valuable source of information on the qualifications, skills and knowledge in demand on the labour market as they are a direct expression of employers' preferences. The study of BGT data presented in this research points to ways in which online job vacancy data can inform policy makers and providers in defining the content of HTE qualifications, and students in planning their careers. It identifies the skills employers expect HTE-qualified to master in specific occupations. It also points to competencies (such as high-level IT skills) that employers value the most and that are presumably in high demand. A particular value of the BGT data is that it is up-to-date and can therefore be used to track emerging skills demands in real time. This is very different from survey data which tend to give a largely historical picture of how qualifications acquired some years previously were valued in the labour market at the time of the survey. This implies that regular analysis of online vacancy data, such as through BGT data, should be used to develop, review and update HTE qualifications and programmes.

In the engineering sector, analysed as a proof of concept (based on the number of ads mentioning HTE qualifications), BGT data demonstrate that the skills attracting the highest wages tend to be associated with degrees rather than HTE. However, this is surely far from inevitable. In principle, level 4 and 5 qualifications could target jobs corresponding to highly paid skills. For example, BGT analysis shows that in the engineering sector advanced IT skills such as programming are associated with a high wage premium. In consultations with employers the current offer of HTE programmes in IT could reviewed and adjusted to match labour market needs drawing on the BGT results. BGT analysis also identifies skills that tend to be required alongside each other (in online vacancies) or are highly unlikely to co-occur. Such analysis might inform, for example, whether all students in engineering programmes need some programming skills, or alternatively are these skills only necessary among IT engineers?

### *5.3.2. Delivery of HTE programmes*

Weak demand for HTE qualifications can also stem from poor quality teaching and inadequate curricula (sometimes lacking workbased learning), failing to deliver the required knowledge and skills. Some students who enter HTE programmes may lack the foundation skills necessary to support learning progress. A worrying proportion of young people in post-secondary education lack basic skills, hindering their capacity to complete and capitalise on the obtained qualification (Kuczera, Field and Windisch, 2016). Depending on the causes, which are not mutually exclusive, different solutions apply. Where students lack foundation skills, a clear indication of entry expectations may need to be linked to screening tests and catch up courses at the beginning of the programme, targeted at students who may need to refresh their knowledge. While these approaches can be helpful in any post-secondary programme, many HTE students have spent some time in the labour market before returning to education, and may therefore particularly benefit from some initial reinforcement of basic and study skills.

### *5.3.3. Finding a unique selling point for HTE qualifications*

BGT analysis of job ads in engineering occupations identified some jobs in which employers are willing to hire HTE-qualified despite having a preference for degree holders. A further study could usefully explore in more depth the factors which might encourage employers to prefer HTE qualifications; for example, if a substantial work placement were routinely included in HTE programmes, would that perhaps encourage employers to consider the HTE-qualified as more job-ready than their more academic degree-qualified counterparts.

### *5.3.4. Locally driven demand for HTE*

The ability of employers to hire their preferred candidates depends partly on workplace location. The network of institutions delivering HTE qualification is denser than that of universities, with more than 540 level 4 and 5 providers compared to around 105 universities (Zaidi et al., 2019) (recognising that there is quite a lot of overlap between HE and HTE providers, notably in universities offering HTE qualifications). Consequently, firms situated further away from universities, in terms of travel time, may rely more on level 4 and 5 providers for their work force than those in vicinity of HE institutions. Identifying these factors can help to plan the provision across the country bearing in mind location of companies and distribution of HTE and HE institutions across the country.  Moreover, HTE providers may capitalise on their local connections through work placements with local employers (as just mentioned) and through other forms of local collaboration with employers that offer HTE-qualified persons a more competitive edge in relation to degree holders.

## 5.4. Conclusions

Over past decades enrolment in bachelor's degree programmes has risen steeply. During the same period participation in Higher Technical Education (HTE, level 4/5 technical qualifications) has stagnated at best. There are different, overlapping, but also partly competing explanations for this pattern. There could have been an expansion in jobs requiring the high level skills associated with degrees (but not HTE) and an increasing complexity of the job content. This changing mix of jobs and tasks performed in the workplace could, in turn, be triggered by new technologies and management methods that drive up the demand for high level skills. It may also be that an increasing supply of highly educated workers contributes to job upskilling, so that, for example, when graduates (here meaning those qualified at level 6) take an administrative job, they find ways of using their higher level skills, gradually changing the nature of the job and the expectations that surround it.

To shed light on the relative decline of HTE, this research study explores the labour market performance of HTE-qualified workers over the last twenty years in the context of a rapidly rising supply of degree holders and the spread of new technologies in workplaces, across and within occupations. In particular, it explores the interplay between qualifications, the tasks performed on the job and the skills necessary to undertake those tasks, and labour market outcomes.

The analysis draws on three datasets that provide information on occupational skills and labour market outcomes in the UK over time. They include: the UK Skills Employment Survey (SES), Labour Force Survey (LFS), Burning Glass Technology (BGT) data on job vacancies advertised online. The SES and LFS provide consistent worker-level data in different time periods, while the BGT contains information on millions of online job vacancies.

The findings point to a worsening labour market performance, on average, of the HTE-qualified over the last twenty years. They show how the HTE-qualified have been gradually displaced from many skilled occupations in response to an influx of degree holders onto the labour market. The research also describes how the growth of employment in more skilled occupations is associated with an increase in the number of graduates in the labour market. The research demonstrates that while on average, the level of tasks performed by the HTE-qualified has been relatively high, they have suffered from a downgrade in terms of skills applied on-the-job. In this respect the position of HTE holders as compared to other groups, and in particular graduates, has weakened over time in some occupations. This trend is observed in skilled professional and technical occupations (SOC major groups 2-3), occupations that have often been prepared for through HTE programmes. One possibility is that in these occupations, the relative productivity of individuals with HTE qualifications and therefore the relative demand for these qualifications fell over time. (This refers to the relative productivity and relative demand in relation to the HTE-qualified as a group with a changing composition, rather than to the changing productivity of individuals over their working lives). The research shows that HTE-qualified workers were particularly likely to have been displaced in skilled jobs by degree holders. Conversely, the share of HTE-qualified increased in semi-skilled trade occupations, in which their comparative advantage was the highest. The share of HTE holders also grew in quickly expanding service sector jobs, in which their comparative advantage was low.

The labour market performance of the HTE-qualified varies according to the area of specialisation. Specialisations in teaching and health saw a sharp drop in earnings, and experienced worsening employment prospects over the last two decades which is almost certainly related to the introduction of a degree requirement for entry into the teaching and nursing professions. Those with engineering and manufacturing HTE specialisations show the strongest employment outcomes. A case study of the engineering sector revealed that employers in this sector associate more productive tasks with degrees, but under some circumstances they are open to employing the HTE-qualified.

While the declining labour market performance of the HTE qualified, relative to those with degrees, is one of the findings of this study, the causal relationships involved are not entirely clear. Drawing on the findings from the analysis of on-line job vacancy data presented in this research, further analysis might usefully include an examination of the factors which encourage employers to prefer HTE qualifications, such as firm characteristics, company geographical location and proximity to universities.

The research sought to differentiate between demand for specific types of skill and certain qualifications, recognising that qualifications seek to package skills in certain ways, while individual occupations also require packages of skills. In principle, employers will be interested in skills rather than qualifications, but they use qualifications as signals of the skills which their recruits are likely to possess. This research study has highlighted the potential, particularly through online vacancy data, but also in other ways to capture the subtleties of employer demand in relation to both skills and qualifications. Regular data of this type might provide, in real time, an important guide for those developing and reviewing programmes and qualifications. More analytical research should allow for an exploration of the extent to which the skills demand of a fast-changing economy can be best met through packaged qualifications, as opposed to specific targeted training exercises concentrating on individual skills.

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# Annexe A. 1. (annex to chapter 2)

## Table A1.1. Classification of individual qualifications by level

| | Individual qualifications | Qualification categories by level |
|---|---|---|
| 1 | NONE/ NO QUALIFICATIONS | Level 2 and below |
| 2 | GCSE D-G/ CSE BELOW GRADE 1/ GNVQ FOUNDATION | Level 2 and below |
| 3 | GCSE A*-C/ GNVQ INTERMEDIATE/ GCE 'O' LEVEL/ CSE GRADE 1/ SC | Level 2 and below |
| 4 | GCE 'A' LEVEL/ GNVQ ADVANCED | Level 3 |
| 5 | SCE STANDARD (4-7)/ ORDINARY (BELOW C) | Level 2 and below |
| 6 | SCE STANDARD (1-3)/ ORDINARY (A-C) OR SLC/SUPE LOWER | Level 2 and below |
| 7 | SCE HIGHER OR SLC/SUPE HIGHER | Level 3 |
| 8 | CERTIFICATE OF SIXTH YEAR STUDIES | Level 3 |
| 9 | NVQ LEVEL 1 (OR SNVQ 1) | Level 2 and below |
| 10 | NVQ LEVEL 2 (OR SNVQ 2) | Level 2 and below |
| 11 | NVQ LEVEL 3 (OR SNVQ 3) OR ONC/OND (OR SNC/SND) | Level 3 |
| 12 | NVQ LEVEL 4 (OR SNVQ 4) OR HNC/HND (OR SHNC/SHND) | HTE |
| 13 | UNIVERSITY CERTIFICATE/ DIPLOMA (NOT DEGREE) | Level 3 |
| 14 | SCOTVEC NATIONAL CERTIFICATE | Level 3 |
| 15 | SCOTBEC/ SCOTEC CERTIFICATE/ DIPLOMA | Level 3 |
| 16 | CLERICAL/ COMMERCIAL (EG. TYPING OR BOOK-KEEPING) | * |
| 17 | NURSING (EG. SCM, SRN, SEN) | Degree |
| 18 | TEACHING | Degree |
| 19 | OTHER PROFESSIONAL (EG. LAW | Degree |
| 20 | UNIVERSITY OR CNAA DEGREE | Degree |
| 21 | MASTERS OR PHD DEGREE | Degree |
| 22 | COMPLETION OF TRADE APPRENTICESHIP | Level 3 |
| 23 | PROFESSIONAL QUALIFICATION WITHOUT SITTING EXAM | * |

*not used to define the level
Source: based on the LFS data

## Table A2.2. On-the-job task/skills variables, SES data

| | |
|---|---|
| thinking ahead? | cahead |
| analysing complex problems in depth? | canalyse |
| adding, subtracting, multiplying or dividing numbers? | ccalca |
| counselling, advising or caring for customers or clients? | ccaring |
| ‘working out the cause of problems or faults?’ | ccause |
| ‘cooperating with colleagues?’ | ccoop |
| ‘spotting problems or faults?’ | cfaults |
| skill or accuracy in using your hands or fingers (for example, to mend, repair, assemble, construct or adjust things)? | chands |
| ‘listening carefully to colleagues?’ | clisten |
| ‘organising your own time?’ | cmytime |
| ‘knowledge of how your organisation works?’ | corgwork |
| dealing with people? | cpeople |
| ‘calculations using decimals, percentages or fractions?’ | cpercent |
| ‘persuading or influencing others?’ | cpersuad |
| planning your own activities? | cplanme |
| planning the activities of others?’ | cplanoth |
| knowledge of particular products or services?’ | cproduct |
| reading written information such as forms, notices or signs? | cread |
| ‘selling a product or service?’ | cselling |
| reading short documents such as short reports, letters or memos?’ | cshort |
| thinking of solutions to problems?’ | csolutn |
| ‘specialist knowledge or understanding?’ | cspecial |
| making speeches or presentations? | cspeech |
| physical stamina (to work for long periods on physical activities | cstamina |
| physical strength (for example, to carry, push or pull heavy obje | cstrengt |
| instructing, training or teaching people, individually or in groups | cteach |
| ‘working with a team of people?’ | cteamwk |
| In your job, how important is knowledge of how to use or operate tools, equipment or machinery? | ctools |
| ‘using a computer, 'PC', or other types of computerised equipment?’ | cusepc |
| writing material such as forms, notices or signs? | cwrite |
| ‘writing short documents (for example, short reports, letters or memos)?’ | cwritesh |

## Table A3.3. Association between wages (log) and skills used on the job

16-60 year-olds

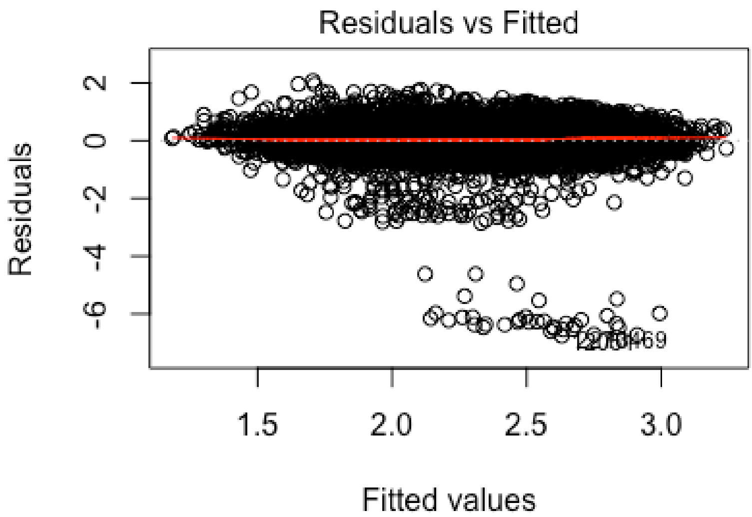
In column 2 and 3 men are the reference group, and 2001 is the reference year. In column 4 men are the reference group, and 2006 is the reference year.

| | (2) | (3) | (4) |
|---|---|---|---|

| | 2001-2017 | 2001-2006 | 2012-2017 |
|---|---|---|---|
| Intercept | 1.78 (0,03)*** | 1.78 (0.04)*** | 2.05 (0.05) *** |
| vwrite | 0.001 (0,006) | 0.003 (0.008) | -0.003 (0.001) |
| vsolut | -0,01 (0,006) | -0.01 (0.008) . | 0.002 (0.009) |
| vphysic | -0,08 (0,005) *** | -0.07 (0.007)*** | -0.08 (0.007) *** |
| vcoop | 0,007 (0,007) | 0.008 (0.01) | 0.007 (0.01) |
| vplan | 0,03 (0,006) *** | 0.04 (0.008) *** | 0.02 (0.01) . |
| vnum | 0,004 (0,004) | 0.004 (0.005) | 0.007 (0.006) |
| vpersuad | 0,09 (0,005)*** | 0.09 (0.008) *** | 0.09 (0.009) *** |
| cpeople | 0,001 (0,006) | -0.002( 0.008) | 0.01 (0.01) |
| cteach | -0,002 (0.003) | 0.003 (0.006) | -0.01 (0.007) |
| cselling | -0,03 (0,004) *** | -0.03 (0.004) *** | -0.03 (0.005) *** |
| ccaring | -0.03 (0,004) *** | -0.02 (0.005) *** | -0.04 (0.006) *** |
| ctools | (0,00) (0,00) | -0.001 (0.005) | (0.007) (0.006) |
| cproduct | -0,01 (0,004). | -0.01 (0.006). | -0.005 (0.006) |
| cspecial | 0,06 (0,006) *** | 0.06 (0.008) *** | 0.06 (0.01) *** |
| corgwork | -0,02 (0,005) *** | -0.01 (0.007) . | -0.05 (0.01) *** |
| cusepc | 0,05 (0,004) *** | 0.05 (0.005) *** | 0.06 (0.007) *** |
| canalyse | 0,04 (0,005) *** | 0.03 (0.006) *** | 0.05 (0.008) *** |
| cplanoth | 0,01 (0,004) ** | 0.01 (0.006) . | 0.02 (0.007) ** |
| female | -0,15 (0,01)*** | -0.17 (0.01) *** | -0.1 (0.02 ) *** |
| Year2006 | 0,16 (0,01) *** | 0.15 (0.013) *** | |
| Year2012 | 0,28 (0,01) *** | | |
| Year2017 | 0,43 (0,02) *** | | 0.15 (0.015) *** |
| | 4081 observations deleted due to missingness<br>F-statistic: 210.7 on 22 and 12754 DF | 2282 observations deleted due to missingness<br>F-statistic: 113.5 on 20 and 8536 DF, p-value: < 2.2e-16 | 1799 observations deleted due to missingness<br>F-statistic: 83.86 on 20 and 4199 DF, p-value: < 2.2e-16 |

Note : Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'
Source : SES, author's calculations

## Figure A1.1. Residuals versus fitted values (Model 1)




Source: SES data, author's calculations

### Table A4.4. Association between wages (log) and skills used on the job 2001-2017, weighted data

(16-60 year-olds), Men are the reference group, and 2001 is the year of reference.

| | |
|---|---|
| (Intercept) | 1.76 (0.035)*** |
| vwrite | 0.002 (0.007) |
| vsolut | -0.01 (0.008) |
| vphysic | -0.07 (0.006)*** |
| vcoop | 0.004 (0.009) |
| vplan | 0.03 (0.007) *** |
| vnum | 0.00 (0.005) |
| vpersuad | 0.09 (0.007) *** |
| cpeople | 0.006 (0.008) |
| cteach | -0.002 (0.006) |
| cselling | -0.03 (0.004) *** |
| ccaring | -0.03 (0.005)*** |
| ctools | 0.00 (0.005) |
| cproduct | -0.02 (0.006)* |
| cspecial | 0.06 (0.007) *** |
| corgwork | -0.01 (0.007). |
| cusepc | 0.05 (0.005) *** |
| canalyse | 0.05 (0.007) *** |
| cplanoth | 0.013 (0.006) * |
| female | -0.14 (0.012) *** |
| year06 | 0.15 (0.015) *** |
| year12 | 0.28 (0.016) *** |
| year17 | 0.42 (0.014) *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'
Source : SES data, author's calculation

### Table A5.5. Hourly wage by the importance of skills on the job, 2001-2017

| | not at all important/does not apply | not very important | important | very important | essential |
|---|---|---|---|---|---|
| vpersuad | 7,56 | 8,7 | 10,68 | 13,27 | 15,59 |
| vphysic | 14,62 | 12,43 | 10,08 | 9,25 | 9,02 |
| vplan | 7,2 | 7,85 | 8,81 | 11,23 | 13,07 |
| vsolut | 8,38 | 8,98 | 9,97 | 11,39 | 12,29 |
| ccaring | 9,94 | 11,76 | 11,86 | 11,49 | 11,37 |
| corgwork | 7,23 | 8,9 | 10,35 | 11,4 | 12,42 |
| cplanoth | 8,58 | 10,31 | 11,86 | 12,93 | 12,92 |
| cproduct | 10,47 | 10,74 | 10,82 | 11,33 | 11,61 |
| cselling | 10,35 | 12,9 | 12,44 | 11,59 | 10,93 |
| cspecial | 7,11 | 7,92 | 8,87 | 10,63 | 12,93 |
| cusepc | 7,31 | 8,36 | 9,82 | 11,42 | 13,27 |
| canalye | 7,69 | 8,8 | 10,18 | 12,32 | 14,51 |

Source: SES data, author's calculations

### Table A6.6. Association between wages and selected skills, coefficients used to construct the wage index variable

Years: 2001-2017

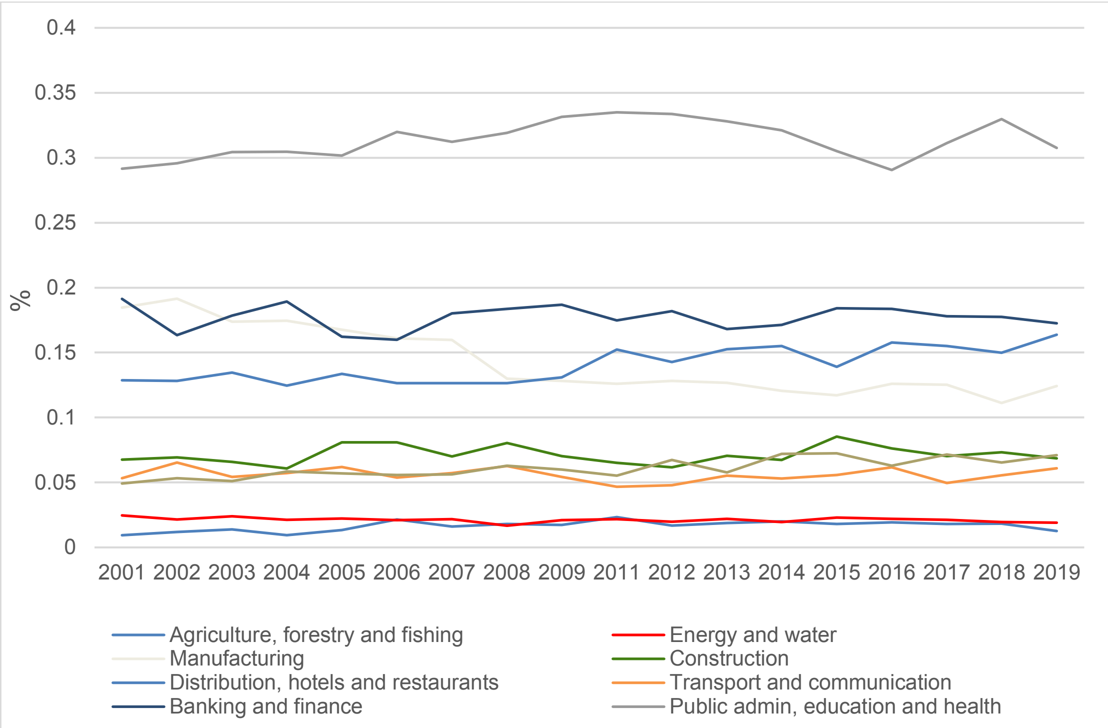
| | |
|---|---|
| (Intercept) | 1.79 (0.02) *** |
| cproduct | -0.01 (0.005) * |
| vphysic | -0.08 (0.004) *** |
| vplan | 0.03 (0.006) *** |
| vpersuad | 0.09 (0.006) *** |
| cselling | -0.03 (0.003) *** |
| ccaring | -0.03 (0.004) *** |
| cspecial | 0.06 (0.006) *** |
| corgwork | -0.02 (0.006) *** |
| cusepc | 0.05 (0.004) *** |
| canalyse | 0.04 (0.005) *** |
| cplanoth | 0.01 (0.004) ** |
| female | -0.15 (0.01) *** |
| year06 | 0.16 (0.01) *** |
| year12 | 0.28 (0.015) *** |
| year17 | 0.43 (0.015) *** |

Source: SES data, author's calculations

## Annexe B. 2. (annex to chapter 3)

### Figure A2.1. Share of the HTE holders by industry sector (SIC)

16-64 year-olds
How to read the chart: In 2001 nearly 30% of the HTE-qualified employees worked in the public administration, education or health sector.




Note: Results are weighted
HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

### Table A7.1. Share of individuals 16-64 year old to whom GCSE question does not apply, by qualification, all years combined

| Qualification | % |
|---|---|
| degree | 13 |
| HTE | 3 |
| leve 3 and 2 | 20 |
| level 1 and below | 63 |
| total | 100 |

Note: Results are weighted
HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data.

## Table A8.2. Share of individuals in each SOC major group, by GCSE's results, 2001-2010

16-64 year-olds

| SOC major group | 5 or more full GCSEs | less than 5 full GCSEs or GCSE below grade C | GCSE is irrelevant |
|---|---|---|---|
| 1 | 0.53 | 0.20 | 0.27 |
| 2 | 0.71 | 0.10 | 0.18 |
| 3 | 0.58 | 0.21 | 0.21 |
| 4 | 0.47 | 0.29 | 0.24 |
| 5 | 0.21 | 0.30 | 0.49 |
| 6 | 0.31 | 0.31 | 0.39 |
| 7 | 0.38 | 0.28 | 0.33 |
| 8 | 0.13 | 0.25 | 0.61 |
| 9 | 0.20 | 0.24 | 0.56 |

Note: Individuals to whom GCSE is irrelevant include those with qualifications below GCSE level and those whose highest qualification is at or the higher level than GCSE but who for various reasons did not pass GCSEs exams.
Source: LFS data, author's calculations

## Table A9.3. Share of individuals in each SOC major group, by GCSE's results, 2011-2019

16-64 year-olds

| SOC major group | 5 or more full GCSEs | less than 5 full GCSEs or GCSE below grade C | GCSE is irrelevant |
|---|---|---|---|
| 1 | 0.58 | 0.17 | 0.25 |
| 2 | 0.70 | 0.09 | 0.21 |
| 3 | 0.64 | 0.16 | 0.19 |
| 4 | 0.57 | 0.22 | 0.20 |
| 5 | 0.32 | 0.29 | 0.40 |
| 6 | 0.40 | 0.27 | 0.33 |
| 7 | 0.48 | 0.24 | 0.28 |
| 8 | 0.21 | 0.25 | 0.54 |
| 9 | 0.28 | 0.23 | 0.49 |

Note: Individuals to whom GCSE is irrelevant include those with qualifications below GCSE level and those whose highest qualification is at or the higher level than GCSE but who for various reasons did not pass GCSEs exams
Source: LFS data

## Table A10.4. Wages in occupations of Managers, Directors and Senior Officials (SOC1), 2001-2010

| SOC1 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.80 | 0.00 | 0.69 | 0.00 | 0.89 | 0.00 | 0.46 | 0.00 |
| 2005/07 | 0.04 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.04 | 0.03 |
| 2008/10 | 0.04 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.02 | 0.30 |
| Level 1 and below | -0.32 | 0.00 | -0.24 | 0.00 | -0.20 | 0.00 | -0.24 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Level 2 and 3 | -0.14 | 0.00 | -0.13 | 0.00 | -0.11 | 0.00 | -0.13 | 0.00 |
| Degree | 0.22 | 0.00 | 0.20 | 0.00 | 0.18 | 0.00 | 0.22 | 0.00 |
| At least 5 full GCSE's | | | 0.15 | 0.00 | 0.13 | 0.00 | 0.15 | 0.00 |
| Missing GCSE's | | | 0.02 | 0.00 | 0.01 | 0.02 | 0.03 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | 0.01 | 0.71 |
| Yr2008/10*degree | | | | | | | 0.01 | 0.65 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.01 | 0.79 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.00 | 0.83 |
| Yr2005/07*level1 and below | | | | | | | -0.01 | 0.80 |
| Yr2008/10*level 1 and below | | | | | | | 0.02 | 0.48 |
| | Residual standard error: 0.5067 on 39546 degrees of freedom F-statistic: 611.9 on 22 and 39546 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5029 on 39544 degrees of freedom F-statistic: 594.3 on 24 and 39544 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4873 on 39515 degrees of freedom F-statistic: 554.4 on 32 and 39515 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5146 on 39590 degrees of freedom F-statistic: 696.7 on 17 and 39590 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data.

## Table A11.5. Wages in occupations of Managers, Directors and Senior Officials (SOC1), 2011-2019

| SOC1 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.76 | 0.00 | 0.61 | 0.00 | 0.88 | 0.00 | 0.28 | 0.00 |
| 2014/16 | -0.01 | 0.38 | -0.01 | 0.57 | 0.00 | 0.71 | 0.01 | 0.68 |
| 2017/19 | -0.01 | 0.58 | 0.00 | 0.97 | 0.00 | 0.84 | -0.02 | 0.59 |
| Level 1 and below | -0.32 | 0.00 | -0.23 | 0.00 | -0.18 | 0.00 | -0.27 | 0.00 |
| Level 3 | -0.13 | 0.00 | -0.13 | 0.00 | -0.10 | 0.00 | -0.13 | 0.00 |
| Degree | 0.24 | 0.00 | 0.22 | 0.00 | 0.20 | 0.00 | 0.26 | 0.00 |
| At least 5 full GCSE's | | | 0.16 | 0.00 | 0.14 | 0.00 | 0.17 | 0.00 |
| Missing GCSE's | | | 0.00 | 0.92 | 0.00 | 0.96 | 0.04 | 0.01 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | -0.02 | 0.59 |
| Yr2017/19*degree | | | | | | | 0.00 | 0.94 |
| Yr2014/16*level 2 and 3 qualif | | | | | | | -0.01 | 0.75 |
| Yr2017/19*level 2 and 3 qualif | | | | | | | 0.02 | 0.59 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yr2014/16*level 1 and below | | | | | | | -0.04 | 0.47 |
| Yr2017/19*level 1 and below | | | | | | | 0.11 | 0.03 |
| | Residual standard error: 0.5939 on 20031 degrees of freedom F-statistic: 225.1 on 22 and 20031 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5897 on 20029 degrees of freedom F-statistic: 221.4 on 24 and 20029 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5717 on 19993 degrees of freedom F-statistic: 216.7 on 32 and 19993 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5988 on 20052 degrees of freedom F-statistic: 267.8 on 17 and 20052 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A12.6. Wages in occupations of Professionals (SOC2) 2001-2010

| SOC2 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.98 | 0.00 | 0.88 | 0.00 | 0.87 | 0.00 | 0.79 | 0.00 |
| 2005/07 | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.06 | 0.00 |
| 2008/10 | 0.04 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.05 | 0.01 |
| Level 1 and below | -0.03 | 0.04 | -0.01 | 0.49 | -0.01 | 0.71 | 0.09 | 0.00 |
| Level 2 and 3 | -0.10 | 0.00 | -0.09 | 0.00 | -0.09 | 0.00 | -0.08 | 0.00 |
| Degree | 0.16 | 0.00 | 0.15 | 0.00 | 0.15 | 0.00 | 0.15 | 0.00 |
| At least 5 full GCSE's | | | 0.10 | 0.00 | 0.10 | 0.00 | 0.11 | 0.00 |
| Missing GCSE's | | | 0.06 | 0.00 | 0.06 | 0.00 | 0.07 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | -0.01 | 0.47 |
| Yr2008/10*degree | | | | | | | -0.01 | 0.76 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.01 | 0.63 |
| Yr2008/10*level 2&3 qualif | | | | | | | -0.05 | 0.05 |
| Yr2005/07*level1 and below | | | | | | | -0.12 | 0.00 |
| Yr2008/10*level 1 and below | | | | | | | -0.12 | 0.00 |
| | Residual standard error: 0.4231 on 35904 degrees of freedom F-statistic: 310 on 22 and 35904 DF, p-value: < 2.2e-16 | | Residual standard error: 0.422 on 35902 degrees of freedom F-statistic: 293.8 on 24 and 35902 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4873 on 39515 degrees of freedom F-statistic: 554.4 on 32 and 39515 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5146 on 39590 degrees of freedom F-statistic: 696.7 on 17 and 39590 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A13.7. Wages in occupations of Professionals (SOC2) 2011-2019

| SOC2 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.91 | 0.00 | 0.75 | 0.00 | 0.73 | 0.00 | 0.66 | 0.00 |
| 2014/16 | -0.02 | 0.00 | -0.02 | 0.00 | -0.02 | 0.00 | 0.01 | 0.73 |
| 2017/19 | -0.02 | 0.00 | -0.02 | 0.00 | -0.02 | 0.00 | 0.01 | 0.47 |
| Level 1 and below | -0.11 | 0.00 | -0.08 | 0.00 | -0.08 | 0.00 | -0.05 | 0.08 |
| Level 3 | -0.08 | 0.00 | -0.07 | 0.00 | -0.08 | 0.00 | -0.05 | 0.00 |
| Degree | 0.16 | 0.00 | 0.15 | 0.00 | 0.16 | 0.00 | 0.17 | 0.00 |
| At least 5 full GCSE's | | | 0.15 | 0.00 | 0.14 | 0.00 | 0.15 | 0.00 |
| Missing GCSE's | | | 0.08 | 0.00 | 0.07 | 0.00 | 0.11 | 0.00 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | -0.03 | 0.16 |
| Yr2017/19*degree | | | | | | | -0.04 | 0.03 |
| Yr2014/16*level 3 qualif | | | | | | | -0.03 | 0.22 |
| Yr2017/19*level 3 qualif | | | | | | | -0.01 | 0.72 |
| Yr2014/16*level2 and below | | | | | | | -0.03 | 0.49 |
| Yr2017/19*level 2 and below | | | | | | | -0.03 | 0.52 |
| | Residual standard error: 0.4238 on 46505 degrees of freedom F-statistic: 478.8 on 22 and 46505 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4215 on 46503 degrees of freedom F-statistic: 464.9 on 24 and 46503 DF, p-value: < 2.2e-16 | | Residual standard error: 0.415 on 46410 degrees of freedom F-statistic: 404.9 on 32 and 46410 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4279 on 46544 degrees of freedom F-statistic: 556.5 on 17 and 46544 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A14.8. Wages in Associate Professional and Technical Occupations (SOC3), 2001-2010

| SOC3 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.05 | 0.00 | 0.94 | 0.00 | 0.93 | 0.00 | 0.76 | 0.00 |
| 2005/07 | 0.05 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.04 | 0.01 |
| 2008/10 | 0.05 | 0.00 | 0.05 | 0.00 | 0.04 | 0.00 | 0.05 | 0.00 |
| Level 1 and below | -0.17 | 0.00 | -0.10 | 0.00 | -0.10 | 0.71 | -0.08 | 0.00 |
| Level 2 and 3 | -0.09 | 0.00 | -0.08 | 0.00 | -0.08 | 0.00 | -0.06 | 0.00 |
| Degree | 0.11 | 0.00 | 0.10 | 0.00 | 0.10 | 0.00 | 0.10 | 0.00 |
| At least 5 full GCSE's | | | 0.11 | 0.00 | 0.10 | 0.00 | 0.12 | 0.00 |
| Missing GCSE's | | | 0.00 | 0.84 | 0.00 | 0.00 | 0.01 | 0.10 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yr2005/07*degree | | | | | | | 0.03 | 0.09 |
| Yr2008/10*degree | | | | | | | 0.02 | 0.33 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.01 | 0.38 |
| Yr2008/10*level 2&3 qualif | | | | | | | -0.04 | 0.03 |
| Yr2005/07*level1 and below | | | | | | | 0.02 | 0.34 |
| Yr2008/10*level 1 and below | | | | | | | -0.03 | 0.18 |
| | Residual standard error: 0.3966 on 39326 degrees of freedom F-statistic: 469.3 on 22 and 39326 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3936 on 39324 degrees of freedom F-statistic: 462 on 24 and 39324 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3887 on 39293 degrees of freedom F-statistic: 387.3 on 32 and 39293 DF, p-value: < 2.2e-16 | | Residual standard error: 0.5146 on 39590 degrees of freedom F-statistic: 696.7 on 17 and 39590 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations.

## Table A15.9. Wages in Associate Professional and Technical Occupations (SOC3), 2011-2019

| SOC3 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.74 | 0.00 | 0.62 | 0.00 | 0.63 | 0.00 | 0.46 | 0.00 |
| 2014/16 | -0.01 | 0.03 | -0.01 | 0.05 | -0.01 | 0.06 | -0.01 | 0.75 |
| 2017/19 | -0.01 | 0.14 | -0.01 | 0.21 | 0.00 | 0.46 | 0.00 | 0.95 |
| Level 1 and below | -0.19 | 0.00 | -0.14 | 0.00 | -0.14 | 0.00 | -0.19 | 0.00 |
| Level 3 | -0.06 | 0.00 | -0.06 | 0.00 | -0.06 | 0.00 | -0.04 | 0.01 |
| Degree | 0.14 | 0.00 | 0.13 | 0.00 | 0.13 | 0.00 | 0.16 | 0.00 |
| At least 5 full GCSE's | | | 0.12 | 0.00 | 0.11 | 0.00 | 0.12 | 0.00 |
| Missing GCSE's | | | 0.04 | 0.00 | 0.03 | 0.00 | 0.08 | 0.00 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | 0.00 | 0.89 |
| Yr2017/19*degree | | | | | | | -0.01 | 0.52 |
| Yr2014/16*level 3 qualif | | | | | | | -0.01 | 0.50 |
| Yr2017/19*level 3 qualif | | | | | | | -0.02 | 0.30 |
| Yr2014/16*level2 and below | | | | | | | 0.04 | 0.28 |
| Yr2017/19*level 2 and below | | | | | | | 0.09 | 0.01 |
| | Residual standard error: 0.4317 on 29883 degrees of freedom F-statistic: 433.6 on 22 and 29883 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4294 on 29881 degrees of freedom F-statistic: 415.2 on 24 and 29881 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4242 on 29820 degrees of freedom F-statistic: 342.3 on 32 and 29820 DF, p-value: < 2.2e-16 | | Residual standard error: 0.4435 on 29911 degrees of freedom F-statistic: 439.2 on 17 and 29911 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A16.10. Wages in Administrative and Secretarial Occupations (SOC4), 2001-2010

| SOC4 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.36 | 0.00 | 1.30 | 0.00 | 1.30 | 0.00 | 1.09 | 0.00 |
| 2005/07 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.07 | 0.00 |
| 2008/10 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.04 | 0.01 |
| Level 1 and below | -0.17 | 0.00 | -0.13 | 0.00 | -0.12 | 0.00 | -0.13 | 0.00 |
| Level 2 and 3 | -0.08 | 0.00 | -0.08 | 0.00 | -0.07 | 0.00 | -0.07 | 0.00 |
| Degree | 0.04 | 0.00 | 0.03 | 0.00 | 0.03 | 0.00 | 0.06 | 0.00 |
| At least 5 full GCSE's | | | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 |
| Missing GCSE's | | | 0.00 | 0.59 | 0.00 | 0.75 | 0.01 | 0.31 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | -0.01 | 0.49 |
| Yr2008/10*degree | | | | | | | 0.00 | 0.90 |
| Yr2005/07*level 2&3 qualif | | | | | | | -0.01 | 0.43 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.00 | 0.92 |
| Yr2005/07*level1 and below | | | | | | | -0.01 | 0.74 |
| Yr2008/10*level 1 and below | | | | | | | 0.04 | 0.07 |
| | Residual standard error: 0.3605 on 37952 degrees of freedom F-statistic: 332.5 on 22 and 37952 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3595 on 37950 degrees of freedom F-statistic: 316 on 24 and 37950 DF, p-value: < 2.2e-16: | | Residual standard error: 0.3557 on 37922 degrees of freedom F-statistic: 267.3 on 32 and 37922 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3727 on 37996 degrees of freedom F-statistic: 258.3 on 17 and 37996 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A17.11. Wages in Administrative and Secretarial Occupations (SOC4), 2011-2019

| SOC4 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.16 | 0.00 | 1.07 | 0.00 | 1.06 | 0.00 | 0.91 | 0.00 |
| 2014/16 | -0.01 | 0.06 | -0.01 | 0.07 | -0.01 | 0.11 | 0.00 | 0.90 |
| 2017/19 | 0.01 | 0.13 | 0.01 | 0.13 | 0.01 | 0.04 | -0.01 | 0.63 |
| Level 1 and below | -0.15 | 0.00 | -0.10 | 0.00 | -0.09 | 0.00 | -0.12 | 0.00 |
| Level 3 | -0.05 | 0.00 | -0.04 | 0.00 | -0.04 | 0.00 | -0.05 | 0.00 |
| Degree | 0.10 | 0.00 | 0.09 | 0.00 | 0.09 | 0.00 | 0.10 | 0.00 |
| At least 5 full GCSE's | | | 0.09 | 0.00 | 0.08 | 0.00 | 0.08 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Missing GCSE's | | | 0.01 | 0.40 | 0.01 | 0.24 | 0.03 | 0.00 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | -0.01 | 0.62 |
| Yr2017/19*degree | | | | | | | 0.02 | 0.36 |
| Yr2014/16*level 3 qualif | | | | | | | -0.01 | 0.58 |
| Yr2017/19*level 3 qualif | | | | | | | 0.02 | 0.39 |
| Yr2014/16*level2 and below | | | | | | | 0.00 | 0.93 |
| Yr2017/19*level 2 and below | | | | | | | 0.04 | 0.14 |
| | Residual standard error: 0.3878 on 25462 degrees of freedom F-statistic: 227 on 22 and 25462 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3861 on 25460 degrees of freedom F-statistic: 219.7 on 24 and 25460 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3811 on 25383 degrees of freedom F-statistic: 191.3 on 32 and 25383 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3969 on 25494 degrees of freedom F-statistic: 212.7 on 17 and 25494 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A18.12. Wages in Skilled Trades Occupations (SOC5), 2001-2010

| SOC5 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.76 | 0.00 | 0.72 | 0.00 | 0.73 | 0.00 | 0.55 | 0.00 |
| 2005/07 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.00 | 0.96 |
| 2008/10 | 0.07 | 0.00 | 0.06 | 0.00 | 0.07 | 0.00 | 0.04 | 0.10 |
| Level 1 and below | -0.32 | 0.00 | -0.28 | 0.00 | -0.26 | 0.00 | -0.31 | 0.00 |
| Level 2 and 3 | -0.15 | 0.00 | -0.14 | 0.00 | -0.13 | 0.00 | -0.16 | 0.00 |
| Degree | 0.02 | 0.29 | 0.02 | 0.38 | 0.03 | 0.14 | 0.04 | 0.27 |
| At least 5 full GCSE's | | | 0.04 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 |
| Missing GCSE's | | | -0.03 | 0.00 | -0.03 | 0.00 | -0.03 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | 0.00 | 0.98 |
| Yr2008/10*degree | | | | | | | -0.01 | 0.77 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.05 | 0.04 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.02 | 0.38 |
| Yr2005/07*level1 and below | | | | | | | 0.07 | 0.02 |
| Yr2008/10*level 1 and below | | | | | | | 0.01 | 0.60 |
| | Residual standard error: 0.3791 on | | Residual standard error: 0.3784 on | | Residual standard error: 0.3681 on | | Residual standard error: 0.3846 on | |

| | | | | |
|---|---|---|---|---|
| | 22549 degrees of freedom F-statistic: 461.1 on 22 and 22549 DF, p-value: < 2.2e-16 | 22547 degrees of freedom F-statistic: 427.9 on 24 and 22547 DF, p-value: < 2.2e-16 | 22527 degrees of freedom F-statistic: 378.9 on 32 and 22527 DF, p-value: < 2.2e-16 | 22582 degrees of freedom F-statistic: 542.4 on 17 and 22582 DF, p-value: < 2.2e-16 |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A19.13. Wages in Skilled Trades Occupations (SOC5), 2011-2019

| SOC5 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 0.92 | 0.00 | 0.87 | 0.00 | 0.84 | 0.00 | 0.73 | 0.00 |
| 2014/16 | 0.00 | 0.82 | 0.00 | 1.00 | 0.00 | 0.73 | -0.02 | 0.56 |
| 2017/19 | 0.04 | 0.00 | 0.03 | 0.00 | 0.04 | 0.00 | -0.04 | 0.14 |
| Level 1 and below | -0.34 | 0.00 | -0.28 | 0.00 | -0.26 | 0.00 | -0.33 | 0.00 |
| Level 3 | -0.17 | 0.00 | -0.16 | 0.00 | -0.15 | 0.00 | -0.20 | 0.00 |
| Degree | -0.01 | 0.60 | -0.01 | 0.72 | 0.00 | 0.97 | -0.03 | 0.34 |
| At least 5 full GCSE's | | | 0.07 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 |
| Missing GCSE's | | | -0.04 | 0.00 | -0.03 | 0.00 | -0.04 | 0.00 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | 0.01 | 0.76 |
| Yr2017/19*degree | | | | | | | 0.07 | 0.09 |
| Yr2014/16*level 2 and 3 qualif | | | | | | | 0.02 | 0.41 |
| Yr2017/19*level 2 and 3 qualif | | | | | | | 0.08 | 0.01 |
| Yr2014/16*level 1 and below | | | | | | | 0.01 | 0.74 |
| Yr2017/19*level 1 and below | | | | | | | 0.08 | 0.02 |
| | Residual standard error: 0.3917 on 15595 degrees of freedom F-statistic: 257.9 on 22 and 15595 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3901 on 15593 degrees of freedom F-statistic: 244 on 24 and 15593 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3763 on 15548 degrees of freedom F-statistic: 231.3 on 32 and 15548 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3967 on 15629 degrees of freedom F-statistic: 302 on 17 and 15629 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A20.14. Wages in Caring, Leisure and Other Service Occupations (SOC6), 2001-2010

| SOC6 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.33 | 0.00 | 1.30 | 0.00 | 1.32 | 0.00 | 0.96 | 0.00 |
| 2005/07 | 0.07 | 0.00 | 0.07 | 0.00 | 0.07 | 0.00 | 0.10 | 0.00 |
| 2008/10 | 0.08 | 0.00 | 0.08 | 0.00 | 0.08 | 0.00 | 0.07 | 0.01 |
| Level 1 and below | -0.17 | 0.00 | -0.15 | 0.00 | -0.15 | 0.00 | -0.15 | 0.00 |
| Level 2 and 3 | -0.09 | 0.00 | -0.09 | 0.00 | -0.09 | 0.00 | -0.08 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Degree | 0.04 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.03 | 0.16 |
| At least 5 full GCSE's | | | 0.03 | 0.00 | 0.02 | 0.00 | 0.03 | 0.00 |
| Missing GCSE's | | | -0.01 | 0.10 | -0.01 | 0.28 | -0.02 | 0.02 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | 0.01 | 0.76 |
| Yr2008/10*degree | | | | | | | 0.03 | 0.30 |
| Yr2005/07*level 2&3 qualif | | | | | | | -0.04 | 0.08 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.00 | 0.98 |
| Yr2005/07*level1 and below | | | | | | | -0.02 | 0.37 |
| Yr2008/10*level 1 and below | | | | | | | 0.02 | 0.45 |
| | Residual standard error: 0.3726 on 23838 degrees of freedom F-statistic: 210.9 on 22 and 23838 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3723 on 23836 degrees of freedom F-statistic: 194.9 on 24 and 23836 DF, p-value: < 2.2e-16 | | Residual standard error: 0.368 on 23818 degrees of freedom F-statistic: 167.4 on 32 and 23818 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3807 on 23872 degrees of freedom F-statistic: 203.1 on 17 and 23872 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A21.15. Wages in Caring, Leisure and Other Service Occupations (SOC6), 2011-2019

| SOC6 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.32 | 0.00 | 1.27 | 0.00 | 1.28 | 0.00 | 1.07 | 0.00 |
| 2014/16 | -0.01 | 0.27 | -0.01 | 0.27 | 0.00 | 0.48 | -0.01 | 0.73 |
| 2017/19 | 0.03 | 0.00 | 0.03 | 0.00 | 0.03 | 0.00 | 0.01 | 0.54 |
| Level 1 and below | -0.12 | 0.00 | -0.09 | 0.00 | -0.10 | 0.00 | -0.11 | 0.00 |
| Level 3 | -0.07 | 0.00 | -0.06 | 0.00 | -0.06 | 0.00 | -0.09 | 0.00 |
| Degree | 0.02 | 0.10 | 0.01 | 0.21 | 0.01 | 0.29 | 0.02 | 0.40 |
| At least 5 full GCSE's | | | 0.04 | 0.00 | 0.03 | 0.00 | 0.04 | 0.00 |
| Missing GCSE's | | | -0.01 | 0.23 | -0.01 | 0.42 | -0.01 | 0.45 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | 0.00 | 0.97 |
| Yr2017/19*degree | | | | | | | 0.00 | 0.88 |
| Yr2014/16*level 2 and 3 qualif | | | | | | | 0.00 | 0.89 |
| Yr2017/19*level 2 and 3 qualif | | | | | | | 0.02 | 0.36 |
| Yr2014/16*level1 and below | | | | | | | -0.03 | 0.35 |
| Yr2017/19*level 1 and below | | | | | | | 0.02 | 0.55 |

| | | | | |
|---|---|---|---|---|
| | Residual standard error: 0.3686 on 21244 degrees of freedom F-statistic: 126.3 on 22 and 21244 DF, p-value: < 2.2e-16 | Residual standard error: 0.3682 on 21242 degrees of freedom F-statistic: 118.1 on 24 and 21242 DF, p-value: < 2.2e-16 | Residual standard error: 0.363 on 21185 degrees of freedom F-statistic: 108.7 on 32 and 21185 DF, p-value: < 2.2e-16 | Residual standard error: 0.3726 on 21286 degrees of freedom F-statistic: 132.3 on 17 and 21286 DF, p-value: < 2.2e-16 |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A22.16. Wages in Sales and Customer Service Caring Occupations (SOC7), 2001-2010

| SOC7 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.44 | 0.00 | 1.37 | 0.00 | 1.45 | 0.00 | 0.95 | 0.00 |
| 2005/07 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.02 | 0.42 |
| 2008/10 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.01 | 0.71 |
| Level 1 and below | -0.18 | 0.00 | -0.14 | 0.00 | -0.10 | 0.00 | -0.19 | 0.00 |
| Level 2 and 3 | -0.07 | 0.00 | -0.07 | 0.00 | -0.05 | 0.00 | -0.10 | 0.00 |
| Degree | 0.02 | 0.17 | 0.01 | 0.41 | 0.01 | 0.34 | 0.03 | 0.29 |
| At least 5 full GCSE's | | | 0.05 | 0.00 | 0.04 | 0.00 | 0.05 | 0.00 |
| Missing GCSE's | | | -0.03 | 0.00 | -0.02 | 0.03 | -0.03 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | 0.03 | 0.44 |
| Yr2008/10*degree | | | | | | | 0.00 | 0.94 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.05 | 0.12 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.05 | 0.11 |
| Yr2005/07*level1 and below | | | | | | | 0.04 | 0.17 |
| Yr2008/10*level 1 and below | | | | | | | 0.08 | 0.01 |
| | Residual standard error: 0.3466 on 22892 degrees of freedom F-statistic: 251.3 on 22 and 22892 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3458 on 22890 degrees of freedom F-statistic: 236 on 24 and 22890 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3323 on 22866 degrees of freedom F-statistic: 251 on 32 and 22866 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3566 on 22941 degrees of freedom F-statistic: 233.6 on 17 and 22941 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A23.17. Wages in Sales and Customer Service Caring Occupations (SOC7), 2011-2019

| SOC7 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.42 | 0.00 | 1.31 | 0.00 | 1.41 | 0.00 | 0.79 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2014/16 | 0.01 | 0.40 | 0.01 | 0.42 | 0.01 | 0.43 | 0.01 | 0.78 |
| 2017/19 | 0.06 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.07 | 0.01 |
| Level 1 and below | -0.16 | 0.00 | -0.11 | 0.00 | -0.09 | 0.00 | -0.16 | 0.00 |
| Level 3 | -0.06 | 0.00 | -0.06 | 0.00 | -0.05 | 0.00 | -0.06 | 0.00 |
| Degree | 0.05 | 0.00 | 0.04 | 0.00 | 0.04 | 0.01 | 0.03 | 0.15 |
| At least 5 full GCSE's | | | 0.08 | 0.00 | 0.07 | 0.00 | 0.09 | 0.00 |
| Missing GCSE's | | | -0.01 | 0.22 | -0.01 | 0.33 | 0.00 | 0.84 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | 0.04 | 0.21 |
| Yr2017/19*degree | | | | | | | 0.03 | 0.40 |
| Yr2014/16*level 2 and3 qualif | | | | | | | -0.02 | 0.52 |
| Yr2017/19*level 2 and3 qualif | | | | | | | -0.02 | 0.50 |
| Yr2014/16*level1 and below | | | | | | | 0.03 | 0.42 |
| Yr2017/19*level 1 and below | | | | | | | 0.01 | 0.79 |
| | Residual standard error: 0.3704 on 17868 degrees of freedom F-statistic: 217.8 on 22 and 17868 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3687 on 17866 degrees of freedom F-statistic: 208.4 on 24 and 17866 DF, p-value: < 2.2e-16 | | Residual standard error: 0.358 on 17792 degrees of freedom F-statistic: 199.6 on 32 and 17792 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3811 on 17931 degrees of freedom F-statistic: 207.7 on 17 and 17931 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A24.18. Wages in occupations of Process, Plant and Machine Operatives (SOC8), 2001-2010

| SOC8 2001/10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.36 | 0.00 | 1.35 | 0.00 | 1.32 | 0.00 | 1.13 | 0.00 |
| 2005/07 | 0.07 | 0.00 | 0.07 | 0.00 | 0.07 | 0.00 | 0.00 | 0.97 |
| 2008/10 | 0.06 | 0.00 | 0.06 | 0.00 | 0.07 | 0.00 | 0.01 | 0.76 |
| Level 1 and below | -0.18 | 0.00 | -0.15 | 0.00 | -0.14 | 0.00 | -0.18 | 0.00 |
| Level 2 and 3 | -0.09 | 0.00 | -0.09 | 0.00 | -0.08 | 0.00 | -0.12 | 0.00 |
| Degree | -0.02 | 0.36 | -0.02 | 0.32 | -0.02 | 0.45 | -0.03 | 0.39 |
| At least 5 full GCSE's | | | 0.03 | 0.00 | 0.03 | 0.00 | 0.02 | 0.02 |
| Missing GCSE's | | | -0.04 | 0.00 | -0.04 | 0.00 | -0.04 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | 0.02 | 0.70 |
| Yr2008/10*degree | | | | | | | 0.01 | 0.90 |
| Yr2005/07*level 2&3 qualif | | | | | | | 0.07 | 0.08 |
| Yr2008/10*level 2&3 qualif | | | | | | | 0.05 | 0.16 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yr2005/07*level1 and below | | | | | | | 0.08 | 0.03 |
| Yr2008/10*level 1 and below | | | | | | | 0.05 | 0.19 |
| | Residual standard error: 0.3501 on 20380 degrees of freedom F-statistic: 181.1 on 22 and 20380 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3497 on 20378 degrees of freedom F-statistic: 168.5 on 24 and 20378 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3421 on 20360 degrees of freedom F-statistic: 160.4 on 32 and 20360 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3559 on 20426 degrees of freedom F-statistic: 188.2 on 17 and 20426 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A25.19. Wages in occupations of Process, Plant and Machine Operatives (SOC8), 2011-2019

| SOC8 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.51 | 0.00 | 1.49 | 0.00 | 1.45 | 0.00 | 1.22 | 0.00 |
| 2014/16 | 0.00 | 0.75 | 0.00 | 0.78 | 0.00 | 0.81 | -0.07 | 0.05 |
| 2017/19 | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | -0.02 | 0.55 |
| Level 1 and below | -0.14 | 0.00 | -0.10 | 0.00 | -0.10 | 0.00 | -0.16 | 0.00 |
| Level 3 | -0.04 | 0.01 | -0.04 | 0.01 | -0.05 | 0.00 | -0.10 | 0.00 |
| Degree | 0.02 | 0.23 | 0.03 | 0.19 | 0.03 | 0.18 | -0.04 | 0.29 |
| At least 5 full GCSE's | | | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 |
| Missing GCSE's | | | -0.04 | 0.00 | -0.04 | 0.00 | -0.04 | 0.00 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | 0.07 | 0.20 |
| Yr2017/19*degree | | | | | | | 0.12 | 0.02 |
| Yr2014/16*level 2 and3 qualif | | | | | | | 0.08 | 0.05 |
| Yr2017/19*level 2 and3 qualif | | | | | | | 0.06 | 0.14 |
| Yr2014/16*level 1 and below | | | | | | | 0.08 | 0.06 |
| Yr2017/19*level 1 and below | | | | | | | 0.07 | 0.07 |
| | Residual standard error: 0.3666 on 12502 degrees of freedom F-statistic: 87.28 on 22 and 12502 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3654 on 12500 degrees of freedom F-statistic: 83.96 on 24 and 12500 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3591 on 12465 degrees of freedom F-statistic: 79.74 on 32 and 12465 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3737 on 12541 degrees of freedom F-statistic: 81.8 on 17 and 12541 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A26.20. Wages in Elementary Occupations (SOC9), 2001-2010

| SOC9 2001/10 | | | | |
|---|---|---|---|---|

| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
|---|---|---|---|---|---|---|---|---|
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.30 | 0.02 | 1.29 | 0.00 | 1.29 | 0.00 | 0.96 | 0.00 |
| 2005/07 | 0.07 | 0.00 | 0.07 | 0.00 | 0.07 | 0.00 | 0.12 | 0.00 |
| 2008/10 | 0.07 | 0.00 | 0.07 | 0.00 | 0.08 | 0.00 | 0.11 | 0.00 |
| Level 1 and below | -0.09 | 0.01 | -0.07 | 0.00 | -0.07 | 0.00 | -0.03 | 0.20 |
| Level 2 and 3 | -0.03 | 0.01 | -0.03 | 0.02 | -0.04 | 0.00 | 0.00 | 0.91 |
| Degree | 0.00 | 0.02 | 0.00 | 0.78 | 0.01 | 0.70 | 0.05 | 0.06 |
| At least 5 full GCSE's | | | 0.01 | 0.04 | 0.02 | 0.00 | 0.00 | 0.74 |
| Missing GCSE's | | | -0.03 | 0.00 | -0.02 | 0.00 | -0.03 | 0.00 |
| Industry dummy | No | | No | | Yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2005/07*degree | | | | | | | -0.06 | 0.10 |
| Yr2008/10*degree | | | | | | | -0.05 | 0.22 |
| Yr2005/07*level 2&3 qualif | | | | | | | -0.05 | 0.11 |
| Yr2008/10*level 2&3 qualif | | | | | | | -0.04 | 0.22 |
| Yr2005/07*level1 and below | | | | | | | -0.05 | 0.08 |
| Yr2008/10*level 1 and below | | | | | | | -0.04 | 0.18 |
| | Residual standard error: 0.3298 on 33856 degrees of freedom F-statistic: 349.3 on 22 and 33856 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3296 on 33854 degrees of freedom F-statistic: 322.3 on 24 and 33854 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3241 on 33834 degrees of freedom F-statistic: 284 on 32 and 33834 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3362 on 33939 degrees of freedom R-squared: 0.1524 F-statistic: 360.1 on 17 and 33939 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations

## Table A27.21. Wages in Elementary Occupations (SOC9), 2011-2019

| SOC9 2011/19 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 14 | | Model 15 | | Model 16 | | Model 17 | |
| | coeff | p-value | coeff | p-value | coeff | p-value | coeff | p-value |
| Intercept | 1.24 | 0.00 | 1.23 | 0.00 | 1.25 | 0.00 | 0.98 | 0.00 |
| 2014/16 | 0.00 | 0.61 | 0.00 | 0.61 | 0.00 | 0.55 | 0.02 | 0.42 |
| 2017/19 | 0.05 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.09 | 0.00 |
| Level 1 and below | -0.07 | 0.00 | -0.06 | 0.00 | -0.06 | 0.00 | -0.04 | 0.03 |
| Level 3 | -0.02 | 0.03 | -0.03 | 0.01 | -0.03 | 0.01 | -0.01 | 0.56 |
| Degree | 0.01 | 0.35 | 0.01 | 0.33 | 0.02 | 0.19 | 0.03 | 0.22 |
| At least 5 full GCSE's | | | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.13 |
| Missing GCSE's | | | -0.02 | 0.00 | -0.02 | 0.00 | -0.01 | 0.05 |
| Industry dummy | no | | no | | yes | | No | |
| Individual characteristics | Yes | | Yes | | yes | | Yes | |
| Employment characteristics | Yes | | Yes | | Yes | | No | |
| Yr2014/16*degree | | | | | | | -0.02 | 0.45 |
| Yr2017/19*degree | | | | | | | -0.02 | 0.45 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yr2014/16*level 2 and 3 qualif | | | | | | | -0.03 | 0.28 |
| Yr2017/19*level 2 and 3 qualif | | | | | | | -0.04 | 0.10 |
| Yr2014/16*level1 and below | | | | | | | -0.02 | 0.50 |
| Yr2017/19*level 1 and below | | | | | | | -0.05 | 0.10 |
| | Residual standard error: 0.3445 on 22900 degrees of freedom F-statistic: 188.6 on 22 and 22900 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3443 on 22898 degrees of freedom F-statistic: 174 on 24 and 22898 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3389 on 22842 degrees of freedom F-statistic: 155.9 on 32 and 22842 DF, p-value: < 2.2e-16 | | Residual standard error: 0.3481 on 22979 degrees of F-statistic: 213 on 17 and 22979 DF, p-value: < 2.2e-16 | |

Note: HTE includes: NVQ level 4, Diploma in higher education, HNC/HND/BTEC higher etc, RSA higher diploma, Level 6 Diploma, Level 6 Certificate, Level 7 Award, Level 5 Diploma, Level 5 Certificate, Level 6 Award, other higher education below degree
Source: LFS data, author's calculations.

## Table A28.22. Employment likelihood by the area of specialisation.

Area of specialisation: Basic pgms

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| Intercept | 3.634884 | 0.265345 | 13.69872 | 1.03E-42 |
| yr0507 | 0.072924 | 0.176429 | 0.413332 | 0.679363 |
| yr0810 | -0.27219 | 0.165263 | -1.64702 | 0.099555 |
| yr1113 | -0.39829 | 0.168716 | -2.36071 | 0.01824 |
| yr1416 | -0.46417 | 0.169971 | -2.7309 | 0.006316 |
| yr1719 | -0.4158 | 0.172949 | -2.40418 | 0.016209 |
| age | -0.04215 | 0.004602 | -9.15888 | 5.24E-20 |
| Ethnicity (being white) | -0.44088 | 0.173339 | -2.54343 | 0.010977 |
| Sex (male) | -0.0854 | 0.116372 | -0.73381 | 0.463062 |

Area of specialisation:Arts and humanities

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 1.415565 | 0.12289 | 11.51899 | 1.06E-30 |
| yr0507 | -0.23897 | 0.106393 | -2.24609 | 0.024698 |
| yr0810 | -0.25704 | 0.105486 | -2.43675 | 0.01482 |
| yr1113 | -0.31605 | 0.106271 | -2.974 | 0.002939 |
| yr1416 | -0.25647 | 0.108905 | -2.35495 | 0.018525 |
| yr1719 | -0.10372 | 0.113328 | -0.9152 | 0.360087 |
| age | 0.003899 | 0.002441 | 1.59722 | 0.110217 |
| Ethnicity (being white) | -0.50051 | 0.101275 | -4.94213 | 7.73E-07 |
| Sex (male) | -0.405 | 0.06338 | -6.39015 | 1.66E-10 |
| | | | | |

Area of specialisation: Social science, journalism, business and admin, law

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 3.175966 | 0.100277 | 31.67196 | 3.8E-220 |
| yr0507 | 0.014315 | 0.07132 | 0.200712 | 0.840924 |
| yr0810 | -0.19491 | 0.068166 | -2.85939 | 0.004245 |
| yr1113 | -0.11305 | 0.071161 | -1.58861 | 0.112148 |
| yr1416 | -0.12947 | 0.071648 | -1.80698 | 0.070766 |
| yr1719 | -0.11336 | 0.072981 | -1.55325 | 0.120363 |
| age | -0.02681 | 0.001923 | -13.9406 | 3.59E-44 |
| Ethnicity (being white) | -0.69677 | 0.061086 | -11.4063 | 3.89E-30 |
| Sex (male) | -0.34321 | 0.042758 | -8.02676 | 1E-15 |

Area of specialisation: Life science, physics, mathematic, computing

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 2.386273 | 0.150955 | 15.80787 | 2.75E-56 |
| yr0507 | 0.020223 | 0.119493 | 0.169244 | 0.865605 |
| yr0810 | -0.22662 | 0.115302 | -1.96547 | 0.049359 |
| yr1113 | -0.16422 | 0.122761 | -1.3377 | 0.180993 |
| yr1416 | -0.21301 | 0.123915 | -1.71898 | 0.085618 |
| yr1719 | -0.04883 | 0.128417 | -0.38023 | 0.703777 |
| age | -0.01612 | 0.00311 | -5.18331 | 2.18E-07 |
| Ethnicity (being white) | -0.43905 | 0.10695 | -4.10523 | 4.04E-05 |
| Sex (male) | -0.39347 | 0.075787 | -5.19178 | 2.08E-07 |

Area of specialisation: Engineering, manufacturing, architecture and building

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 5.363497 | 0.137471 | 39.01548 | 0 |
| yr0507 | 0.082903 | 0.07787 | 1.064641 | 0.287039 |
| yr0810 | -0.05934 | 0.077147 | -0.76919 | 0.441782 |
| yr1113 | -0.01163 | 0.080762 | -0.14396 | 0.88553 |
| yr1416 | 0.135391 | 0.084155 | 1.608831 | 0.107653 |
| yr1719 | 0.055952 | 0.085394 | 0.655228 | 0.512321 |
| age | -0.07017 | 0.002525 | -27.7859 | 6.4E-170 |
| Ethnicity (being white) | -0.42941 | 0.09723 | -4.41646 | 1E-05 |
| Sex (male) | -0.85569 | 0.091545 | -9.34719 | 9E-21 |

Area of specialisation: Agriculture, forestry, fishery, veterinary

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 2.854552 | 0.320897 | 8.895551 | 5.81E-19 |

| | | | | |
|---|---|---|---|---|
| yr0507 | -0.33495 | 0.254899 | -1.31405 | 0.188831 |
| yr0810 | -0.40409 | 0.24855 | -1.62581 | 0.10399 |
| yr1113 | -0.08906 | 0.266297 | -0.33443 | 0.738056 |
| yr1416 | -0.10035 | 0.266733 | -0.37624 | 0.706741 |
| yr1719 | -0.18114 | 0.255182 | -0.70983 | 0.477809 |
| age | -0.01139 | 0.005877 | -1.9376 | 0.052672 |
| Ethnicity (being white) | -0.14902 | 0.468346 | -0.31817 | 0.750353 |
| Sex (male) | -0.91512 | 0.147699 | -6.19586 | 5.8E-10 |

Area of specialisation: Health and social services

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 2.74193 | 0.165205 | 16.59717 | 7.31E-62 |
| yr0507 | 0.027244 | 0.125234 | 0.217543 | 0.827785 |
| yr0810 | -0.37077 | 0.112734 | -3.28894 | 0.001006 |
| yr1113 | -0.32103 | 0.114579 | -2.80184 | 0.005081 |
| yr1416 | -0.57506 | 0.11201 | -5.13407 | 2.84E-07 |
| yr1719 | -0.48904 | 0.113146 | -4.32219 | 1.54E-05 |
| age | -0.01296 | 0.002676 | -4.84461 | 1.27E-06 |
| Ethnicity (being white) | -0.08298 | 0.097915 | -0.84749 | 0.396723 |
| Sex (male) | -0.29742 | 0.094462 | -3.14857 | 0.001641 |

Area of specialisation: Personal services, transport, security, environment

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 2.384992 | 0.158238 | 15.07217 | 2.47E-51 |
| yr0507 | -0.06331 | 0.13535 | -0.46775 | 0.639962 |
| yr0810 | -0.0805 | 0.133109 | -0.60475 | 0.545348 |
| yr1113 | -0.11026 | 0.133032 | -0.82886 | 0.407186 |
| yr1416 | -0.13679 | 0.131201 | -1.04262 | 0.297126 |
| yr1719 | 0.1262 | 0.135199 | 0.933437 | 0.350595 |
| age | -0.01029 | 0.003057 | -3.36767 | 0.000758 |
| Ethnicity (being white) | -0.7766 | 0.124074 | -6.25914 | 3.87E-10 |
| Sex (male) | -0.54809 | 0.077896 | -7.03621 | 1.98E-12 |

Area of specialisation: Personal skills

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 2.529629 | 0.686579 | 3.684396 | 0.000229 |
| yr0507 | 0.74873 | 0.611571 | 1.224273 | 0.220849 |
| yr0810 | -0.05705 | 0.526444 | -0.10837 | 0.913703 |
| yr1113 | -0.69654 | 0.469976 | -1.48208 | 0.138318 |
| yr1416 | 0.393178 | 0.618029 | 0.63618 | 0.524659 |
| yr1719 | -0.21727 | 0.490406 | -0.44304 | 0.657734 |

| | | | | |
|---|---|---|---|---|
| age | -0.01059 | 0.014135 | -0.74944 | 0.453594 |
| Ethnicity (being white) | 0.281077 | 0.590833 | 0.475731 | 0.634266 |
| Sex (male) | -0.65574 | 0.364127 | -1.80085 | 0.071726 |

Source: LFS data, author's calculations

# Annexe C. 3. (annex to chapter 4)

## Table A29.1. Distribution by SOC in LFS and BGT

100% - all SOC categories by year, separately for BGT and LFS data

| Year | SOC1 major groups | BGT | LFS |
|---|---|---|---|
| 2014 | 1 | 0.11 | 0.06 |
| 2015 | 1 | 0.11 | 0.05 |
| 2016 | 1 | 0.11 | 0.06 |
| 2017 | 1 | 0.11 | 0.06 |
| 2018 | 1 | 0.10 | 0.06 |
| 2019 | 1 | 0.10 | 0.07 |
| 2014 | 2 | 0.34 | 0.16 |
| 2015 | 2 | 0.35 | 0.16 |
| 2016 | 2 | 0.34 | 0.17 |
| 2017 | 2 | 0.35 | 0.16 |
| 2018 | 2 | 0.33 | 0.16 |
| 2019 | 2 | 0.31 | 0.17 |
| 2014 | 3 | 0.17 | 0.13 |
| 2015 | 3 | 0.17 | 0.12 |
| 2016 | 3 | 0.17 | 0.13 |
| 2017 | 3 | 0.17 | 0.13 |
| 2018 | 3 | 0.18 | 0.14 |
| 2019 | 3 | 0.18 | 0.14 |
| 2014 | 4 | 0.08 | 0.10 |
| 2015 | 4 | 0.08 | 0.11 |
| 2016 | 4 | 0.08 | 0.09 |
| 2017 | 4 | 0.09 | 0.10 |
| 2018 | 4 | 0.09 | 0.10 |
| 2019 | 4 | 0.09 | 0.09 |
| 2014 | 5 | 0.06 | 0.10 |
| 2015 | 5 | 0.06 | 0.09 |
| 2016 | 5 | 0.06 | 0.09 |
| 2017 | 5 | 0.06 | 0.09 |
| 2018 | 5 | 0.06 | 0.09 |
| 2019 | 5 | 0.06 | 0.09 |
| 2014 | 6 | 0.06 | 0.11 |
| 2015 | 6 | 0.05 | 0.12 |
| 2016 | 6 | 0.05 | 0.11 |
| 2017 | 6 | 0.06 | 0.11 |
| 2018 | 6 | 0.06 | 0.11 |
| 2019 | 6 | 0.07 | 0.11 |

| | | | |
|---|---|---|---|
| 2014 | 7 | 0.10 | 0.11 |
| 2015 | 7 | 0.09 | 0.11 |
| 2016 | 7 | 0.10 | 0.11 |
| 2017 | 7 | 0.09 | 0.11 |
| 2018 | 7 | 0.09 | 0.11 |
| 2019 | 7 | 0.09 | 0.10 |
| 2014 | 8 | 0.03 | 0.07 |
| 2015 | 8 | 0.03 | 0.06 |
| 2016 | 8 | 0.03 | 0.07 |
| 2017 | 8 | 0.03 | 0.06 |
| 2018 | 8 | 0.04 | 0.07 |
| 2019 | 8 | 0.04 | 0.06 |
| 2014 | 9 | 0.04 | 0.17 |
| 2015 | 9 | 0.04 | 0.18 |
| 2016 | 9 | 0.04 | 0.17 |
| 2017 | 9 | 0.04 | 0.18 |
| 2018 | 9 | 0.05 | 0.17 |
| 2019 | 9 | 0.06 | 0.16 |

Source: BGT, author's calculations

### Table A30.2. Number of observations and share of ads in each SOC digit 3 category, 2014-2019

all qualifications combined

| Occupation SOC 3 digit | Number of observations | Percentage |
|---|---|---|
| 231 | 1155801 | 13.92 |
| 223 | 833718 | 10.04 |
| 213 | 661607 | 7.97 |
| 212 | 418609 | 5.04 |
| 221 | 364547 | 4.39 |
| 242 | 318450 | 3.84 |
| 113 | 283896 | 3.42 |
| 354 | 262866 | 3.17 |
| 241 | 261693 | 3.15 |
| 614 | 250167 | 3.01 |
| 612 | 207365 | 2.50 |
| 311 | 201639 | 2.43 |
| 712 | 193777 | 2.33 |
| 356 | 180158 | 2.17 |
| 243 | 164309 | 1.98 |
| 353 | 162129 | 1.95 |
| 125 | 156221 | 1.88 |
| 222 | 136521 | 1.64 |
| 244 | 125156 | 1.51 |
| 313 | 114806 | 1.38 |
| 415 | 113610 | 1.37 |
| 211 | 107833 | 1.30 |
| 523 | 96299 | 1.16 |

| | | |
|---|---|---|
| 246 | 79865 | 0.96 |
| 118 | 78714 | 0.95 |
| 524 | 76096 | 0.92 |
| 721 | 74205 | 0.89 |
| 321 | 72908 | 0.88 |
| 421 | 70795 | 0.85 |
| 412 | 64181 | 0.77 |
| 413 | 63719 | 0.77 |
| 543 | 58958 | 0.71 |
| 112 | 53770 | 0.65 |
| 711 | 50693 | 0.61 |
| 323 | 43852 | 0.53 |
| 247 | 40815 | 0.49 |
| 531 | 40222 | 0.48 |
| 341 | 39281 | 0.47 |
| 416 | 34448 | 0.41 |
| 344 | 32101 | 0.39 |
| 352 | 30287 | 0.36 |
| 522 | 30055 | 0.36 |
| 622 | 27600 | 0.33 |
| 312 | 26673 | 0.32 |
| 342 | 25824 | 0.31 |
| 124 | 24726 | 0.30 |
| 722 | 22333 | 0.27 |
| 921 | 21358 | 0.26 |
| 927 | 20303 | 0.24 |
| 713 | 18219 | 0.22 |
| 544 | 17143 | 0.21 |
| 111 | 15192 | 0.18 |
| 812 | 15111 | 0.18 |
| 331 | 14150 | 0.17 |
| 821 | 12457 | 0.15 |
| 116 | 12067 | 0.15 |
| 214 | 11749 | 0.14 |
| 122 | 11547 | 0.14 |
| 923 | 9925 | 0.12 |
| 926 | 9521 | 0.11 |
| 924 | 9152 | 0.11 |
| 521 | 8590 | 0.10 |
| 811 | 8561 | 0.10 |
| 621 | 8415 | 0.10 |
| 813 | 7725 | 0.09 |
| 623 | 6331 | 0.08 |
| 215 | 6186 | 0.07 |
| 119 | 6046 | 0.07 |
| 532 | 5305 | 0.06 |

| | | |
|---|---|---|
| 411 | 4786 | 0.06 |
| 613 | 4743 | 0.06 |
| 245 | 4383 | 0.05 |
| 814 | 4019 | 0.05 |
| 511 | 3969 | 0.05 |
| 912 | 3914 | 0.05 |
| 542 | 3626 | 0.04 |
| 913 | 3426 | 0.04 |
| 624 | 3257 | 0.04 |
| 823 | 3004 | 0.04 |
| 117 | 2576 | 0.03 |
| 541 | 2456 | 0.03 |
| 351 | 2235 | 0.03 |
| 525 | 2083 | 0.03 |
| 911 | 1816 | 0.02 |
| 533 | 1767 | 0.02 |
| 822 | 1669 | 0.02 |
| 115 | 626 | 0.01 |
| 121 | 458 | 0.01 |
| 925 | 443 | 0.01 |
| 355 | 346 | 0.00 |
| Missing | 58263 | 0.70 |

Source: BGT data, author's calculations

### Table A31.3. Share of ads requiring HTE qualifications by SOC digit 3, 2014-2019

| SOC3 | Number of ads targeting HTE | Share of ads in the occupation requiring HTE qualifications |
|---|---|---|
| 124 | 14738 | 59.6052738 |
| 312 | 12183 | 45.6754021 |
| 112 | 16186 | 30.1022875 |
| 533 | 501 | 28.3531409 |
| 212 | 113155 | 27.0311914 |
| 722 | 5875 | 26.3063628 |
| 311 | 51784 | 25.6815398 |
| 246 | 19956 | 24.9871658 |
| 524 | 18871 | 24.7989382 |
| 522 | 7077 | 23.5468308 |
| 243 | 35751 | 21.7583942 |
| 814 | 781 | 19.4326947 |
| 353 | 30397 | 18.7486508 |
| 812 | 2697 | 17.8479254 |
| 613 | 774 | 16.3187856 |
| 125 | 25430 | 16.2782212 |
| 624 | 523 | 16.0577218 |

| | | |
|---|---|---|
| 118 | 11629 | 14.7737378 |
| 122 | 1673 | 14.4886118 |
| 525 | 292 | 14.0182429 |
| 823 | 412 | 13.7150466 |
| 521 | 1077 | 12.5378347 |
| 813 | 963 | 12.4660194 |
| 511 | 487 | 12.2700932 |
| 116 | 1436 | 11.9002238 |
| 121 | 50 | 10.9170306 |
| 416 | 3685 | 10.6972829 |
| 341 | 4166 | 10.6056363 |
| 926 | 1003 | 10.5346077 |
| 356 | 18859 | 10.4680336 |
| 713 | 1875 | 10.291454 |
| 621 | 858 | 10.1960784 |
| 342 | 2460 | 9.5260223 |
| 323 | 4155 | 9.47505245 |
| 913 | 324 | 9.45709282 |
| 119 | 571 | 9.44426067 |
| 614 | 22459 | 8.97760296 |
| 321 | 6196 | 8.49838152 |
| 313 | 9435 | 8.21821159 |
| 927 | 1654 | 8.14657932 |
| 541 | 196 | 7.98045603 |
| 911 | 143 | 7.87444934 |
| 411 | 368 | 7.68909319 |
| 117 | 184 | 7.14285714 |
| 331 | 996 | 7.03886926 |
| 351 | 157 | 7.0246085 |
| 544 | 1176 | 6.85994283 |
| NA | 3915 | 6.71953041 |
| 111 | 1014 | 6.67456556 |
| 542 | 239 | 6.59128516 |
| 354 | 15872 | 6.03805741 |
| 912 | 229 | 5.85079203 |
| 531 | 2342 | 5.8226841 |
| 413 | 3627 | 5.69217973 |
| 623 | 358 | 5.65471489 |
| 924 | 510 | 5.57255245 |
| 242 | 16605 | 5.21431936 |
| 113 | 14650 | 5.16034041 |
| 923 | 510 | 5.13853904 |

| | | |
|---|---|---|
| 412 | 3267 | 5.09029152 |
| 344 | 1609 | 5.01230491 |
| 214 | 585 | 4.97914716 |
| 421 | 3147 | 4.44522918 |
| 712 | 8463 | 4.36739138 |
| 622 | 1195 | 4.32971014 |
| 822 | 71 | 4.25404434 |
| 213 | 27764 | 4.19644895 |
| 355 | 14 | 4.04624277 |
| 115 | 25 | 3.99361022 |
| 921 | 848 | 3.97040921 |
| 543 | 2317 | 3.92991621 |
| 811 | 333 | 3.88973251 |
| 245 | 156 | 3.55920602 |
| 415 | 3903 | 3.43543702 |
| 612 | 7027 | 3.38871073 |
| 215 | 208 | 3.3624313 |
| 821 | 395 | 3.17090792 |
| 711 | 1528 | 3.01422287 |
| 211 | 2971 | 2.75518626 |
| 523 | 2519 | 2.61581117 |
| 925 | 11 | 2.48306998 |
| 721 | 1827 | 2.46209824 |
| 247 | 970 | 2.37657724 |
| 244 | 2645 | 2.11336252 |
| 231 | 15473 | 1.33872526 |
| 532 | 71 | 1.33836004 |
| 352 | 321 | 1.05986067 |
| 221 | 3185 | 0.87368707 |
| 222 | 839 | 0.61455747 |
| 223 | 4128 | 0.49513145 |
| 241 | 291 | 0.111199 |
| | | |

Source: BGT data, author's calculations

### Table A32.4. List of the most common skills in SOC 212 (sample with education), 2014-2019

ordered by occurrence

| |
|---|
| CommunicationSkills |
| MechanicalEngineering |
| ProjectManagement |
| CivilEngineering |

| |
|---|
| Budgeting |
| AutoCAD |
| Planning |
| ProblemSolving |
| Calculation |
| TeamworkCollaboration |
| MechanicalDesign |
| Commissioning |
| MicrosoftOffice |
| Research |
| Writing |
| MicrosoftExcel |
| CustomerService |
| OrganisationalSkills |
| ElectricalEngineering |
| TechnicalSupport |
| EngineeringDesignandInstallation |
| SolidWorks |
| EngineeringDesign |
| ComputerLiteracy |
| Scheduling |
| Creativity |
| QualityAssuranceandControl |
| ProductDevelopment |
| Procurement |
| DetailOrientated |
| Mentoring |
| ElectricalDesign |
| ProductDesign |
| ElectronicsIndustryKnowledge |
| Leadership |
| English |
| QualityManagement |
| BuildingEffectiveRelationships |
| ManufacturingProcesses |
| ProjectDesign |
| StructuralDesign |
| PresentationSkills |
| ProcessDesign |
| Surveys |
| HighwayDesign |
| HVAC |
| Simulation |
| ReportWriting |
| TechnicalRecruiting |
| SystemsEngineering |

| |
|---|
| Physics |
| EngineeringManagement |
| ProjectPlanningandDevelopmentSkills |
| ProcessEngineering |
| X3DmodellingDesign |
| BusinessDevelopment |
| CustomerContact |
| MeetingDeadlines |
| SystemDesign |
| Revit |
| WrittenCommunication |
| DesignSoftware |
| ElectronicsDesignandEngineering |
| TimeManagement |
| VerbalOralCommunication |
| CostControl |
| ComputerAidedDraughtingDesignCAD |
| MicrosoftWord |
| ElectronicEngineering |
| Wiring |
| EngineeringDocumentation |
| MicrosoftPowerpoint |
| Packaging |
| ElectricalSystems |
| EngineeringProjects |
| Troubleshooting |
| FailureModeandEffectsAnalysisFMEA |
| StaffManagement |
| PreventiveMaintenance |
| ProjectEngineering |
| FeasibilityStudies |
| PredictivePreventativeMaintenance |
| EngineeringDrawings |
| KeyPerformanceIndicatorsKPIs |
| SiemensNixdorfHardware |
| PeopleManagement |
| TechnicalWritingEditing |
| Sales |
| AnalyticalSkills |
| SixSigma |
| MicrosoftProject |
| IndustrialEngineeringIndustryExpertise |
| OriginalEquipmentManufacturerOEM |
| SchematicDiagrams |
| GeotechnicalEngineering |
| Purchasing |

| |
|---|
| EngineeringSupport |
| Prototyping |
| CATIA |
| Robotics |
| TestEquipment |
| ContractPreparation |
| EngineeringActivities |
| MATLAB |
| Hydraulics |
| SiteSurveys |
| C |
| Welding |
| Telecommunications |
| Plumbing |
| DesignandConstruction |
| Estimating |
| Machining |
| DrainageDesign |
| TechnicalDrawings |
| ClientBaseRetention |
| SelfStarter |
| Teaching |
| NewProductDevelopment |
| CostEstimation |
| StakeholderManagement |
| MultiTasking |
| SCADA |
| DecisionMaking |
| ISO9001Standards |
| SoftwareEngineering |
| Optimisation |
| Masonry |
| LeanManufacturing |
| ProcessImprovement |
| AutomotiveIndustryKnowledge |
| ElectronicDesign |
| Autodesk |
| Ventilation |
| SoftwareDevelopment |
| SAP |
| PreparingProposals |
| Calibration |
| WaterTreatment |
| DataAnalysis |
| EnvironmentalEngineering |
| ProductSales |

| |
|---|
| SiteInvestigations |
| PCBLayoutandDesign |
| Costing |
| Python |
| ContractReview |
| RootCauseAnalysis |
| CircuitDesign |
| TroubleshootingTechnicalIssues |
| CatiaV5 |
| PTCCreo |
| ChangeManagement |
| ComputerNumericalControlCNC |
| HumanMachineInterfaceHMI |
| AutomotiveEngineering |
| ContractManagement |
| StructuralFailureAnalysis |
| PrioritisingTasks |
| ElectricalDiagramsSchematics |
| HAZOP |
| PowerGeneration |
| SystemsIntegration |
| RiskAssessment |
| AssetManagementIndustryKnowledge |
| ElectricalWork |
| BillofMaterials |
| Articulate |
| LINUX |
| ProgrammableLogicControllerPLCProgramming |
| EmbeddedSoftware |
| ProcessControl |
| FacilitiesMaintenanceIndustryKnowledge |
| NegotiationSkills |
| VHSIChardwaredescriptionlanguageVHDL |
| PositiveDisposition |
| HardwareExperience |
| ProENGINEER |
| RetailIndustryKnowledge |
| Boilers |
| ConstructionManagement |
| MechanicalMaintenance |
| Civil3D |
| SelfMotivation |
| Microcontrollers |
| RenewableEnergy |
| SoftwareArchitecture |
| EnterpriseResourcePlanningERP |

| |
|---|
| TeamManagement |
| SQL |
| EmergencyLighting |
| RecordKeeping |
| DigitalDesign |
| FacilityManagement |
| Java |
| MicrosoftC |
| Energetic |
| SalesEngineering |
| ServiceLevelAgreement |
| Cabling |
| OperationsManagement |
| AdobePhotoshop |
| MicrosoftWindows |
| NetworkEngineering |
| Cleaning |
| ChildCare |
| ForkliftOperation |
| Vmware |
| Cisco |
| TransmissionControlProtocolInternetProtocolTCPIP |
| MicrosoftActiveDirectory |
| ITIL |
| WindowsServer |
| DomainNameSystemDNS |
| WideAreaNetworkWAN |
| Virtualisation |
| MicrosoftExchange |
| DevOps |
| MicrosoftPowerShell |
| Citrix |
| DynamicHostConfigurationProtocolDHCP |
| HyperV |
| MicrosoftAzure |
| |

Source: BGT data, author's calculations

### Table A33.5. Share of ads (SOC 212) with a specific skill by qualification (HTE/degree) and the associated clusters, 2014-2019

| Skills | HTE | degree | cluster |
|---|---|---|---|
| Adobe.Photoshop | 3.010204082 | 96.98979592 | 1 |
| Analytical.Skills | 9.245339747 | 90.75466025 | 1 |
| Articulate | 8.39114635 | 91.60885365 | 1 |
| Automotive.Engineering | 6.360708535 | 93.63929147 | 1 |

| | | | |
|---|---|---|---|
| Business.Development | 5.52734375 | 94.47265625 | 1 |
| C.. | 2.859477124 | 97.14052288 | 1 |
| Calculation | 12.17833447 | 87.82166553 | 1 |
| Change.Management | 9.703808181 | 90.29619182 | 1 |
| Circuit.Design | 8.05482087 | 91.94517913 | 1 |
| Cisco | 6.177924217 | 93.82207578 | 1 |
| Citrix | 4.230769231 | 95.76923077 | 1 |
| Civil.3D | 6.722984864 | 93.27701514 | 1 |
| Civil.Engineering | 9.644953872 | 90.35504613 | 1 |
| Creativity | 5.992343117 | 94.00765688 | 1 |
| Data.Analysis | 6.583003082 | 93.41699692 | 1 |
| Design.Software | 11.10228176 | 88.89771824 | 1 |
| DevOps | 1.628664495 | 98.3713355 | 1 |
| Digital.Design | 3.366111952 | 96.63388805 | 1 |
| Domain.Name.System..DNS. | 3.355704698 | 96.6442953 | 1 |
| Drainage.Design | 4.32618683 | 95.67381317 | 1 |
| Dynamic.Host.Configuration.Protocol..DHCP | 2.8 | 97.2 | 1 |
| Electronic.Design | 7.148777455 | 92.85122254 | 1 |
| Electronic.Engineering | 6.86704695 | 93.13295305 | 1 |
| Electronics.Design.and.Engineering | 6.361242759 | 93.63875724 | 1 |
| Electronics.Industry.Knowledge | 0.231702331 | 99.76829767 | 1 |
| Embedded.Software | 3.468208092 | 96.53179191 | 1 |
| Energetic | 9.706190976 | 90.29380902 | 1 |
| Engineering.Design | 9.813664596 | 90.1863354 | 1 |
| Engineering.Design.and.Installation | 10.23051592 | 89.76948408 | 1 |
| Engineering.Projects | 11.52258065 | 88.47741935 | 1 |
| English | 7.046151545 | 92.95384846 | 1 |
| Environmental.Engineering | 2.310574521 | 97.68942548 | 1 |
| Feasibility.Studies | 8.702449192 | 91.29755081 | 1 |
| Geotechnical.Engineering | 0.623960067 | 99.37603993 | 1 |
| Hardware.Experience | 6.162373655 | 93.83762634 | 1 |
| Highway.Design | 8.580459236 | 91.41954076 | 1 |
| Hyper.V | 5.720823799 | 94.2791762 | 1 |
| ITIL | 3.90199637 | 96.09800363 | 1 |
| Java | 1.705930138 | 98.29406986 | 1 |
| LINUX | 2.609929078 | 97.39007092 | 1 |
| Masonry | 0.77212806 | 99.22787194 | 1 |
| MATLAB | 0.788221297 | 99.2117787 | 1 |
| Mentoring | 5.405238066 | 94.59476193 | 1 |
| Microcontrollers | 2.226027397 | 97.7739726 | 1 |
| Microsoft.Active.Directory | 6.284153005 | 93.71584699 | 1 |
| Microsoft.Azure | 1.160092807 | 98.83990719 | 1 |
| Microsoft.C. | 6.720302887 | 93.27969711 | 1 |
| Microsoft.Exchange | 6.570512821 | 93.42948718 | 1 |
| Microsoft.PowerShell | 1.54373928 | 98.45626072 | 1 |
| Multi.Tasking | 11.73235564 | 88.26764436 | 1 |

| | | | |
|---|---|---|---|
| Network.Engineering | 8.333333333 | 91.66666667 | 1 |
| New.Product.Development | 11.47712967 | 88.52287033 | 1 |
| PCB.Layout.and.Design | 8.708571429 | 91.29142857 | 1 |
| Physics | 2.17666185 | 97.82333815 | 1 |
| Preparing.Proposals | 8.781994704 | 91.2180053 | 1 |
| Presentation.Skills | 6.943951756 | 93.05604824 | 1 |
| Process.Design | 9.965290464 | 90.03470954 | 1 |
| Product.Design | 9.397163121 | 90.60283688 | 1 |
| Product.Development | 8.89216264 | 91.10783736 | 1 |
| Prototyping | 7.950969024 | 92.04903098 | 1 |
| PTC.Creo | 9.17377242 | 90.82622758 | 1 |
| Python | 1.686640036 | 98.31335996 | 1 |
| Renewable.Energy | 11.95410807 | 88.04589193 | 1 |
| Report.Writing | 6.31054265 | 93.68945735 | 1 |
| Research | 5.560361777 | 94.43963822 | 1 |
| Retail.Industry.Knowledge | 10.93394077 | 89.06605923 | 1 |
| Revit | 11.65738009 | 88.34261991 | 1 |
| Simulation | 3.098121819 | 96.90187818 | 1 |
| Site.Investigations | 3.353396389 | 96.64660361 | 1 |
| Software.Development | 3.948992184 | 96.05100782 | 1 |
| Software.Engineering | 4.798578199 | 95.2014218 | 1 |
| SQL | 5.005775895 | 94.9942241 | 1 |
| Stakeholder.Management | 9.239693391 | 90.76030661 | 1 |
| Structural.Design | 2.511278195 | 97.4887218 | 1 |
| Structural.Failure.Analysis | 1.43274078 | 98.56725922 | 1 |
| System.Design | 9.656911104 | 90.3430889 | 1 |
| Systems.Engineering | 10.27628702 | 89.72371298 | 1 |
| Systems.Integration | 12.05607477 | 87.94392523 | 1 |
| Team.Management | 9.007936508 | 90.99206349 | 1 |
| Transmission.Control.Protocol...Internet.Prot | 9.44595822 | 90.55404178 | 1 |
| Verbal...Oral.Communication | 10.82601054 | 89.17398946 | 1 |
| VHSIC.hardware.description.language..VHD | 1.09123977 | 98.90876023 | 1 |
| Virtualisation | 1.383125864 | 98.61687414 | 1 |
| VMware | 3.906836965 | 96.09316304 | 1 |
| Wide.Area.Network..WAN. | 5.180533752 | 94.81946625 | 1 |
| Windows.Server | 5.215419501 | 94.7845805 | 1 |
| Writing | 11.30755533 | 88.69244467 | 1 |
| Written.Communication | 10.07673211 | 89.92326789 | 1 |
| Boilers | 46.629659 | 53.370341 | 2 |
| Cabling | 31.15124153 | 68.84875847 | 2 |
| Calibration | 29.91642085 | 70.08357915 | 2 |
| Commissioning | 31.72961163 | 68.27038837 | 2 |
| Computer.Literacy | 26.71570281 | 73.28429719 | 2 |
| Computer.Numerical.Control..CNC. | 42.60243979 | 57.39756021 | 2 |
| Costing | 27.90507365 | 72.09492635 | 2 |
| Electrical.Diagrams...Schematics | 47.76180698 | 52.23819302 | 2 |

| | | | |
|---|---|---|---|
| Engineering.Drawings | 32.75862069 | 67.24137931 | 2 |
| Engineering.Management | 27.82133523 | 72.17866477 | 2 |
| Engineering.Support | 27.53677155 | 72.46322845 | 2 |
| Facility.Management | 42.66517357 | 57.33482643 | 2 |
| Human.Machine.Interface..HMI. | 38.47429519 | 61.52570481 | 2 |
| HVAC | 33.63293187 | 66.36706813 | 2 |
| Hydraulics | 34.03773585 | 65.96226415 | 2 |
| ISO.9001.Standards | 34.20987348 | 65.79012652 | 2 |
| Key.Performance.Indicators..KPIs. | 33.2591356 | 66.7408644 | 2 |
| Lean.Manufacturing | 36.78716904 | 63.21283096 | 2 |
| Machining | 36.53222068 | 63.46777932 | 2 |
| Operations.Management | 32.20796759 | 67.79203241 | 2 |
| Plumbing | 44.82142857 | 55.17857143 | 2 |
| Process.Control | 28.88461538 | 71.11538462 | 2 |
| Programmable.Logic.Controller..PLC..Progra | 40.86251067 | 59.13748933 | 2 |
| Record.Keeping | 34.75429248 | 65.24570752 | 2 |
| SAP | 32.33792751 | 67.66207249 | 2 |
| SCADA | 30.53040103 | 69.46959897 | 2 |
| Schematic.Diagrams | 29.13370998 | 70.86629002 | 2 |
| Service.Level.Agreement | 27.94577685 | 72.05422315 | 2 |
| Siemens.Nixdorf.Hardware | 41.38408304 | 58.61591696 | 2 |
| Site.Surveys | 28.67783985 | 71.32216015 | 2 |
| Technical.Drawings | 32.71723476 | 67.28276524 | 2 |
| Test.Equipment | 29.98225902 | 70.01774098 | 2 |
| Ventilation | 32.31684641 | 67.68315359 | 2 |
| Water.Treatment | 28.22700297 | 71.77299703 | 2 |
| Welding | 40.89099054 | 59.10900946 | 2 |
| Wiring | 43.99347338 | 56.00652662 | 2 |
| Asset.Management.Industry.Knowledge | 14.97233748 | 85.02766252 | 3 |
| AutoCAD | 19.68369524 | 80.31630476 | 3 |
| Autodesk | 22.00654818 | 77.99345182 | 3 |
| Automotive.Industry.Knowledge | 18.67483549 | 81.32516451 | 3 |
| Bill.of.Materials | 26.16438356 | 73.83561644 | 3 |
| Budgeting | 15.22547928 | 84.77452072 | 3 |
| Building.Effective.Relationships | 13.93892606 | 86.06107394 | 3 |
| CATIA | 13.26367983 | 86.73632017 | 3 |
| Catia.V5 | 13.79310345 | 86.20689655 | 3 |
| Child.Care | 18.45703125 | 81.54296875 | 3 |
| Cleaning | 25.33495737 | 74.66504263 | 3 |
| Client.Base.Retention | 15.73696145 | 84.26303855 | 3 |
| Communication.Skills | 13.66525666 | 86.33474334 | 3 |
| Computer.Aided.Draughting.Design..CAD. | 23.58367983 | 76.41632017 | 3 |
| Construction.Management | 15.301807 | 84.698193 | 3 |
| Contract.Management | 17.47336377 | 82.52663623 | 3 |
| Contract.Preparation | 13.07583274 | 86.92416726 | 3 |
| Contract.Review | 23.4295416 | 76.5704584 | 3 |

| | | | |
|---|---|---|---|
| Cost.Control | 20.54829618 | 79.45170382 | 3 |
| Cost.Estimation | 15.86004609 | 84.13995391 | 3 |
| Customer.Contact | 15.4467894 | 84.5532106 | 3 |
| Customer.Service | 18.96335079 | 81.03664921 | 3 |
| Decision.Making | 12.62603116 | 87.37396884 | 3 |
| Design.and.Construction | 12.98598776 | 87.01401224 | 3 |
| Detail.Orientated | 17.99675369 | 82.00324631 | 3 |
| Electrical.Design | 26.13408568 | 73.86591432 | 3 |
| Electrical.Engineering | 25.68497213 | 74.31502787 | 3 |
| Electrical.Systems | 23.72395047 | 76.27604953 | 3 |
| Engineering.Activities | 20.60955213 | 79.39044787 | 3 |
| Engineering.Documentation | 15.82495866 | 84.17504134 | 3 |
| Enterprise.Resource.Planning..ERP. | 25.06404782 | 74.93595218 | 3 |
| Estimating | 25.325346 | 74.674654 | 3 |
| Facilities.Maintenance.Industry.Knowledge | 22.4852071 | 77.5147929 | 3 |
| Failure.Mode.and.Effects.Analysis..FMEA. | 14.06147809 | 85.93852191 | 3 |
| HAZOP | 16.20341124 | 83.79658876 | 3 |
| Industrial.Engineering.Industry.Expertise | 16.92669015 | 83.07330985 | 3 |
| Leadership | 12.9938606 | 87.0061394 | 3 |
| Manufacturing.Processes | 21.485997 | 78.514003 | 3 |
| Mechanical.Design | 18.71693353 | 81.28306647 | 3 |
| Mechanical.Engineering | 22.47262738 | 77.52737262 | 3 |
| Meeting.Deadlines | 16.59244033 | 83.40755967 | 3 |
| Microsoft.Excel | 18.87898687 | 81.12101313 | 3 |
| Microsoft.Office | 18.57104984 | 81.42895016 | 3 |
| Microsoft.Powerpoint | 15.5874706 | 84.4125294 | 3 |
| Microsoft.Project | 18.19953925 | 81.80046075 | 3 |
| Microsoft.Windows | 13.75698324 | 86.24301676 | 3 |
| Microsoft.Word | 21.74959872 | 78.25040128 | 3 |
| Negotiation.Skills | 18.49734586 | 81.50265414 | 3 |
| Optimisation | 13.49223239 | 86.50776761 | 3 |
| Organisational.Skills | 17.26113737 | 82.73886263 | 3 |
| Original.Equipment.Manufacturer..OEM. | 12.52884932 | 87.47115068 | 3 |
| Packaging | 24.01758359 | 75.98241641 | 3 |
| People.Management | 15.41817088 | 84.58182912 | 3 |
| Planning | 16.0214168 | 83.9785832 | 3 |
| Positive.Disposition | 18.92012494 | 81.07987506 | 3 |
| Power.Generation | 21.58544955 | 78.41455045 | 3 |
| Prioritising.Tasks | 19.53125 | 80.46875 | 3 |
| Pro.ENGINEER | 12.39511823 | 87.60488177 | 3 |
| Problem.Solving | 16.13918094 | 83.86081906 | 3 |
| Process.Engineering | 18.9713414 | 81.0286586 | 3 |
| Process.Improvement | 21.84579439 | 78.15420561 | 3 |
| Procurement | 20.74894658 | 79.25105342 | 3 |
| Product.Sales | 13.44098789 | 86.55901211 | 3 |
| Project.Design | 14.24408639 | 85.75591361 | 3 |

| | | | |
|---|---|---|---|
| Project.Engineering | 21.09317138 | 78.90682862 | 3 |
| Project.Management | 14.00792936 | 85.99207064 | 3 |
| Project.Planning.and.Development.Skills | 13.40423292 | 86.59576708 | 3 |
| Purchasing | 22.86842578 | 77.13157422 | 3 |
| Quality.Assurance.and.Control | 20.85270288 | 79.14729712 | 3 |
| Quality.Management | 21.06931354 | 78.93068646 | 3 |
| Risk.Assessment | 16.49241147 | 83.50758853 | 3 |
| Robotics | 23.86384889 | 76.13615111 | 3 |
| Root.Cause.Analysis | 24.59677419 | 75.40322581 | 3 |
| Sales | 19.19047619 | 80.80952381 | 3 |
| Sales.Engineering | 24.6876859 | 75.3123141 | 3 |
| Scheduling | 23.61383793 | 76.38616207 | 3 |
| Self.Motivation | 21.39755231 | 78.60244769 | 3 |
| Self.Starter | 12.96942335 | 87.03057665 | 3 |
| Six.Sigma | 18.53593015 | 81.46406985 | 3 |
| Software.Architecture | 14.1439206 | 85.8560794 | 3 |
| SolidWorks | 18.07186473 | 81.92813527 | 3 |
| Staff.Management | 13.44239945 | 86.55760055 | 3 |
| Surveys | 15.09473684 | 84.90526316 | 3 |
| Teaching | 14.23194542 | 85.76805458 | 3 |
| Teamwork...Collaboration | 13.18627927 | 86.81372073 | 3 |
| Technical.Recruiting | 23.46496234 | 76.53503766 | 3 |
| Technical.Support | 23.33151581 | 76.66848419 | 3 |
| Technical.Writing...Editing | 19.81088203 | 80.18911797 | 3 |
| Telecommunications | 14.15238095 | 85.84761905 | 3 |
| Time.Management | 17.68605378 | 82.31394622 | 3 |
| Troubleshooting | 20.97685684 | 79.02314316 | 3 |
| Troubleshooting.Technical.Issues | 13.81095069 | 86.18904931 | 3 |
| X3D.Modelling...Design | 19.72689313 | 80.27310687 | 3 |
| Electrical.Work | 64.38698916 | 35.61301084 | 4 |
| Emergency.Lighting | 55 | 45 | 4 |
| Forklift.Operation | 69.34306569 | 30.65693431 | 4 |
| Mechanical.Maintenance | 79.62466488 | 20.37533512 | 4 |
| Predictive...Preventative.Maintenance | 74.6884273 | 25.3115727 | 4 |
| Preventive.Maintenance | 73.32010207 | 26.67989793 | 4 |

Source: BGT data, author's calculations

### Table A34.6. Ads with HTE by specific skills, SOC 212, 2014-2019

Values in column 3 do not add to 100% as there can be more than one skill within one ad.

| Skill | Nb. of HTE ads with a specific skills | Share of HTE ads with a specific skill |
|---|---|---|
| Communication.Skills | 11953 | 22.4 |
| Mechanical.Engineering | 11617 | 21.8 |
| AutoCAD | 7841 | 14.7 |
| Project.Management | 7773 | 14.6 |

| | | |
|---|---|---|
| Commissioning | 7116 | 13.3 |
| Planning | 6613 | 12.4 |
| Budgeting | 6425 | 12.0 |
| Problem.Solving | 6002 | 11.2 |
| Mechanical.Design | 5342 | 10.0 |
| Civil.Engineering | 4485 | 8.4 |
| Electrical.Engineering | 4331 | 8.1 |
| Technical.Support | 4279 | 8.0 |
| Microsoft.Office | 4203 | 7.9 |
| Teamwork...Collaboration | 4071 | 7.6 |
| Microsoft.Excel | 4025 | 7.5 |
| Computer.Literacy | 3959 | 7.4 |
| Calculation | 3928 | 7.4 |
| Customer.Service | 3622 | 6.8 |
| Organisational.Skills | 3615 | 6.8 |
| Electrical.Design | 3520 | 6.6 |
| Scheduling | 3488 | 6.5 |
| Quality.Assurance.and.Control | 3140 | 5.9 |
| SolidWorks | 3078 | 5.8 |
| Procurement | 3053 | 5.7 |
| Writing | 2667 | 5.0 |
| Detail.Orientated | 2661 | 5.0 |
| Preventive.Maintenance | 2586 | 4.8 |
| Quality.Management | 2526 | 4.7 |
| Predictive...Preventative.Maintenance | 2517 | 4.7 |
| Manufacturing.Processes | 2432 | 4.6 |
| Siemens.Nixdorf.Hardware | 2392 | 4.5 |
| Engineering.Management | 2342 | 4.4 |
| Wiring | 2157 | 4.0 |
| Technical.Recruiting | 2056 | 3.9 |
| Engineering.Drawings | 1938 | 3.6 |
| HVAC | 1871 | 3.5 |
| Engineering.Design.and.Installation | 1864 | 3.5 |
| Computer.Aided.Draughting.Design..C | 1815 | 3.4 |
| Packaging | 1803 | 3.4 |
| Leadership | 1799 | 3.4 |
| Key.Performance.Indicators..KPIs. | 1793 | 3.4 |
| Process.Engineering | 1741 | 3.3 |
| Engineering.Design | 1738 | 3.3 |
| Project.Design | 1662 | 3.1 |
| Welding | 1643 | 3.1 |
| Microsoft.Word | 1626 | 3.0 |
| Building.Effective.Relationships | 1625 | 3.0 |
| Cost.Control | 1604 | 3.0 |
| Machining | 1576 | 3.0 |
| Electrical.Systems | 1571 | 2.9 |

| | | |
|---|---|---|
| Troubleshooting | 1559 | 2.9 |
| Schematic.Diagrams | 1547 | 2.9 |
| Test.Equipment | 1521 | 2.8 |
| Product.Development | 1509 | 2.8 |
| Engineering.Support | 1479 | 2.8 |
| Meeting.Deadlines | 1453 | 2.7 |
| Lean.Manufacturing | 1445 | 2.7 |
| Surveys | 1434 | 2.7 |
| Project.Engineering | 1424 | 2.7 |
| Research | 1414 | 2.6 |
| Time.Management | 1414 | 2.6 |
| ISO.9001.Standards | 1379 | 2.6 |
| Product.Design | 1378 | 2.6 |
| Customer.Contact | 1376 | 2.6 |
| Technical.Drawings | 1363 | 2.6 |
| Computer.Numerical.Control..CNC. | 1362 | 2.6 |
| Hydraulics | 1353 | 2.5 |
| Technical.Writing...Editing | 1278 | 2.4 |
| Robotics | 1276 | 2.4 |
| Purchasing | 1274 | 2.4 |
| Project.Planning.and.Development.Skill | 1273 | 2.4 |
| SAP | 1267 | 2.4 |
| Microsoft.Powerpoint | 1259 | 2.4 |
| Engineering.Documentation | 1244 | 2.3 |
| Site.Surveys | 1232 | 2.3 |
| Estimating | 1226 | 2.3 |
| Calibration | 1217 | 2.3 |
| Sales | 1209 | 2.3 |
| SCADA | 1180 | 2.2 |
| Electrical.Diagrams...Schematics | 1163 | 2.2 |
| Human.Machine.Interface..HMI. | 1160 | 2.2 |
| Engineering.Activities | 1109 | 2.1 |
| Six.Sigma | 1104 | 2.1 |
| Process.Design | 1091 | 2.0 |
| Creativity | 1080 | 2.0 |
| Failure.Mode.and.Effects.Analysis..FM | 1075 | 2.0 |
| Revit | 1067 | 2.0 |
| Systems.Engineering | 1034 | 1.9 |
| Microsoft.Project | 1027 | 1.9 |
| People.Management | 1025 | 1.9 |
| Costing | 1023 | 1.9 |
| Industrial.Engineering.Industry.Expertis | 1009 | 1.9 |
| Staff.Management | 986 | 1.8 |
| Design.Software | 978 | 1.8 |
| Programmable.Logic.Controller..PLC..P | 957 | 1.8 |
| English | 942 | 1.8 |

| | | |
|---|---|---|
| Autodesk | 941 | 1.8 |
| Process.Improvement | 935 | 1.8 |
| Verbal...Oral.Communication | 924 | 1.7 |
| Highway.Design | 923 | 1.7 |
| Engineering.Projects | 893 | 1.7 |
| Written.Communication | 893 | 1.7 |
| Mechanical.Maintenance | 891 | 1.7 |
| System.Design | 881 | 1.7 |
| Mentoring | 873 | 1.6 |
| Ventilation | 869 | 1.6 |
| Root.Cause.Analysis | 854 | 1.6 |
| Contract.Review | 828 | 1.6 |
| Automotive.Industry.Knowledge | 823 | 1.5 |
| Presentation.Skills | 783 | 1.5 |
| Electrical.Work | 772 | 1.4 |
| Bill.of.Materials | 764 | 1.4 |
| Water.Treatment | 761 | 1.4 |
| Original.Equipment.Manufacturer..OEM | 760 | 1.4 |
| Cost.Estimation | 757 | 1.4 |
| Process.Control | 751 | 1.4 |
| CATIA | 749 | 1.4 |
| Telecommunications | 743 | 1.4 |
| Contract.Preparation | 738 | 1.4 |
| Client.Base.Retention | 694 | 1.3 |
| Report.Writing | 671 | 1.3 |
| Feasibility.Studies | 668 | 1.3 |
| Design.and.Construction | 658 | 1.2 |
| Optimisation | 634 | 1.2 |
| Self.Starter | 632 | 1.2 |
| Power.Generation | 629 | 1.2 |
| Electronic.Engineering | 626 | 1.2 |
| Analytical.Skills | 615 | 1.2 |
| Teaching | 605 | 1.1 |
| Electronics.Design.and.Engineering | 604 | 1.1 |
| Boilers | 588 | 1.1 |
| Enterprise.Resource.Planning..ERP. | 587 | 1.1 |
| Record.Keeping | 587 | 1.1 |
| Contract.Management | 574 | 1.1 |
| Business.Development | 566 | 1.1 |
| Product.Sales | 566 | 1.1 |
| Decision.Making | 551 | 1.0 |
| Prioritising.Tasks | 550 | 1.0 |
| New.Product.Development | 547 | 1.0 |
| Self.Motivation | 542 | 1.0 |
| HAZOP | 513 | 1.0 |
| Multi.Tasking | 512 | 1.0 |

| | | |
|---|---|---|
| Troubleshooting.Technical.Issues | 507 | 0.9 |
| Plumbing | 502 | 0.9 |
| Facilities.Maintenance.Industry.Knowle | 494 | 0.9 |
| Risk.Assessment | 489 | 0.9 |
| Catia.V5 | 480 | 0.9 |
| Prototyping | 480 | 0.9 |
| Operations.Management | 477 | 0.9 |
| Negotiation.Skills | 453 | 0.8 |
| Stakeholder.Management | 446 | 0.8 |
| Asset.Management.Industry.Knowledg | 433 | 0.8 |
| Positive.Disposition | 424 | 0.8 |
| Sales.Engineering | 415 | 0.8 |
| Cabling | 414 | 0.8 |
| Construction.Management | 398 | 0.7 |
| Preparing.Proposals | 398 | 0.7 |
| Systems.Integration | 387 | 0.7 |
| Facility.Management | 381 | 0.7 |
| PCB.Layout.and.Design | 381 | 0.7 |
| Simulation | 353 | 0.7 |
| Electronic.Design | 345 | 0.6 |
| Change.Management | 344 | 0.6 |
| Software.Architecture | 342 | 0.6 |
| Circuit.Design | 335 | 0.6 |
| Structural.Design | 334 | 0.6 |
| Pro.ENGINEER | 325 | 0.6 |
| Renewable.Energy | 323 | 0.6 |
| PTC.Creo | 312 | 0.6 |
| Data.Analysis | 299 | 0.6 |
| Emergency.Lighting | 297 | 0.6 |
| Forklift.Operation | 285 | 0.5 |
| Service.Level.Agreement | 268 | 0.5 |
| Articulate | 254 | 0.5 |
| Software.Engineering | 243 | 0.5 |
| Physics | 241 | 0.5 |
| Retail.Industry.Knowledge | 240 | 0.4 |
| Automotive.Engineering | 237 | 0.4 |
| Team.Management | 227 | 0.4 |
| Drainage.Design | 226 | 0.4 |
| Cleaning | 208 | 0.4 |
| Microsoft.Windows | 197 | 0.4 |
| Software.Development | 192 | 0.4 |
| Civil.3D | 191 | 0.4 |
| Child.Care | 189 | 0.4 |
| Hardware.Experience | 189 | 0.4 |
| Energetic | 185 | 0.3 |
| C.. | 175 | 0.3 |

| | | |
|---|---|---|
| Site.Investigations | 156 | 0.3 |
| Microsoft.C. | 142 | 0.3 |
| SQL | 130 | 0.2 |
| Network.Engineering | 121 | 0.2 |
| Embedded.Software | 114 | 0.2 |
| Environmental.Engineering | 111 | 0.2 |
| Transmission.Control.Protocol...Internet | 104 | 0.2 |
| LINUX | 92 | 0.2 |
| Digital.Design | 89 | 0.2 |
| Python | 76 | 0.1 |
| Cisco | 75 | 0.1 |
| Microsoft.Active.Directory | 69 | 0.1 |
| Microcontrollers | 65 | 0.1 |
| Adobe.Photoshop | 59 | 0.1 |
| Structural.Failure.Analysis | 54 | 0.1 |
| MATLAB | 53 | 0.1 |
| VMware | 52 | 0.1 |
| Windows.Server | 46 | 0.1 |
| Geotechnical.Engineering | 45 | 0.1 |
| ITIL | 43 | 0.1 |
| Java | 42 | 0.1 |
| Masonry | 41 | 0.1 |
| Microsoft.Exchange | 41 | 0.1 |
| VHSIC.hardware.description.language.. | 36 | 0.1 |
| Electronics.Industry.Knowledge | 34 | 0.1 |
| Wide.Area.Network..WAN. | 33 | 0.1 |
| Domain.Name.System..DNS. | 25 | 0.0 |
| Hyper.V | 25 | 0.0 |
| Citrix | 22 | 0.0 |
| Dynamic.Host.Configuration.Protocol.. | 14 | 0.0 |
| DevOps | 10 | 0.0 |
| Virtualisation | 10 | 0.0 |
| Microsoft.PowerShell | 9 | 0.0 |
| Microsoft.Azure | 5 | 0.0 |
| X3D.Modelling...Design | 1748 | 3.3 |

Source: BGT data, author's calculations

## Table A35.7. Co-occurrence of Mechanical Engineering skill with other skills, 2014-2019

HTE qualifications only

| | two skills co-occurring | all skills | MechEngineering occurrence | Other skills occurrence | Chi2 | Expected co-occurrence | Corr. Significance | Type of co-occurrence |
|---|---|---|---|---|---|---|---|---|
| Mechanical.Engineering | 0 | 1949730 | 63126 | 63126 | 2181.8 | 2043.8 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Civil.Engineering | 108 | 1949730 | 63126 | 17662 | 391.5 | 571.8 | p<.001 | Antitype |
| Electrical.Design | 224 | 1949730 | 63126 | 20666 | 308.6 | 669.1 | p<.001 | Antitype |
| Highway.Design | 0 | 1949730 | 63126 | 5693 | 190 | 184.3 | p<.001 | Antitype |
| Electrical.Engineering | 357 | 1949730 | 63126 | 21652 | 175.9 | 701.0 | p<.001 | Antitype |
| Electronics.Design.and.Engineering | 12 | 1949730 | 63126 | 3717 | 100.1 | 120.3 | p<.001 | Antitype |
| Human.Machine.Interface..HMI. | 96 | 1949730 | 63126 | 7993 | 105.6 | 258.8 | p<.001 | Antitype |
| Programmable.Logic.Controller..PLC..Programming | 72 | 1949730 | 63126 | 6585 | 96.3 | 213.2 | p<.001 | Antitype |
| Quality.Management | 338 | 1949730 | 63126 | 18035 | 107.6 | 583.9 | p<.001 | Antitype |
| Siemens.Nixdorf.Hardware | 270 | 1949730 | 63126 | 15072 | 101 | 488.0 | p<.001 | Antitype |
| Software.Architecture | 12 | 1949730 | 63126 | 2713 | 66.9 | 87.8 | p<.001 | Antitype |
| Cabling | 27 | 1949730 | 63126 | 3464 | 66.2 | 112.2 | p<.001 | Antitype |
| Electronic.Engineering | 23 | 1949730 | 63126 | 3178 | 63.4 | 102.9 | p<.001 | Antitype |
| PCB.Layout.and.Design | 15 | 1949730 | 63126 | 2662 | 60 | 86.2 | p<.001 | Antitype |
| SCADA | 114 | 1949730 | 63126 | 7530 | 71.1 | 243.8 | p<.001 | Antitype |
| Schematic.Diagrams | 194 | 1949730 | 63126 | 10873 | 73.3 | 352.0 | p<.001 | Antitype |
| Design.and.Construction | 50 | 1949730 | 63126 | 4506 | 64.6 | 145.9 | p<.001 | Antitype |
| Quality.Assurance.and.Control | 429 | 1949730 | 63126 | 19824 | 73.3 | 641.8 | p<.001 | Antitype |
| Test.Equipment | 144 | 1949730 | 63126 | 8639 | 67.8 | 279.7 | p<.001 | Antitype |
| Telecommunications | 52 | 1949730 | 63126 | 4499 | 61.7 | 145.7 | p<.001 | Antitype |
| Wiring | 289 | 1949730 | 63126 | 14418 | 70.1 | 466.8 | p<.001 | Antitype |
| Electronic.Design | 12 | 1949730 | 63126 | 2141 | 48.2 | 69.3 | p<.001 | Antitype |
| Civil.3D | 0 | 1949730 | 63126 | 1163 | 37.9 | 37.7 | p<.001 | Antitype |
| Drainage.Design | 0 | 1949730 | 63126 | 1169 | 38.1 | 37.8 | p<.001 | Antitype |
| Circuit.Design | 16 | 1949730 | 63126 | 2355 | 48.4 | 76.2 | p<.001 | Antitype |
| Electrical.Diagrams...Schematics | 146 | 1949730 | 63126 | 8238 | 56.2 | 266.7 | p<.001 | Antitype |
| Systems.Engineering | 102 | 1949730 | 63126 | 6385 | 54.5 | 206.7 | p<.001 | Antitype |
| Planning | 1190 | 1949730 | 63126 | 45353 | 55.6 | 1468.4 | p<.001 | Antitype |
| Microsoft.Project | 185 | 1949730 | 63126 | 9422 | 48.7 | 305.1 | p<.001 | Antitype |
| Electrical.Systems | 206 | 1949730 | 63126 | 10029 | 44.7 | 324.7 | p<.001 | Antitype |
| Project.Management | 1329 | 1949730 | 63126 | 49262 | 46.8 | 1594.9 | p<.001 | Antitype |
| Six.Sigma | 159 | 1949730 | 63126 | 8129 | 42.4 | 263.2 | p<.001 | Antitype |
| Microsoft.Office | 877 | 1949730 | 63126 | 33810 | 45.3 | 1094.7 | p<.001 | Antitype |
| Construction.Management | 26 | 1949730 | 63126 | 2418 | 35.4 | 78.3 | p<.001 | Antitype |
| Engineering.Activities | 154 | 1949730 | 63126 | 7813 | 39.8 | 253.0 | p<.001 | Antitype |
| People.Management | 133 | 1949730 | 63126 | 6687 | 33 | 216.5 | p<.001 | Antitype |
| Network.Engineering | 1 | 1949730 | 63126 | 759 | 22.4 | 24.6 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Embedded.Software | 1 | 1949730 | 63126 | 760 | 22.4 | 24.6 | p<.001 | Antitype |
| Prioritising.Tasks | 83 | 1949730 | 63126 | 4656 | 31.1 | 150.7 | p<.001 | Antitype |
| Site.Investigations | 5 | 1949730 | 63126 | 965 | 21.9 | 31.2 | p<.001 | Antitype |
| Negotiation.Skills | 62 | 1949730 | 63126 | 3654 | 27.3 | 118.3 | p<.001 | Antitype |
| Microsoft.Excel | 924 | 1949730 | 63126 | 33986 | 29.6 | 1100.4 | p<.001 | Antitype |
| C.. | 12 | 1949730 | 63126 | 1319 | 22.1 | 42.7 | p<.001 | Antitype |
| Software.Development | 12 | 1949730 | 63126 | 1327 | 22.3 | 43.0 | p<.001 | Antitype |
| Site.Surveys | 218 | 1949730 | 63126 | 9502 | 26.8 | 307.6 | p<.001 | Antitype |
| Microsoft.Active.Directory | 0 | 1949730 | 63126 | 510 | 16.1 | 16.5 | p<.001 | Antitype |
| LINUX | 2 | 1949730 | 63126 | 687 | 18.1 | 22.2 | p<.001 | Antitype |
| Team.Management | 17 | 1949730 | 63126 | 1519 | 21.1 | 49.2 | p<.001 | Antitype |
| Transmission.Control.Protocol...Internet.Protocol..TCP...IP. | 4 | 1949730 | 63126 | 794 | 18.1 | 25.7 | p<.001 | Antitype |
| Stakeholder.Management | 60 | 1949730 | 63126 | 3374 | 22.5 | 109.2 | p<.001 | Antitype |
| Writing | 521 | 1949730 | 63126 | 19926 | 24.7 | 645.1 | p<.001 | Antitype |
| Budgeting | 1273 | 1949730 | 63126 | 45062 | 24.9 | 1459.0 | p<.001 | Antitype |
| Software.Engineering | 25 | 1949730 | 63126 | 1860 | 20.7 | 60.2 | p<.001 | Antitype |
| Commissioning | 1262 | 1949730 | 63126 | 44684 | 24.8 | 1446.7 | p<.001 | Antitype |
| Written.Communication | 153 | 1949730 | 63126 | 6843 | 21.7 | 221.6 | p<.001 | Antitype |
| Microcontrollers | 0 | 1949730 | 63126 | 434 | 13.5 | 14.1 | p<.001 | Antitype |
| Cisco | 3 | 1949730 | 63126 | 657 | 15.3 | 21.3 | p<.001 | Antitype |
| Microsoft.C. | 8 | 1949730 | 63126 | 947 | 16.6 | 30.7 | p<.001 | Antitype |
| Hardware.Experience | 17 | 1949730 | 63126 | 1386 | 17.3 | 44.9 | p<.001 | Antitype |
| VMware | 0 | 1949730 | 63126 | 397 | 12.3 | 12.9 | p<.001 | Antitype |
| Decision.Making | 106 | 1949730 | 63126 | 4915 | 18 | 159.1 | p<.001 | Antitype |
| Teamwork...Collaboration | 801 | 1949730 | 63126 | 28701 | 18.4 | 929.2 | p<.001 | Antitype |
| Verbal...Oral.Communication | 219 | 1949730 | 63126 | 8927 | 17.4 | 289.0 | p<.001 | Antitype |
| Digital.Design | 3 | 1949730 | 63126 | 577 | 12.8 | 18.7 | p<.001 | Antitype |
| SQL | 11 | 1949730 | 63126 | 1003 | 14 | 32.5 | p<.001 | Antitype |
| Python | 4 | 1949730 | 63126 | 614 | 12.3 | 19.9 | p<.001 | Antitype |
| ITIL | 0 | 1949730 | 63126 | 332 | 10.1 | 10.7 | p<.001 | Antitype |
| Change.Management | 67 | 1949730 | 63126 | 3303 | 15.1 | 106.9 | p<.001 | Antitype |
| VHSIC.hardware.description.language..VHDL. | 0 | 1949730 | 63126 | 338 | 10.3 | 10.9 | p<.001 | Antitype |
| Windows.Server | 0 | 1949730 | 63126 | 325 | 9.9 | 10.5 | p<.001 | Antitype |
| Microsoft.Exchange | 0 | 1949730 | 63126 | 305 | 9.2 | 9.9 | p<.001 | Antitype |
| Environmental.Engineering | 5 | 1949730 | 63126 | 586 | 9.9 | 19.0 | p<.001 | Antitype |
| Mentoring | 139 | 1949730 | 63126 | 5719 | 11.7 | 185.2 | p<.001 | Antitype |
| Scheduling | 700 | 1949730 | 63126 | 24563 | 11.8 | 795.3 | p<.001 | Antitype |
| Building.Effective.Relationships | 328 | 1949730 | 63126 | 12199 | 11.6 | 395.0 | p<.001 | Antitype |
| Microsoft.Powerpoint | 351 | 1949730 | 63126 | 12953 | 11.4 | 419.4 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Contract.Review | 152 | 1949730 | 63126 | 6133 | 11.1 | 198.6 | p<.01 | Antitype |
| Business.Development | 96 | 1949730 | 63126 | 4133 | 10.8 | 133.8 | p<.01 | Antitype |
| Hyper.V | 0 | 1949730 | 63126 | 241 | 7.1 | 7.8 | p<.01 | Antitype |
| Wide.Area.Network..WAN. | 1 | 1949730 | 63126 | 301 | 7.2 | 9.7 | p<.01 | Antitype |
| Risk.Assessment | 97 | 1949730 | 63126 | 4108 | 9.8 | 133.0 | p<.01 | Antitype |
| Organisational.Skills | 785 | 1949730 | 63126 | 27029 | 9.6 | 875.1 | p<.01 | Antitype |
| Adobe.Photoshop | 6 | 1949730 | 63126 | 535 | 7 | 17.3 | p<.01 | Antitype |
| Optimisation | 134 | 1949730 | 63126 | 5296 | 8.3 | 171.5 | p<.01 | Antitype |
| Self.Motivation | 98 | 1949730 | 63126 | 4032 | 8.1 | 130.5 | p<.01 | Antitype |
| System.Design | 175 | 1949730 | 63126 | 6682 | 8 | 216.3 | p<.01 | Antitype |
| Computer.Literacy | 873 | 1949730 | 63126 | 29639 | 8.1 | 959.6 | p<.01 | Antitype |
| Electronics.Industry.Knowledge | 1 | 1949730 | 63126 | 260 | 5.9 | 8.4 | p<.01 | Antitype |
| SAP | 237 | 1949730 | 63126 | 8759 | 7.8 | 283.6 | p<.01 | Antitype |
| | | | | | | | | |
| Mechanical.Design | 2787 | 1949730 | 63126 | 32681 | 2967.5 | 1058.1 | p<.001 | Type |
| SolidWorks | 1444 | 1949730 | 63126 | 20646 | 938.7 | 668.5 | p<.001 | Type |
| Mechanical.Maintenance | 446 | 1949730 | 63126 | 3633 | 946.3 | 117.6 | p<.001 | Type |
| Teaching | 279 | 1949730 | 63126 | 1561 | 1063.5 | 50.5 | p<.001 | Type |
| Hydraulics | 601 | 1949730 | 63126 | 6961 | 647.6 | 225.4 | p<.001 | Type |
| Welding | 700 | 1949730 | 63126 | 10401 | 406 | 336.8 | p<.001 | Type |
| X3D.Modelling...Design | 778 | 1949730 | 63126 | 12685 | 340.8 | 410.7 | p<.001 | Type |
| Boilers | 261 | 1949730 | 63126 | 2780 | 334.2 | 90.0 | p<.001 | Type |
| Machining | 656 | 1949730 | 63126 | 11121 | 252 | 360.1 | p<.001 | Type |
| Water.Treatment | 308 | 1949730 | 63126 | 3989 | 255.1 | 129.2 | p<.001 | Type |
| Forklift.Operation | 149 | 1949730 | 63126 | 1229 | 307.1 | 39.8 | p<.001 | Type |
| CATIA | 361 | 1949730 | 63126 | 5199 | 227.3 | 168.3 | p<.001 | Type |
| Autodesk | 424 | 1949730 | 63126 | 6601 | 213.5 | 213.7 | p<.001 | Type |
| HVAC | 551 | 1949730 | 63126 | 10098 | 158.8 | 326.9 | p<.001 | Type |
| Catia.V5 | 246 | 1949730 | 63126 | 3376 | 175.7 | 109.3 | p<.001 | Type |
| PTC.Creo | 189 | 1949730 | 63126 | 2421 | 160.1 | 78.4 | p<.001 | Type |
| Product.Design | 534 | 1949730 | 63126 | 10494 | 114.8 | 339.8 | p<.001 | Type |
| Calculation | 1147 | 1949730 | 63126 | 26386 | 104.7 | 854.3 | p<.001 | Type |
| Engineering.Drawings | 648 | 1949730 | 63126 | 13450 | 107.4 | 435.5 | p<.001 | Type |
| Manufacturing.Processes | 791 | 1949730 | 63126 | 17254 | 100.4 | 558.6 | p<.001 | Type |
| Computer.Numerical.Control..CNC. | 426 | 1949730 | 63126 | 8107 | 105.1 | 262.5 | p<.001 | Type |
| Predictive...Preventative.Maintenance | 673 | 1949730 | 63126 | 14685 | 85 | 475.5 | p<.001 | Type |
| Preventive.Maintenance | 675 | 1949730 | 63126 | 15069 | 74.3 | 487.9 | p<.001 | Type |
| Ventilation | 269 | 1949730 | 63126 | 4984 | 73.7 | 161.4 | p<.001 | Type |
| Computer.Aided.Draughting.Design..CAD. | 569 | 1949730 | 63126 | 12874 | 57.4 | 416.8 | p<.001 | Type |
| Engineering.Management | 661 | 1949730 | 63126 | 15317 | 56.9 | 495.9 | p<.001 | Type |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Client.Base.Retention | 209 | 1949730 | 63126 | 3889 | 56.1 | 125.9 | p<.001 | Type |
| Technical.Recruiting | 423 | 1949730 | 63126 | 9223 | 53.4 | 298.6 | p<.001 | Type |
| Pro.ENGINEER | 147 | 1949730 | 63126 | 2481 | 56.4 | 80.3 | p<.001 | Type |
| New.Product.Development | 218 | 1949730 | 63126 | 4178 | 51.8 | 135.3 | p<.001 | Type |
| Automotive.Engineering | 106 | 1949730 | 63126 | 1639 | 53.6 | 53.1 | p<.001 | Type |
| Power.Generation | 200 | 1949730 | 63126 | 3787 | 49.9 | 122.6 | p<.001 | Type |
| Plumbing | 148 | 1949730 | 63126 | 2569 | 51.5 | 83.2 | p<.001 | Type |
| Packaging | 443 | 1949730 | 63126 | 9984 | 45.7 | 323.2 | p<.001 | Type |
| Enterprise.Resource.Planning..ERP. | 230 | 1949730 | 63126 | 4667 | 42.1 | 151.1 | p<.001 | Type |
| Engineering.Support | 438 | 1949730 | 63126 | 10117 | 38.3 | 327.6 | p<.001 | Type |
| Bill.of.Materials | 289 | 1949730 | 63126 | 6260 | 37.7 | 202.7 | p<.001 | Type |
| Product.Development | 465 | 1949730 | 63126 | 10932 | 35.9 | 353.9 | p<.001 | Type |
| Physics | 80 | 1949730 | 63126 | 1225 | 41.4 | 39.7 | p<.001 | Type |
| Purchasing | 428 | 1949730 | 63126 | 10221 | 29.3 | 330.9 | p<.001 | Type |
| Industrial.Engineering.Industry.Expertise | 283 | 1949730 | 63126 | 6577 | 23.6 | 212.9 | p<.001 | Type |
| Detail.Orientated | 789 | 1949730 | 63126 | 20641 | 22.6 | 668.3 | p<.001 | Type |
| Creativity | 357 | 1949730 | 63126 | 8642 | 21.8 | 279.8 | p<.001 | Type |
| Engineering.Design.and.Installation | 588 | 1949730 | 63126 | 15246 | 18.6 | 493.6 | p<.001 | Type |
| Engineering.Design | 557 | 1949730 | 63126 | 14402 | 18.2 | 466.3 | p<.001 | Type |
| Process.Design | 330 | 1949730 | 63126 | 8167 | 16.6 | 264.4 | p<.001 | Type |
| AutoCAD | 1763 | 1949730 | 63126 | 49692 | 15.6 | 1608.9 | p<.001 | Type |
| Facilities.Maintenance.Industry.Knowledge | 112 | 1949730 | 63126 | 2366 | 16.4 | 76.6 | p<.001 | Type |
| Contract.Management | 177 | 1949730 | 63126 | 4087 | 15.3 | 132.3 | p<.001 | Type |
| Sales.Engineering | 99 | 1949730 | 63126 | 2070 | 15.3 | 67.0 | p<.001 | Type |
| Project.Engineering | 374 | 1949730 | 63126 | 9710 | 11.5 | 314.4 | p<.01 | Type |
| Facility.Management | 94 | 1949730 | 63126 | 2042 | 11.7 | 66.1 | p<.01 | Type |
| Process.Improvement | 256 | 1949730 | 63126 | 6501 | 10 | 210.5 | p<.01 | Type |
| Communication.Skills | 2719 | 1949730 | 63126 | 79425 | 9 | 2571.5 | p<.01 | Type |

Source: BGT data, author's calculations

## Table A36.8. Co-occurrence of communication skill with other skills, 2014-2019

HTE qualifications only

| | Two skills co-occurring | all skills | Communication occurrence | Other skills occurrence | Chi2 | expected co-occurrence | Corr Significance | Type of co-occurrence |
|---|---|---|---|---|---|---|---|---|
| Communication.Skills | 0 | 1949730 | 79425 | 79425 | 3515 | 3235.5 | p<.001 | Antitype |
| Project.Design | 246 | 1949730 | 79425 | 11502 | 110.4 | 468.6 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mechanical.Design | 976 | 1949730 | 79425 | 32681 | 100.3 | 1331.3 | p<.001 | Antitype |
| Technical.Recruiting | 201 | 1949730 | 79425 | 9223 | 84.6 | 375.7 | p<.001 | Antitype |
| Human.Machine.Interface..HMI. | 171 | 1949730 | 79425 | 7993 | 76.3 | 325.6 | p<.001 | Antitype |
| HAZOP | 47 | 1949730 | 79425 | 3744 | 75.5 | 152.5 | p<.001 | Antitype |
| Calculation | 812 | 1949730 | 79425 | 26386 | 67.7 | 1074.9 | p<.001 | Antitype |
| SolidWorks | 632 | 1949730 | 79425 | 20646 | 54.5 | 841.0 | p<.001 | Antitype |
| Bill.of.Materials | 141 | 1949730 | 79425 | 6260 | 52.8 | 255.0 | p<.001 | Antitype |
| Six.Sigma | 210 | 1949730 | 79425 | 8129 | 46 | 331.1 | p<.001 | Antitype |
| X3D.Modelling...Design | 374 | 1949730 | 79425 | 12685 | 41.1 | 516.7 | p<.001 | Antitype |
| Commissioning | 1565 | 1949730 | 79425 | 44684 | 38 | 1820.3 | p<.001 | Antitype |
| Electrical.Engineering | 704 | 1949730 | 79425 | 21652 | 37.7 | 882.0 | p<.001 | Antitype |
| Lean.Manufacturing | 293 | 1949730 | 79425 | 10010 | 33.6 | 407.8 | p<.001 | Antitype |
| Optimisation | 136 | 1949730 | 79425 | 5296 | 30.4 | 215.7 | p<.001 | Antitype |
| Scheduling | 833 | 1949730 | 79425 | 24563 | 29.5 | 1000.6 | p<.001 | Antitype |
| Design.and.Construction | 112 | 1949730 | 79425 | 4506 | 28.7 | 183.6 | p<.001 | Antitype |
| Design.Software | 202 | 1949730 | 79425 | 7131 | 27.9 | 290.5 | p<.001 | Antitype |
| Pro.ENGINEER | 49 | 1949730 | 79425 | 2481 | 27.5 | 101.1 | p<.001 | Antitype |
| Autodesk | 186 | 1949730 | 79425 | 6601 | 26.4 | 268.9 | p<.001 | Antitype |
| Schematic.Diagrams | 339 | 1949730 | 79425 | 10873 | 25.3 | 442.9 | p<.001 | Antitype |
| AutoCAD | 1812 | 1949730 | 79425 | 49692 | 23.7 | 2024.3 | p<.001 | Antitype |
| Systems.Engineering | 183 | 1949730 | 79425 | 6385 | 23.6 | 260.1 | p<.001 | Antitype |
| Engineering.Design | 473 | 1949730 | 79425 | 14402 | 22.9 | 586.7 | p<.001 | Antitype |
| Engineering.Design.and.Installation | 505 | 1949730 | 79425 | 15246 | 22.6 | 621.1 | p<.001 | Antitype |
| Software.Architecture | 62 | 1949730 | 79425 | 2713 | 21.8 | 110.5 | p<.001 | Antitype |
| Transmission.Control.Protocol...Internet.Protocol..TCP...IP. | 6 | 1949730 | 79425 | 794 | 21.5 | 32.3 | p<.001 | Antitype |
| Electrical.Work | 94 | 1949730 | 79425 | 3677 | 21.3 | 149.8 | p<.001 | Antitype |
| Programmable.Logic.Controller..PLC..Programming | 194 | 1949730 | 79425 | 6585 | 21.2 | 268.2 | p<.001 | Antitype |
| Root.Cause.Analysis | 183 | 1949730 | 79425 | 6238 | 20.5 | 254.1 | p<.001 | Antitype |
| Electrical.Design | 720 | 1949730 | 79425 | 20666 | 18.4 | 841.9 | p<.001 | Antitype |
| SCADA | 235 | 1949730 | 79425 | 7530 | 17.3 | 306.7 | p<.001 | Antitype |
| Process.Engineering | 362 | 1949730 | 79425 | 10998 | 17.1 | 448.0 | p<.001 | Antitype |
| Engineering.Drawings | 453 | 1949730 | 79425 | 13450 | 17.1 | 547.9 | p<.001 | Antitype |
| Engineering.Documentation | 358 | 1949730 | 79425 | 10818 | 16.1 | 440.7 | p<.001 | Antitype |
| Automotive.Industry.Knowledge | 158 | 1949730 | 79425 | 5303 | 16 | 216.0 | p<.001 | Antitype |
| Siemens.Nixdorf.Hardware | 519 | 1949730 | 79425 | 15072 | 15.3 | 614.0 | p<.001 | Antitype |
| Project.Planning.and.Development.Skills | 348 | 1949730 | 79425 | 10481 | 15.1 | 427.0 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Computer.Aided.Draughting.Design..CAD. | 438 | 1949730 | 79425 | 12874 | 14.8 | 524.4 | p<.001 | Antitype |
| PTC.Creo | 61 | 1949730 | 79425 | 2421 | 14.6 | 98.6 | p<.001 | Antitype |
| Sales | 218 | 1949730 | 79425 | 6881 | 14.3 | 280.3 | p<.001 | Antitype |
| Electrical.Diagrams...Schematics | 268 | 1949730 | 79425 | 8238 | 14 | 335.6 | p<.001 | Antitype |
| Enterprise.Resource.Planning..ERP. | 140 | 1949730 | 79425 | 4667 | 13.5 | 190.1 | p<.001 | Antitype |
| Welding | 352 | 1949730 | 79425 | 10401 | 12.5 | 423.7 | p<.001 | Antitype |
| Quality.Assurance.and.Control | 712 | 1949730 | 79425 | 19824 | 11.8 | 807.6 | p<.01 | Antitype |
| Wiring | 507 | 1949730 | 79425 | 14418 | 11.4 | 587.3 | p<.01 | Antitype |
| Machining | 389 | 1949730 | 79425 | 11121 | 9.3 | 453.0 | p<.01 | Antitype |
| Process.Control | 172 | 1949730 | 79425 | 5256 | 8.5 | 214.1 | p<.01 | Antitype |
| CATIA | 170 | 1949730 | 79425 | 5199 | 8.4 | 211.8 | p<.01 | Antitype |
| Construction.Management | 70 | 1949730 | 79425 | 2418 | 8.3 | 98.5 | p<.01 | Antitype |
| Technical.Drawings | 285 | 1949730 | 79425 | 8278 | 8.3 | 337.2 | p<.01 | Antitype |
| Computer.Numerical.Control..CNC. | 279 | 1949730 | 79425 | 8107 | 8.2 | 330.3 | p<.01 | Antitype |
| Circuit.Design | 68 | 1949730 | 79425 | 2355 | 8.2 | 95.9 | p<.01 | Antitype |
| Embedded.Software | 16 | 1949730 | 79425 | 760 | 7 | 31.0 | p<.01 | Antitype |
| | | | | | | | | |
| Verbal...Oral.Communication | 924 | 1949730 | 79425 | 8927 | 902.6 | 363.7 | p<.001 | Type |
| Organisational.Skills | 1718 | 1949730 | 79425 | 27029 | 364.8 | 1101.1 | p<.001 | Type |
| Problem.Solving | 2489 | 1949730 | 79425 | 43558 | 306.4 | 1774.4 | p<.001 | Type |
| Computer.Literacy | 1795 | 1949730 | 79425 | 29639 | 302.2 | 1207.4 | p<.001 | Type |
| Time.Management | 841 | 1949730 | 79425 | 12196 | 249.4 | 496.8 | p<.001 | Type |
| Teamwork...Collaboration | 1667 | 1949730 | 79425 | 28701 | 223.8 | 1169.2 | p<.001 | Type |
| Writing | 1214 | 1949730 | 79425 | 19926 | 209.5 | 811.7 | p<.001 | Type |
| Detail.Orientated | 1231 | 1949730 | 79425 | 20641 | 190.3 | 840.8 | p<.001 | Type |
| Teaching | 165 | 1949730 | 79425 | 1561 | 167.1 | 63.6 | p<.001 | Type |
| Analytical.Skills | 405 | 1949730 | 79425 | 5612 | 141.5 | 228.6 | p<.001 | Type |
| English | 488 | 1949730 | 79425 | 7138 | 139.3 | 290.8 | p<.001 | Type |
| Planning | 2299 | 1949730 | 79425 | 45353 | 117.5 | 1847.5 | p<.001 | Type |
| Service.Level.Agreement | 143 | 1949730 | 79425 | 1606 | 94.7 | 65.4 | p<.001 | Type |
| Meeting.Deadlines | 685 | 1949730 | 79425 | 11847 | 88.6 | 482.6 | p<.001 | Type |
| Building.Effective.Relationships | 695 | 1949730 | 79425 | 12199 | 82.4 | 496.9 | p<.001 | Type |
| People.Management | 417 | 1949730 | 79425 | 6687 | 79.7 | 272.4 | p<.001 | Type |
| Positive.Disposition | 234 | 1949730 | 79425 | 3315 | 75 | 135.0 | p<.001 | Type |
| Report.Writing | 322 | 1949730 | 79425 | 5036 | 69 | 205.1 | p<.001 | Type |
| Civil.Engineering | 922 | 1949730 | 79425 | 17662 | 59.7 | 719.5 | p<.001 | Type |
| Plumbing | 181 | 1949730 | 79425 | 2569 | 57.4 | 104.7 | p<.001 | Type |
| Microsoft.Office | 1626 | 1949730 | 79425 | 33810 | 47.5 | 1377.3 | p<.001 | Type |
| Prioritising.Tasks | 278 | 1949730 | 79425 | 4656 | 42.5 | 189.7 | p<.001 | Type |
| Record.Keeping | 211 | 1949730 | 79425 | 3420 | 38 | 139.3 | p<.001 | Type |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Test.Equipment | 464 | 1949730 | 79425 | 8639 | 37 | 351.9 | p<.001 | Type |
| Customer.Service | 1077 | 1949730 | 79425 | 22171 | 35.1 | 903.2 | p<.001 | Type |
| Presentation.Skills | 349 | 1949730 | 79425 | 6316 | 33.8 | 257.3 | p<.001 | Type |
| Customer.Contact | 481 | 1949730 | 79425 | 9111 | 33.7 | 371.1 | p<.001 | Type |
| Decision.Making | 281 | 1949730 | 79425 | 4915 | 33.6 | 200.2 | p<.001 | Type |
| Microsoft.Excel | 1588 | 1949730 | 79425 | 33986 | 31.6 | 1384.5 | p<.001 | Type |
| Stakeholder.Management | 188 | 1949730 | 79425 | 3374 | 19 | 137.4 | p<.001 | Type |
| Engineering.Activities | 393 | 1949730 | 79425 | 7813 | 18.1 | 318.3 | p<.001 | Type |
| Staff.Management | 361 | 1949730 | 79425 | 7337 | 13.3 | 298.9 | p<.01 | Type |
| Ventilation | 254 | 1949730 | 79425 | 4984 | 13.1 | 203.0 | p<.01 | Type |
| Predictive...Preventative.Maintenance | 682 | 1949730 | 79425 | 14685 | 12.2 | 598.2 | p<.01 | Type |
| Highway.Design | 284 | 1949730 | 79425 | 5693 | 12 | 231.9 | p<.01 | Type |
| Preventive.Maintenance | 697 | 1949730 | 79425 | 15069 | 11.7 | 613.9 | p<.01 | Type |
| Energetic | 80 | 1949730 | 79425 | 1351 | 11.3 | 55.0 | p<.01 | Type |
| Operations.Management | 171 | 1949730 | 79425 | 3259 | 11.2 | 132.8 | p<.01 | Type |
| Microsoft.Powerpoint | 602 | 1949730 | 79425 | 12953 | 10.8 | 527.7 | p<.01 | Type |
| Child.Care | 54 | 1949730 | 79425 | 850 | 10.7 | 34.6 | p<.01 | Type |
| Structural.Failure.Analysis | 27 | 1949730 | 79425 | 357 | 10.3 | 14.5 | p<.01 | Type |
| Emergency.Lighting | 82 | 1949730 | 79425 | 1416 | 10.3 | 57.7 | p<.01 | Type |
| Microsoft.Word | 698 | 1949730 | 79425 | 15238 | 10 | 620.7 | p<.01 | Type |
| Mechanical.Engineering | 2719 | 1949730 | 79425 | 63126 | 9 | 2571.5 | p<.01 | Type |
| Articulate | 101 | 1949730 | 79425 | 1846 | 8.9 | 75.2 | p<.01 | Type |
| Civil.3D | 68 | 1949730 | 79425 | 1163 | 8.9 | 47.4 | p<.01 | Type |

Source: BGT data, author's calculations

## Table A37.9. Co-occurrence of DevOps skill with other skills, 2014-2019

HTE qualifications only

| | Two skills co-occurring | All skills | DevOps occurrence | Other skills occurrence | Chi2 | Expected co-occurrence | Corr Significance | Type of co-occurrence |
|---|---|---|---|---|---|---|---|---|
| Autodesk | 0 | 25996650 | 26402 | 61633 | 61.8 | 62.6 | p<.001 | Antitype |
| Automotive.Engineering | 0 | 25996650 | 26402 | 37668 | 37.4 | 38.3 | p<.001 | Antitype |
| Boilers | 0 | 25996650 | 26402 | 29036 | 28.6 | 29.5 | p<.001 | Antitype |
| Calibration | 0 | 25996650 | 26402 | 47933 | 47.8 | 48.7 | p<.001 | Antitype |
| Civil.3D | 0 | 25996650 | 26402 | 32514 | 32.1 | 33.0 | p<.001 | Antitype |
| Construction.Management | 0 | 25996650 | 26402 | 28302 | 27.8 | 28.7 | p<.001 | Antitype |
| Design.and.Construction | 0 | 25996650 | 26402 | 64857 | 65.1 | 65.9 | p<.001 | Antitype |
| DevOps | 0 | 25996650 | 26402 | 26402 | 25.9 | 26.8 | p<.001 | Antitype |
| Drainage.Design | 0 | 25996650 | 26402 | 51194 | 51.1 | 52.0 | p<.001 | Antitype |
| Emergency.Lighting | 0 | 25996650 | 26402 | 19566 | 18.9 | 19.9 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Engineering.Drawings | 0 | 25996650 | 26402 | 93995 | 94.9 | 95.5 | p<.001 | Antitype |
| Geotechnical.Engineering | 0 | 25996650 | 26402 | 45420 | 45.3 | 46.1 | p<.001 | Antitype |
| Highway.Design | 0 | 25996650 | 26402 | 120082 | 121.6 | 122.0 | p<.001 | Antitype |
| Lean.Manufacturing | 0 | 25996650 | 26402 | 59061 | 59.2 | 60.0 | p<.001 | Antitype |
| Masonry | 0 | 25996650 | 26402 | 35130 | 34.8 | 35.7 | p<.001 | Antitype |
| Original.Equipment.Manufacturer..OEM. | 0 | 25996650 | 26402 | 74441 | 74.9 | 75.6 | p<.001 | Antitype |
| Pro.ENGINEER | 0 | 25996650 | 26402 | 36519 | 36.2 | 37.1 | p<.001 | Antitype |
| Revit | 0 | 25996650 | 26402 | 92797 | 93.7 | 94.2 | p<.001 | Antitype |
| Site.Investigations | 0 | 25996650 | 26402 | 34969 | 34.6 | 35.5 | p<.001 | Antitype |
| Site.Surveys | 0 | 25996650 | 26402 | 80636 | 81.2 | 81.9 | p<.001 | Antitype |
| Ventilation | 0 | 25996650 | 26402 | 51193 | 51.1 | 52.0 | p<.001 | Antitype |
| Water.Treatment | 0 | 25996650 | 26402 | 46099 | 46 | 46.8 | p<.001 | Antitype |
| Mechanical.Engineering | 12 | 25996650 | 26402 | 559105 | 555.6 | 567.8 | p<.001 | Antitype |
| Civil.Engineering | 7 | 25996650 | 26402 | 360891 | 357 | 366.5 | p<.001 | Antitype |
| AutoCAD | 6 | 25996650 | 26402 | 478575 | 482.5 | 486.0 | p<.001 | Antitype |
| Mechanical.Design | 18 | 25996650 | 26402 | 351212 | 325.4 | 356.7 | p<.001 | Antitype |
| Commissioning | 12 | 25996650 | 26402 | 359007 | 345.1 | 364.6 | p<.001 | Antitype |
| Calculation | 13 | 25996650 | 26402 | 392250 | 377.9 | 398.4 | p<.001 | Antitype |
| Electrical.Engineering | 7 | 25996650 | 26402 | 218926 | 209.6 | 222.3 | p<.001 | Antitype |
| Electrical.Design | 3 | 25996650 | 26402 | 171326 | 168.3 | 174.0 | p<.001 | Antitype |
| SolidWorks | 9 | 25996650 | 26402 | 223160 | 210.1 | 226.6 | p<.001 | Antitype |
| Computer.Literacy | 6 | 25996650 | 26402 | 247154 | 240.7 | 251.0 | p<.001 | Antitype |
| Engineering.Design.and.Installation | 6 | 25996650 | 26402 | 252206 | 245.9 | 256.1 | p<.001 | Antitype |
| Budgeting | 171 | 25996650 | 26402 | 599312 | 321.7 | 608.7 | p<.001 | Antitype |
| HVAC | 2 | 25996650 | 26402 | 105634 | 102.9 | 107.3 | p<.001 | Antitype |
| Microsoft.Excel | 42 | 25996650 | 26402 | 362796 | 292.7 | 368.5 | p<.001 | Antitype |
| Engineering.Design | 10 | 25996650 | 26402 | 246279 | 232 | 250.1 | p<.001 | Antitype |
| Technical.Recruiting | 15 | 25996650 | 26402 | 106286 | 79.6 | 107.9 | p<.001 | Antitype |
| Procurement | 16 | 25996650 | 26402 | 215903 | 189.3 | 219.3 | p<.001 | Antitype |
| Project.Design | 4 | 25996650 | 26402 | 155956 | 150.6 | 158.4 | p<.001 | Antitype |
| Surveys | 1 | 25996650 | 26402 | 129926 | 129.7 | 132.0 | p<.001 | Antitype |
| Customer.Service | 88 | 25996650 | 26402 | 306846 | 161.8 | 311.6 | p<.001 | Antitype |
| Microsoft.Office | 63 | 25996650 | 26402 | 384923 | 278.6 | 390.9 | p<.001 | Antitype |
| Product.Design | 13 | 25996650 | 26402 | 176024 | 154 | 178.8 | p<.001 | Antitype |
| Manufacturing.Processes | 6 | 25996650 | 26402 | 157528 | 148.3 | 160.0 | p<.001 | Antitype |
| Preventive.Maintenance | 1 | 25996650 | 26402 | 94363 | 93.3 | 95.8 | p<.001 | Antitype |
| Predictive...Preventative.Maintenance | 1 | 25996650 | 26402 | 89854 | 88.7 | 91.3 | p<.001 | Antitype |
| X3D.Modelling...Design | 2 | 25996650 | 26402 | 129358 | 127.2 | 131.4 | p<.001 | Antitype |
| Structural.Design | 6 | 25996650 | 26402 | 89406 | 78.6 | 90.8 | p<.001 | Antitype |
| Wiring | 3 | 25996650 | 26402 | 102811 | 98 | 104.4 | p<.001 | Antitype |
| Report.Writing | 1 | 25996650 | 26402 | 110616 | 109.9 | 112.3 | p<.001 | Antitype |
| Electrical.Systems | 2 | 25996650 | 26402 | 99983 | 97.1 | 101.5 | p<.001 | Antitype |
| Process.Engineering | 10 | 25996650 | 26402 | 107208 | 89.4 | 108.9 | p<.001 | Antitype |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Hydraulics | 2 | 25996650 | 26402 | 67759 | 64.1 | 68.8 | p<.001 | Antitype |
| Design.Software | 1 | 25996650 | 26402 | 102659 | 101.8 | 104.3 | p<.001 | Antitype |
| Plumbing | 1 | 25996650 | 26402 | 45725 | 43.6 | 46.4 | p<.001 | Antitype |
| Welding | 2 | 25996650 | 26402 | 70281 | 66.7 | 71.4 | p<.001 | Antitype |
| Computer.Aided.Draughting.Design..CAD. | 3 | 25996650 | 26402 | 110219 | 105.6 | 111.9 | p<.001 | Antitype |
| Project.Management | 374 | 25996650 | 26402 | 731867 | 188.5 | 743.3 | p<.001 | Antitype |
| Microsoft.Word | 3 | 25996650 | 26402 | 142062 | 138.3 | 144.3 | p<.001 | Antitype |
| Siemens.Nixdorf.Hardware | 8 | 25996650 | 26402 | 101657 | 87.4 | 103.2 | p<.001 | Antitype |
| Failure.Mode.and.Effects.Analysis..FMEA. | 2 | 25996650 | 26402 | 109305 | 106.6 | 111.0 | p<.001 | Antitype |
| Machining | 1 | 25996650 | 26402 | 73903 | 72.4 | 75.1 | p<.001 | Antitype |
| Feasibility.Studies | 2 | 25996650 | 26402 | 99395 | 96.5 | 100.9 | p<.001 | Antitype |
| Test.Equipment | 1 | 25996650 | 26402 | 69255 | 67.6 | 70.3 | p<.001 | Antitype |
| Schematic.Diagrams | 3 | 25996650 | 26402 | 89219 | 84.1 | 90.6 | p<.001 | Antitype |
| Process.Design | 21 | 25996650 | 26402 | 142812 | 105.9 | 145.0 | p<.001 | Antitype |
| Engineering.Projects | 5 | 25996650 | 26402 | 93734 | 84.9 | 95.2 | p<.001 | Antitype |
| Technical.Drawings | 1 | 25996650 | 26402 | 67337 | 65.7 | 68.4 | p<.001 | Antitype |
| Purchasing | 4 | 25996650 | 26402 | 91718 | 84.8 | 93.1 | p<.001 | Antitype |
| Simulation | 16 | 25996650 | 26402 | 120543 | 92.2 | 122.4 | p<.001 | Antitype |
| Scheduling | 80 | 25996650 | 26402 | 254929 | 124.3 | 258.9 | p<.001 | Antitype |
| Microsoft.Powerpoint | 11 | 25996650 | 26402 | 143032 | 124 | 145.3 | p<.001 | Antitype |
| Engineering.Management | 23 | 25996650 | 26402 | 121043 | 80.9 | 122.9 | p<.001 | Antitype |
| Industrial.Engineering.Industry.Expertise | 6 | 25996650 | 26402 | 73436 | 62.4 | 74.6 | p<.001 | Antitype |
| SCADA | 4 | 25996650 | 26402 | 70595 | 63.2 | 71.7 | p<.001 | Antitype |
| Quality.Management | 45 | 25996650 | 26402 | 186707 | 110.4 | 189.6 | p<.001 | Antitype |
| CATIA | 7 | 25996650 | 26402 | 80726 | 68 | 82.0 | p<.001 | Antitype |
| Estimating | 7 | 25996650 | 26402 | 76669 | 63.8 | 77.9 | p<.001 | Antitype |
| Six.Sigma | 4 | 25996650 | 26402 | 82696 | 75.5 | 84.0 | p<.001 | Antitype |
| Computer.Numerical.Control..CNC. | 4 | 25996650 | 26402 | 53001 | 45.3 | 53.8 | p<.001 | Antitype |
| Project.Engineering | 13 | 25996650 | 26402 | 95456 | 72.2 | 96.9 | p<.001 | Antitype |
| Human.Machine.Interface..HMI. | 2 | 25996650 | 26402 | 57444 | 53.6 | 58.3 | p<.001 | Antitype |
| Contract.Preparation | 6 | 25996650 | 26402 | 85536 | 74.7 | 86.9 | p<.001 | Antitype |
| Electrical.Work | 3 | 25996650 | 26402 | 30768 | 24.7 | 31.2 | p<.001 | Antitype |
| Mechanical.Maintenance | 1 | 25996650 | 26402 | 25691 | 23.2 | 26.1 | p<.001 | Antitype |
| MATLAB | 4 | 25996650 | 26402 | 61888 | 54.4 | 62.9 | p<.001 | Antitype |
| Electronic.Design | 4 | 25996650 | 26402 | 53804 | 46.2 | 54.6 | p<.001 | Antitype |
| Electrical.Diagrams...Schematics | 1 | 25996650 | 26402 | 50607 | 48.6 | 51.4 | p<.001 | Antitype |
| Electronics.Industry.Knowledge | 27 | 25996650 | 26402 | 111834 | 65.6 | 113.6 | p<.001 | Antitype |
| Electronic.Engineering | 31 | 25996650 | 26402 | 88194 | 37.8 | 89.6 | p<.001 | Antitype |
| Costing | 3 | 25996650 | 26402 | 59034 | 53.3 | 60.0 | p<.001 | Antitype |
| Microsoft.Project | 10 | 25996650 | 26402 | 100251 | 82.3 | 101.8 | p<.001 | Antitype |

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|---|---|---|---|---|---|---|---|---|
| Electronics.Design.and.Engineering | 30 | 25996650 | 26402 | 98032 | 48.1 | 99.6 | p<.001 | Antitype |
| Meeting.Deadlines | 36 | 25996650 | 26402 | 141245 | 80.3 | 143.4 | p<.001 | Antitype |
| Cost.Estimation | 5 | 25996650 | 26402 | 73850 | 64.7 | 75.0 | p<.001 | Antitype |
| ISO.9001.Standards | 7 | 25996650 | 26402 | 69276 | 56.4 | 70.4 | p<.001 | Antitype |
| Project.Planning.and.Development.Skills | 34 | 25996650 | 26402 | 146531 | 88.4 | 148.8 | p<.001 | Antitype |
| Facility.Management | 1 | 25996650 | 26402 | 24149 | 21.7 | 24.5 | p<.001 | Antitype |
| Programmable.Logic.Controller..PLC..Programming | 2 | 25996650 | 26402 | 44976 | 40.9 | 45.7 | p<.001 | Antitype |
| Sales.Engineering | 2 | 25996650 | 26402 | 29465 | 25.2 | 29.9 | p<.001 | Antitype |
| Power.Generation | 1 | 25996650 | 26402 | 37273 | 35 | 37.9 | p<.001 | Antitype |
| Sales | 45 | 25996650 | 26402 | 95651 | 27.6 | 97.1 | p<.001 | Antitype |
| Contract.Review | 5 | 25996650 | 26402 | 53773 | 44.3 | 54.6 | p<.001 | Antitype |
| Facilities.Maintenance.Industry.Knowledge | 1 | 25996650 | 26402 | 27008 | 24.6 | 27.4 | p<.001 | Antitype |
| Structural.Failure.Analysis | 1 | 25996650 | 26402 | 36888 | 34.6 | 37.5 | p<.001 | Antitype |
| Environmental.Engineering | 4 | 25996650 | 26402 | 29295 | 21.5 | 29.8 | p<.001 | Antitype |
| Forklift.Operation | 1 | 25996650 | 26402 | 14575 | 12 | 14.8 | p<.001 | Antitype |
| Preparing.Proposals | 7 | 25996650 | 26402 | 61148 | 48.2 | 62.1 | p<.001 | Antitype |
| Cost.Control | 35 | 25996650 | 26402 | 123495 | 64.8 | 125.4 | p<.001 | Antitype |
| PTC.Creo | 3 | 25996650 | 26402 | 47176 | 41.3 | 47.9 | p<.001 | Antitype |
| Packaging | 55 | 25996650 | 26402 | 112816 | 30.6 | 114.6 | p<.001 | Antitype |
| Catia.V5 | 7 | 25996650 | 26402 | 50881 | 37.9 | 51.7 | p<.001 | Antitype |
| HAZOP | 1 | 25996650 | 26402 | 38308 | 36.1 | 38.9 | p<.001 | Antitype |
| Staff.Management | 34 | 25996650 | 26402 | 113531 | 56.9 | 115.3 | p<.001 | Antitype |
| Contract.Management | 5 | 25996650 | 26402 | 49858 | 40.4 | 50.6 | p<.001 | Antitype |
| Engineering.Support | 19 | 25996650 | 26402 | 75426 | 42.7 | 76.6 | p<.001 | Antitype |
| Engineering.Activities | 15 | 25996650 | 26402 | 67184 | 40.9 | 68.2 | p<.001 | Antitype |
| Process.Control | 4 | 25996650 | 26402 | 40406 | 32.6 | 41.0 | p<.001 | Antitype |
| New.Product.Development | 13 | 25996650 | 26402 | 63904 | 40.9 | 64.9 | p<.001 | Antitype |
| Bill.of.Materials | 6 | 25996650 | 26402 | 51462 | 40.2 | 52.3 | p<.001 | Antitype |
| Automotive.Industry.Knowledge | 16 | 25996650 | 26402 | 54885 | 27.7 | 55.7 | p<.001 | Antitype |
| Cleaning | 7 | 25996650 | 26402 | 22182 | 10 | 22.5 | p<.001 | Antitype |
| Product.Development | 100 | 25996650 | 26402 | 206195 | 57.2 | 209.4 | p<.001 | Antitype |
| Physics | 28 | 25996650 | 26402 | 76181 | 31 | 77.4 | p<.001 | Antitype |
| Organisational.Skills | 185 | 25996650 | 26402 | 336770 | 72.6 | 342.0 | p<.001 | Antitype |
| Microcontrollers | 5 | 25996650 | 26402 | 36794 | 27.2 | 37.4 | p<.001 | Antitype |
| PCB.Layout.and.Design | 13 | 25996650 | 26402 | 52146 | 29.5 | 53.0 | p<.001 | Antitype |
| Self.Motivation | 4 | 25996650 | 26402 | 37830 | 30 | 38.4 | p<.001 | Antitype |
| Prototyping | 25 | 25996650 | 26402 | 79811 | 38.2 | 81.1 | p<.001 | Antitype |
| English | 77 | 25996650 | 26402 | 158719 | 43.8 | 161.2 | p<.001 | Antitype |
| Digital.Design | 9 | 25996650 | 26402 | 30789 | 15.2 | 31.3 | p<.001 | Antitype |
| Business.Development | 71 | 25996650 | 26402 | 131286 | 28.8 | 133.3 | p<.001 | Antitype |

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|---|---|---|---|---|---|---|---|---|
| Adobe.Photoshop | 11 | 25996650 | 26402 | 33167 | 14.6 | 33.7 | p<.001 | Antitype |
| Negotiation.Skills | 12 | 25996650 | 26402 | 43387 | 22.7 | 44.1 | p<.001 | Antitype |
| Circuit.Design | 18 | 25996650 | 26402 | 46105 | 17.2 | 46.8 | p<.001 | Antitype |
| Renewable.Energy | 11 | 25996650 | 26402 | 27679 | 9.8 | 28.1 | p<.001 | Antitype |
| System.Design | 62 | 25996650 | 26402 | 120828 | 29.7 | 122.7 | p<.001 | Antitype |
| Multi.Tasking | 32 | 25996650 | 26402 | 84113 | 32.9 | 85.4 | p<.001 | Antitype |
| VHSIC.hardware.description.language..VHDL. | 15 | 25996650 | 26402 | 29819 | 7.2 | 30.3 | p<.01 | Antitype |
| Cabling | 14 | 25996650 | 26402 | 31972 | 10 | 32.5 | p<.001 | Antitype |
| Customer.Contact | 81 | 25996650 | 26402 | 135878 | 23.3 | 138.0 | p<.001 | Antitype |
| Building.Effective.Relationships | 120 | 25996650 | 26402 | 204785 | 37.1 | 208.0 | p<.001 | Antitype |
| Detail.Orientated | 156 | 25996650 | 26402 | 255849 | 41.5 | 259.8 | p<.001 | Antitype |
| Prioritising.Tasks | 22 | 25996650 | 26402 | 55518 | 20.4 | 56.4 | p<.001 | Antitype |
| Risk.Assessment | 20 | 25996650 | 26402 | 45209 | 14.1 | 45.9 | p<.001 | Antitype |
| Record.Keeping | 16 | 25996650 | 26402 | 29650 | 6.2 | 30.1 | p<.01 | Antitype |
| Communication.Skills | 958 | 25996650 | 26402 | 1141022 | 36.3 | 1158.8 | p<.001 | Antitype |
| Planning | 459 | 25996650 | 26402 | 588712 | 32.8 | 597.9 | p<.001 | Antitype |
| Data.Analysis | 30 | 25996650 | 26402 | 52341 | 9.7 | 53.2 | p<.001 | Antitype |
| Research | 221 | 25996650 | 26402 | 264037 | 8.2 | 268.2 | p<.01 | Antitype |
| SAP | 41 | 25996650 | 26402 | 64482 | 8.8 | 65.5 | p<.01 | Antitype |
| Presentation.Skills | 105 | 25996650 | 26402 | 159088 | 19.6 | 161.6 | p<.001 | Antitype |
| Time.Management | 91 | 25996650 | 26402 | 143884 | 20.6 | 146.1 | p<.001 | Antitype |
| Verbal...Oral.Communication | 93 | 25996650 | 26402 | 130594 | 11.6 | 132.6 | p<.001 | Antitype |
| Engineering.Documentation | 86 | 25996650 | 26402 | 135910 | 19.4 | 138.0 | p<.001 | Antitype |
| Technical.Support | 238 | 25996650 | 26402 | 280090 | 7.5 | 284.5 | p<.01 | Antitype |
| | | | | | | | | |
| LINUX | 2536 | 25996650 | 26402 | 89153 | 66316.3 | 90.5 | p<.001 | Type |
| Python | 1845 | 25996650 | 26402 | 60496 | 51920.5 | 61.4 | p<.001 | Type |
| Java | 1309 | 25996650 | 26402 | 43315 | 36446.2 | 44.0 | p<.001 | Type |
| Microsoft.PowerShell | 878 | 25996650 | 26402 | 43659 | 15697.7 | 44.3 | p<.001 | Type |
| SQL | 900 | 25996650 | 26402 | 91253 | 7056 | 92.7 | p<.001 | Type |
| Microsoft.Azure | 609 | 25996650 | 26402 | 35944 | 8984.2 | 36.5 | p<.001 | Type |
| VMware | 865 | 25996650 | 26402 | 127824 | 4182.6 | 129.8 | p<.001 | Type |
| Software.Development | 626 | 25996650 | 26402 | 68073 | 4493.7 | 69.1 | p<.001 | Type |
| Microsoft.C. | 457 | 25996650 | 26402 | 36088 | 4821.1 | 36.7 | p<.001 | Type |
| Virtualisation | 534 | 25996650 | 26402 | 62279 | 3508.2 | 63.3 | p<.001 | Type |
| Software.Engineering | 535 | 25996650 | 26402 | 63061 | 3467.8 | 64.0 | p<.001 | Type |
| Domain.Name.System..DNS. | 475 | 25996650 | 26402 | 64637 | 2555.4 | 65.6 | p<.001 | Type |
| Windows.Server | 555 | 25996650 | 26402 | 95065 | 2182.4 | 96.5 | p<.001 | Type |
| Troubleshooting | 685 | 25996650 | 26402 | 164948 | 1607.3 | 167.5 | p<.001 | Type |
| Transmission.Control.Protocol...Internet.Protocol..TCP...IP. | 337 | 25996650 | 26402 | 46739 | 1764.9 | 47.5 | p<.001 | Type |

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|---|---|---|---|---|---|---|---|---|
| ITIL | 361 | 25996650 | 26402 | 61037 | 1442.4 | 62.0 | p<.001 | Type |
| Microsoft.Active.Directory | 451 | 25996650 | 26402 | 107559 | 1071.7 | 109.2 | p<.001 | Type |
| C.. | 334 | 25996650 | 26402 | 71993 | 930.8 | 73.1 | p<.001 | Type |
| Hyper.V | 248 | 25996650 | 26402 | 55182 | 656.1 | 56.0 | p<.001 | Type |
| Dynamic.Host.Configuration.Protocol..DHCP. | 203 | 25996650 | 26402 | 47024 | 502.8 | 47.8 | p<.001 | Type |
| Cisco | 289 | 25996650 | 26402 | 80384 | 526.3 | 81.6 | p<.001 | Type |
| Teamwork...Collaboration | 797 | 25996650 | 26402 | 447827 | 261.5 | 454.8 | p<.001 | Type |
| Microsoft.Windows | 251 | 25996650 | 26402 | 79162 | 361.4 | 80.4 | p<.001 | Type |
| Change.Management | 175 | 25996650 | 26402 | 68505 | 158.8 | 69.6 | p<.001 | Type |
| Network.Engineering | 128 | 25996650 | 26402 | 32766 | 267.4 | 33.3 | p<.001 | Type |
| Microsoft.Exchange | 166 | 25996650 | 26402 | 67316 | 138.5 | 68.4 | p<.001 | Type |
| Wide.Area.Network..WAN. | 128 | 25996650 | 26402 | 43829 | 155.1 | 44.5 | p<.001 | Type |
| Stakeholder.Management | 191 | 25996650 | 26402 | 86912 | 118.9 | 88.3 | p<.001 | Type |
| Optimisation | 158 | 25996650 | 26402 | 65149 | 126.5 | 66.2 | p<.001 | Type |
| Articulate | 122 | 25996650 | 26402 | 51161 | 93.4 | 52.0 | p<.001 | Type |
| Systems.Engineering | 250 | 25996650 | 26402 | 131443 | 101.4 | 133.5 | p<.001 | Type |
| Quality.Assurance.and.Control | 308 | 25996650 | 26402 | 223697 | 28.7 | 227.2 | p<.001 | Type |
| Citrix | 103 | 25996650 | 26402 | 55881 | 37 | 56.8 | p<.001 | Type |
| Product.Sales | 117 | 25996650 | 26402 | 60649 | 49.1 | 61.6 | p<.001 | Type |
| Writing | 374 | 25996650 | 26402 | 319389 | 7.5 | 324.4 | p<.01 | Type |
| Self.Starter | 115 | 25996650 | 26402 | 77400 | 16.5 | 78.6 | p<.001 | Type |
| Embedded.Software | 72 | 25996650 | 26402 | 36580 | 31.8 | 37.2 | p<.001 | Type |
| Service.Level.Agreement | 70 | 25996650 | 26402 | 42240 | 16.5 | 42.9 | p<.001 | Type |
| Software.Architecture | 57 | 25996650 | 26402 | 37336 | 9.1 | 37.9 | p<.01 | Type |
| Telecommunications | 117 | 25996650 | 26402 | 76782 | 19.1 | 78.0 | p<.001 | Type |
| Energetic | 48 | 25996650 | 26402 | 29210 | 10.7 | 29.7 | p<.01 | Type |
| Retail.Industry.Knowledge | 56 | 25996650 | 26402 | 33051 | 14.4 | 33.6 | p<.001 | Type |

Source: BGT data, author's calculations