GRADUATE DESTINATIONS AND LABOUR MARKET STRATIFICATION ACROSS DIFFERENT FIELDS OF STUDY

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Abstract

There has been a large expansion of the higher education sector in the past two and a half decades. This has led to significant research interests about the implications of this growth in degree holders on the state of inequalities in the graduate labour market. However few have focussed on the extent to which inequalities by sex, socioeconomic background, and so forth varies across different fields of study. For instance, the earnings difference between similarly able graduates from different socioeconomic background may be larger for individual that studied 'soft' subjects, such as the arts, compared to 'hard' subjects, such as the sciences (Hansen 2001). This thesis investigates whether there is any evidence of variations in stratification across fields of study, and attempts to explain why these variations exist. The study tests a number of explanations ranging from competition in the labour market (Brown and Hesketh 2004) to the types of skills used across different occupations.

This thesis uses information from two large scale graduate surveys, and a qualitative study of 21 recent graduates to address these issues. Two types of labour market outcomes are considered: earnings and the extent to which individuals make use of their skills in their work. Looking at individuals with a bachelor's degree, there is evidence that stratification by sex and educational attainment varies across different fields of study. There is no evidence to support claims that stratification by socioeconomic background varies across field of study. In general some of these variations could be explained by the skills used in an occupation. However substantial amounts of the variations in stratification across different fields of study cannot be explained by the theories typically presented in the literature.

Acknowledgements

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Contents

List of abbreviations

DLHE: Destination of leavers from higher education. Refers to a graduate destinations survey administered by the Higher Education Statistics Agency (HESA).

HE: Higher education.

HEI: Higher education institution. Another way of referring to universities and other HE providers

HESA: Higher Education Statistics Agency.

OLS: Ordinary Least Squares. A method for estimating parameters in a linear regression model.

ONS: Office for National Statistics.

SOC: Social Occupational Classification. The classification of occupations used by the ONS.

UCAS: Universities and College Admissions Service. A charity that provides the admissions process used by almost all UK universities.

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Chapter 1

Introduction

There have been a large number of studies looking at differences in earnings between graduates based on their sex (Machin and Puhani 2002; Chevalier 2006); socioeconomic background (Macmillian, Taylor, and Vignoles 2013; Blasko 2002; Naylor, Smith and McKnight 2002); where they went to university (Chevalier and Conlon 2003; Wilton 2011; Ramsey 2008) and so forth. Labour market stratification is another way of referring to the phenomenon whereby workers' earnings, occupational status, and other outcomes systematically differ depending on attributes such as education and family background. These differences in outcomes may persist even amongst people who are similar in all other respects (e.g. working in the same jobs; have the same educational qualification etc).

Stratification is a properties of societies and social systems, and describes how categories of people are organised into hierarchical groups. The most well-known example of stratification is social stratification: the phenomena whereby groups of people in a society are differentiated by their occupation, income, or status (amongst other things). In general stratification theories may be viewed as attempts to find and explain how differential in power, privilege, or other outcomes arise (Grusky 2014)[1]. Many studies looking at labour market stratification amongst graduates have been motivated by the rapid increase in student numbers in higher education (HE) over the past two and a half decades. For reasons that I will discuss later, academics and policy makers have been concerned about the implications of the expansion of HE on the state of equality and competition in the labour market.

The concerns of this study are no different; this thesis also examines whether there are any differences in labour market outcomes between graduates by sex, socioeconomic background, and educational attainment. However this thesis takes a different perspective from other studies. Whilst everyone with a bachelor's degree has the same *level* of education, they do not all receive the same *type* of education or have the same qualifications.

Students in HE study a wide range of subjects. An individual's field of study can have a significant impact on their labour market opportunities after graduation. Some occupations are only open to those with qualifications in particular fields of study. One cannot become a doctor without a medical degree for instance. Graduates across different fields of study may also naturally gravitate towards

[1] However there is no agreed upon definition of stratification in the academic literature or how it is to be researched: 'If one engages in only a cursory review of the literature on stratification, however, it becomes immediately evident that there is little consensus over what stratification is... Typically, after a number of analytical distinctions are made—say, between inequality, class, status, and power—everything that is separated gets thrown back together and "a" theory is developed about "the" composite phenomenon.' (Turner 1984 cited in Yitzhaki and Lerman 1991).

work in a particular set of occupations or in certain industries based on their career ambitions and the skills they acquired in HE. In addition, employers in one sector of the labour market may attach more importance to different factors, such as one's personality or educational attainment, than employers in other sectors for various reasons. The same qualities that makes someone a productive engineer may not necessarily make for a good teacher or salesperson. Because of these–and other–reasons, it is possible that levels of labour market stratification by sex, socioeconomic background, and educational attainment will differ depending on what graduates studied at university. This has implications for our understanding of stratification in the graduate labour market.[2] Instead of talking about inequality in the graduate labour market—as a singular entity—it may be more useful to talk about inequality in different graduate labour *markets*.

However there have been few studies looking at variations in stratification across fields of study. Existing studies have often only focussed on stratification by socioeconomic background and have studied labour markets outside of the UK. Furthermore these studies have not considered the potential impact of unequal increases in student numbers across fields of study on labour market stratification.

This study not only investigates whether levels of stratification by sex or socioeconomic background, amongst other factors, varies between fields of study but also tries to explain why these variations occur. For example, why is difference in earnings between men and women so high for science graduates compared to other subjects? The study draws upon a number of theories in order to explain any variations in stratification. These theories provide different explanations as to why certain workers earn more than others in the labour market. This may be due to differences in skills between groups of workers (Becker 1975); the possession of valuable signals of productivity (Spence 1973, Stiglitz 1975); employer biases or discrimination; or the relative supply for workers compared to demand (Brown and Hesketh 2004), to name just a few. I will also address other topics that have been of concern to academics including the question of whether greater competition for jobs between graduates necessarily leads to greater social inequalities (as well as inequalities by sex and educational attainment). I will also introduce some methodological improvements to the literature on stratification in the graduate labour market. This includes a method for dealing with sample selection issues in a major UK survey of graduates. The structure of the rest of this thesis is as follows:

Chapter 2 summarises the history of HE in Britain and pays particular attention to the expansion of HE since the Second World War. One of the underlying rationales behind this expansion was to promote greater social mobility and fairness in society, especially in the face of challenges brought about by globalisation and technological change. Many have been concerned that the expansion of HE has also had unintended consequences in the form of increasing inequalities between graduates in the labour market. I also discuss how studies of labour market stratification amongst graduates informs contemporary debates in HE studies about employability and equality of opportunity. Whilst there is evidence of stratification in the graduate labour market, few studies have looked whether this phenomena varies by fields of study.

Chapter 3 discusses the various theories explaining why workers are stratified in the labour market by factors including sex, socioeconomic background and education qualifications. In particular it focuses on three theories: human capital theory, signalling theory, and positional competition theories. I then discuss why the extent of labour market stratification amongst graduates may vary depending on their field of study. Explanations include the characteristics of qualifications in certain fields of study

[2] A term denoting the labour market for workers with advanced skills that could have been acquired as a result of higher education.

(reflecting the knowledge content of specific subject areas); levels of bureaucracy in different firms and industries; and skill requirements across different sectors of the labour market. I then summarise the empirical evidence for the existence of any variations in stratification by sex, socioeconomic background, the type of university (or higher education institution (HEI)) people attended, and graduates' degree classification across fields of study. In addition I offer an explanation for variations in stratification across field of study based upon differing levels of competition in the graduate labour market.

Chapter 4 introduces the two main sources of information that I will use in this thesis: a qualitative study of recent graduates, and the Destination of Leaver from Higher Education (DLHE) survey. The former involves interviews with 21 recent graduates across different fields of study whilst the latter is a large survey of graduates' activities after leaving HE. The chapter also briefly discusses some methodological details about how some of the analyses in this thesis were conducted. Interested readers can find proofs and further details in the appendix chapters.

Chapter 5 is the first findings chapter of the thesis and it uses qualitative data to look at how graduates found work after finishing their studies. In addition, it discusses what factors these graduates thought were important to employers. I discuss whether both of these findings varied across respondents from different fields of studies.

In the next three chapters I look at whether labour market stratification actually varies by fields of study and, if so, why. I focus on two labour market outcomes: workers' earnings and the extent to which graduates make use of their skills in their current jobs. The analysis is primarily concerned with differences in outcomes between graduates who are otherwise similar with respects to their previous education and background characteristics. The analysis in chapter 6 reveals that stratification by socioeconomic background does not vary by fields of study. However differences in outcomes between graduates based on sex, private education prior to HE, degree classification, and type of HEI attended does vary from field to field.

In order to examine whether levels of stratification are affected by competition in the labour market I look at the destinations of a cohort of graduates who entered the labour market *prior* to the 2008 recession. Then I compare their outcomes to another cohort of graduates who entered the labour market *after* the recession in order to estimate the effects of increased competition on labour stratification. The results of this analysis are reported in chapter 7. Contrary to expectation I do not find any evidence that greater competition actually leads to greater stratification. As such there is no reason to believe that the state of competition for work in different fields of study is responsible for any variations in stratification.

Chapter 8 examines whether bureaucracy and skills requirements across different sectors of the labour market are responsible for variations in stratification across field of study. I find that there is little evidence that these factors can explain much of the variations found in chapter 6. I then discuss the overall implications of the findings for our understanding of inequalities in the graduate labour market in chapter 9.

As I mentioned at the start of this chapter the motivations for many studies investigating inequalities between graduates in the labour market have been linked to the expansion of HE in the UK. I will therefore begin by considering this topic in the next chapter.

1.1 The development of the study

The research questions and design of this study has changed considerably over the lifetime of the project. Initially I had set out to explore graduates' perception of employability[3] and their experiences of underemployment shortly after the 2008 recession. The project was conceived amidst concerns and uncertainty following the recession about the prospect of a 'lost generation' of young people who would be entering a labour market with fewer opportunities. This fear was also supported by statistics which showed a large increase in the rate of unemployment amongst young people and new graduates (ONS 2012a, 2013). The initial research design relied heavily on qualitative interviews with recent graduates. However, over time, the focus of the study changed from studying people's experiences and perceptions to studying actual labour market outcomes.

This shift in focus was caused by a few things: first there was already an extensive and recent (at the time) body of studies which looked at graduates' perception of employability (Tomlinson 2005; Smetherham 2005; Brown and Hesketh 2004; Bathmaker et al. 2013—to name just a few). From early pilot interviews with graduates there was not much in the way of original research, in terms of questions or findings, that was not already covered by other studies. I also felt that it was increasing important to research what factors affected labour market outcomes rather than people's experiences. Least of all because the former topic seemed far more important to graduates themselves—especially given the changes to tuition fees and HE funding at the time (see Browne 2010). To this end, studying graduates' perceptions of employability alone is not a sufficient method to research how different factors affect labour market outcomes.

The pilot interviews with graduates also suggested a new direction for the project. Whilst there was an extensive literature looking at labour market outcomes for graduates there were few studies that looked whether factors that affected outcomes differed across fields of study. From the pilot interviews (as well as later interviews), it was clear early on that the ways that some graduates found work differed depending on their field of study. Graduates who did degrees related to medicine gained work almost exclusively through formal job applications. In contrast, those studying the arts were more likely to have found work through word of mouth. From speaking with different graduates, it also seemed that the existence of accrediting bodies, such as the institute of Civil Engineers, in some fields of study may increase the value of postgraduate qualification for certain graduates.

These factors influenced the thesis you are reading now which focuses largely on using large scale survey data to look at labour market outcomes. I was personally interested in the causal relationship between factors, such as degree classification, and labour market outcomes. However, for a range of reasons, these causal relationships are very difficult to study. Instead this study focuses on associations and answers questions such as: 'do similarly male and female graduates earn the same amount of money?'; 'are differences in earnings between graduates with first and upper second class honours degrees higher for fields of study compared to others?'. The answers to these questions are of use to various stakeholder who wish to increase opportunities and outcomes for various disadvantaged groups in society. In addition, these questions may be suggestive of causality—after all correlation does not imply causation but causation does necessarily entail correlation. Despite these large changes, the original research design has influenced the current study. Interviews that were collected for the original project was used to help inform the research design, the collection of secondary data, and the statistical

[3]There is no strict definition of employability but one widely cited definition is given by Hillage and Pollard as 'the capacity [of individuals] to gain initial employment, maintain employment and obtain new employment if required' (p. 1, 1998).

analyses used in later chapters. The recession is still a part of the study although instead focussing on graduates' perceptions of the recession and its aftermath, I use the event as a natural experiment to look at the effects of increased competition for work on stratification in the graduate labour market.

Chapter 2

Higher education in Britain today

This thesis looks at whether levels of inequality or stratification amongst graduates in the labour market varies across different fields of study. Given the specialised nature of the research topic it is important to answer two questions: why study stratification amongst graduates and why focus on fields of study. The answers to both questions are addressed in the following two chapter. My motivations are linked to the expansion of higher education (HE) in Britain; a phenomena that has been taking place since the end of the Second World War. This chapter will provide a general summary of the history behind this expansion as well as the reasons that motivated these changes and the state of HE in Britain today. It then discusses the topic of labour market stratification amongst graduates; a subject that has interested researchers concerned about the implications of HE expansion. Whilst the study of labour market inequalities is important, I will argue that the HE system is diverse, and that graduates are not a homogenous group with respect to their career opportunities and trajectories. One neglected area of research is how field of study may mediate the relationship between labour market outcomes and characteristics, such as sex and socioeconomic background.

2.1 The history of higher education in Britain

2.1.1 The expansion of higher education in the 1960s

From their establishment in the middle ages until the early nineteenth century, Oxford and Cambridge were the only universities in England. During this time, four universities were established in Scotland but none in Wales. It was not until the industrial revolution that more universities were created through private funding (Beloff 1970). However until the 1960s, Britain had an 'elite' system of HE whereby only a very small minority of individuals had a university education. This is displayed in figure 2.1.

At the start of the 1960s only around 5 percent of individuals entered HE before the age of 21. During this decade there was major growth in the HE sector driven by an increase in the number of universities which lead to increases in student numbers. These new universities were either entirely new entities or were created from previously existing Colleges of Advanced Technology. These institutions are commonly referred to as Plateglass universities in reference to their modern architecture and vision (Beloff 1970). This was in contrast to the institutions formed during the industrial revolution, which

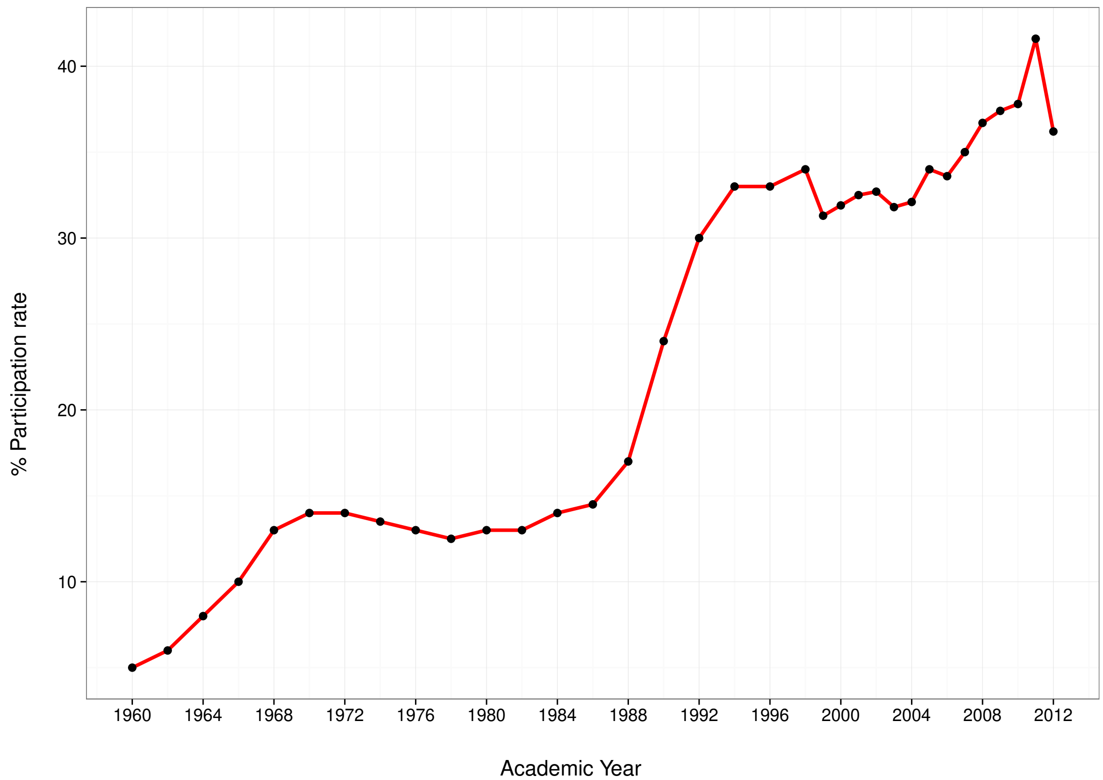

Figure 2.1: % 18-20 year olds in higher education (England) (Source: table D.1)

were known as Red Brick universities, and the older institutions of Oxford and Cambridge (in addition to the four Scottish universities).

Plateglass universities are usually spoken of in relation to the Robbins report which was published in 1963 and had recommended an expansion of the university sector. In reality many of the new institutions had been approved, but had not yet received their Royal Charters, prior to the commissioning of the report by the British government in 1961 (Perkins 1991). The demand for an expansion of the HE sector was caused by several factors: the sharp rise in birth rates after the Second World War, general interest in social justice after the war, and the reluctance of existing institutions to increase their student intake (Coffield and Williamson 1997). The creation of new HE institutions was also intended to encourage pedagogical change in HE and these institutions were expected to increase interest in research through leading by example (Perkins 1991).

Whist the Robbins report did not contribute solely towards the expansion of HE, it does however express prevailing policy attitudes towards HE at the time. The aims of HE were to provide instructions in skills, promote general powers of the mind, advancement of learning (through research), and the transmission of a common culture and standards of citizenship (p. 6-7, CoHE 1963). Even in the 1960s report the link between HE and the labour market, in terms of private returns to the individual and the UK economy, was recognised. The report interestingly notes that this is an often undervalued or ignored function of HE (p.6, *ibid*). This point becomes anything but underemphasised in later government policies.

2.1.2 The expansion of higher education after the 1980s

After the 1960s expansion of HE, participation rates for under 21s reached a peak of almost 14 percent in the 1970s before staying around that figure until the late 1980s (Mayhew, Deer and Dua 2004). In 1989, the government called for an increase in student number leading to a rapid rise in participation until a cap was placed on student numbers between 1994 to 2001 (Bathmaker 2003, NCIHE 1997). The second rapid expansion of HE in the early 1990s coincided with the unification of the HE system.

After the Robbins report, the HE system was split into two system. Universities received public sector funding but were otherwise independent private institutions with degree awarding powers. On the other hand, polytechnics and HE colleges were public sector institutions which were controlled and funded by local education authorities (LEAs), and had their HE qualifications accredited through either a university or the UK Council for National Academic Awards (Walford 1991). This continued until polytechnics and HE colleges were freed from LEA control in 1988 and ultimately given degree awarding powers under the 1992 Further and Higher Education Act. This bought all HE institutions under a unified system of regulation whereby all institutions were funded by the Higher Education Funding Councils for England, Wales, and Scotland respectively. Northern Ireland, to this day, has no independent funding council; this role is directly fulfilled by the Department for Employment and Learning. Former polytechnics under the old system, now mostly rebranded as universities, and any institutions created after this period of expansion are commonly referred to as Post-1992 universities.

The underlying rational behind the unification of the HE system was in part to encourage greater competition in the HE sector. However, unlike the 1960s expansion, the second expansion of HE was accompanied by less government funding per student (p. 67, Mayhew, Deer and Dua 2003). This lead to the subsequent problem of how to fund the HE sector and the introduction of tuition fees.

2.1.3 The introduction of tuition fees

From the end of the Second World War to 1998, there were no costs to studying for a degree for individuals who were domiciled in the UK. The cost of tuition was paid for by LEAs, and maintenance grants were also awarded to students to cover their costs of living. However maintenance grants were gradually reduced from 1990 onwards and the grant amount became increasingly dependent on students' household incomes. To offset the gap in financial support, a system of student loans were introduced. At the time of writing, maintenance grants are to be abolished altogether from the 2016/17 academic year onwards (for students domiciled in England). Yet, for students, there were still no upfront costs to HE until 1998. After the 1997 general election the Dearing report was published. The report recommended an end to free HE and a system for student to repay tuition fees through a graduate tax (p. 323, NCIHE 1997). The Labour government at the time did not follow the review's recommendations and introduced a fixed tuition fee of £1,000 per annum, which was subsequently enacted the following year across the UK (Bathmaker 2003). However, in 1998 successive parliamentary acts passed legislative powers to the devolved governments of Scotland, Wales and Northern Ireland. Devolution allowed each of the national governments to diverge with respect to the issue of tuition fees after 1998.

For individuals in England, the cost of tuition at any UK university remained at £1,000 until the introduction of top-up fees which came into place in 2006. This raised the maximum cost of tuition fees to £3,000 per annum. Yet continuing concerns regarding the future financial sustainability of HE sector resulted in the commissioning of the Browne review in 2010. The review recommended the total removal of caps on tuition fees in order to introduce more market based mechanisms into the HE sector. Following the review, the tuition fees cap was raised to £9,000 for course starting in 2012. However every university that wished to charge over £6,000 a year in tuition fees had to ensure adequate plans were in place to attract disadvantaged students and their fees must be approved by the Office for Fair Access.

Not all institutions opted to charge up to the full cap initially for all their undergraduate courses although over 50 percent of institution did (65 out of 119 where data is available, Buckley-Irvine and Burn-Murdoch 2012). This proportion subsequently increased and around 80 percent of universities and colleges charged up to the cap for all their undergraduate courses in 2014 (106 out of 132, The Complete University Guide 2014).

In theory there now exists potential for greater variability in the price of tuition fees for English students across degree programmes; some institutions can choose to seek an edge by undercutting their competitors. Furthermore it is also perfectly possible for individual institutions to charge different fees for different degree programmes. However most do not and it remains to be seen whether this will still be the case as time goes on. Greater price competition could appear as a result of the decision to grant degree awarding powers to colleges that previously only offered further education, and an influx of private HE providers into the sector. Once again it is difficult at present to judge whether this will be the case in the future (see next section, Parry 2009). Despite increases in the cost of HE borne by the individual, the overall cost of HE in the UK is still heavily subsidised by the state through the various HE funding councils, or a government department in the case of Northern Ireland.

Turning to the other nations in the UK, not all chose to follow England's lead on tuition fees. After devolution, tuition fees for students domiciled in Scotland studying in Scottish universities were abolished in 1999. This remains the case up to the present day. Tuition fees for Welsh students studying in the UK remains around £3,600 per annum and not the cap of £9,000 paid by students in England. A similar case exists for students from Northern Ireland studying in Northern Ireland who pay tuition fees of up to £3,800. However, students who elect to study at an institution outside their home countries of Scotland, Wales or Norther Ireland will be subject to tuition fee caps of £9,000.

2.1.4 The state of higher education in Britain today

Current rates of participation in higher education

Following the expansion of HE in the late 1980s and early 1990s participation rates in HE for under 21s, who make up the bulk of first time students, has remained steady at around 33 percent. Figure 2.1 shows that sudden increases in participation did occur for the academic year 2005/06 and 2011/12. These were the last academic years before further increases to student tuition fees were introduced (at least in England). The increase in participation is probably in part down to individuals who would have otherwise deferred entry to HE after finishing secondary education but chose not to in order to avoid the increase in tuition fees. Despite successive increases to the cost of HE for students, there seems to be no sign of a fall in the demand for HE. This may be down to several factors, including the perceived rates of return to HE and the structure of the student loans system. Unlike most personal loans, mandatory annual repayments on student loans are based on an individual's income. This is currently 9 percent of an individuals' income above £21,000, and these loans are repaid after graduation. In many respects the student loan system works much like a graduate tax with an upper limit on collection.

The current estimate for the rate of initial participation in HE for 17-30 year olds is 43 percent for the academic year 2012/13 for students from England (DBIS 2014). This constitutes a significant minority of that age range but falls shorts of the ambitious 50 percent participation target set by the previous Labour government (HEFCE 2001). Making comparisons between England and other nations in the UK is difficult: the publication of participation statistics is the responsibility of the different national HE funding councils, or the government in Northern Ireland. As such, published participation rates are calculated slightly differently across Britain. I will present rough equivalent statistics between different nations and England for the purposes of making comparisons about participation rates across the UK.

Participation rates for Wales are lower at 27.4 percent (18-19 year olds for 2009/10, table 5 HEFCW 2014) compared to an estimated 33.1 percent for the same group of individuals in England (18-19 year olds for 2012/13, table 2 DBIS 2014). Whilst the rate for Northern Ireland is much higher at 50.7 percent for the same age group (DELNI 2011). The initial participation rates for Scotland is also much higher at 56.1 percent for 2011/12 (16-30 year olds, table 1, SFC 2013) compared to 43 percent in England (17-30 year olds, 2012/13 DBIS 2014).

Other higher education providers

It should be noted that universities are not the only providers of HE in Britain. Whilst all UK universities have been granted degree awarding power by Royal Charter, other recognised bodies have also been granted such powers through an Act of Parliament or the Privy Council. As such, other providers of HE also exist in the form of other privately funded organisations and Further Education (FE) colleges. Often these FE colleges and privately funded organisation provide courses as part of a franchising agreement with universities.

However the majority of HE qualifications awarded by FE colleges are at an undergraduate level and below that of a bachelor's degree. The proportion of students studying for a bachelor's degrees who are also enrolled in FE colleges is only around 2 percent in England (table 3.2 p. 63, 2009-10: Parry et al 2012). The role of FE colleges in the HE system is not given special attention in subsequent chapters given the relatively small part it plays in a sector dominated by universities.

There also exists other private HE providers that, unlike universities, do not receive public sector funding for teaching. Also, unlike universities and other publically funded providers of HE, these institutions are not subject to price restrictions on tuition fees. In 2011, the Department for Business, Innovations and Skills (DBIS) published a white paper calling for a commitment to open up the HE sector to more competition, which included privately funded organisations. These sentiments also echoed the recommendation of the Browne review (2010). However, most private HE providers predate both publications. For example, the University of Buckingham received its Royal Charter in 1983 and is directly funded by student fees. Full population data on privately funded providers of HE is lacking. There were a *minimum* of 672 privately funded HE providers in the UK in 2012. Most began operating relatively recently—the median age of a private provider was 12 years—and are relatively small compared to universities (less than 250 students; see table 3, p. 30, Hughes et al 2013). Furthermore most only offer degree programmes in a narrow range of subjects (table 5, p33, Hughes et al 2013). These providers only account for a small proportion of HE learners in the UK (around 160,000 compared to roughly 2.3 million overall, 2012-13 HESA estimates). As with FE colleges, graduates from these institutions are not given any attention in later chapters.

2.2 Causes of changes to higher education policy

Much of the expansion of HE in Britain was down to the actions of successive governments. Governments have influenced HE participation through various means. For instance, governments have had power over HE funding, and can decide who has degree awarding powers and who doesn't. The expansion of HE during the 1960s and the dissolution of the binary divide between universities and polytechnics in the 1990s are the two obvious examples of the latter type of power. As I mentioned before, the post-war expansion of HE was in large part down to a demand for HE fuelled by prevailing attitudes towards increasing equality of opportunity in a previously elite education system and a lack of places at existing universities.

The role of HE in growing the economy through the provision of skilled workers and research was also a factor. As previously highlighted, the Robbins report shows that the instrumental view that HE ought to—in some way—serve the needs of the economy is not new. However, this view has become increasingly prominent in policy discourse and debates about HE in recent decades and has been intimately tied to the idea of the Knowledge Economy (Drucker 1993).

2.2.1 The Knowledge Economy

Over the last three decades, the demand for routine or low skilled manufacturing and services has fallen in developed nations due to the automation of work as a result of technology and the ability of companies to outsource work to other countries with lower labour costs. Conversely, it has been argued, the demand for highly skilled non-manual work has dramatically increased (Reich 1991). This is due to an increased demand for knowledge intensive work, such as consultancy or research, across the globe as well as high growth in new technology sectors like ICT (DIUS 2008). The definition of knowledge intensive work can be rather broad and ambiguous but it is generally used to denote work that requires a high level of skills, knowledge, or creativity and innovation. These skills may include organisational and personal communication skills as well as any expertise or knowledge acquired through education (see DIUS 2008, Purcell and Elias 2009).

The argument is that Britain and other developed economies should focus on competing for knowledge intensive work. This is in part due to the advantages that these countries have in terms of their infrastructure and institutions compared to developing economies like China or India (Becker 2006). For example, Britain's advantages are thought to include 'a flexible labour market, an extraordinary record of scientific discovery, a large and growing supply of high quality university graduates and an open economy with an international outlook' (p. 14, Sainsbury Review 2007). A highly skilled workforce is also thought to drive productivity and innovations in firms through identifying opportunities and new ideas that can be capitalised on (Drucker 1993). Therefore, not only does a highly skilled workforce satisfy the increasing demand for knowledge intensive work but it is also expected to generate further innovations which *itself* in turn results in more work leading to a virtuous cycle of growth. A more downbeat argument for focusing on knowledge intensive work is that the loss of routine and low skilled work is permanent, and will continue as a consequence of technology and globalisation. With a shrinking proportion of jobs that require only low levels of skill, developed nations must seek to upskill their workforce or face the prospect of growing inequality gaps in the population (Reich 1991).

The role of HE, alongside other forms of training and education, in the knowledge economy is clear to see across various policy documents (e.g. Browne review 2010, Sainsbury review 2007, DIUS

2008). For instance, quoting the Leitch review:

> *'Unless the UK can build on reforms to schools, colleges and universities and make its skills base one of its strengths, UK businesses will find it increasingly difficult to compete. As a result of low skills, the UK risks increasing inequality, deprivation and child poverty, and risks a generation cut off permanently from labour market opportunity... Skills were once a key lever for prosperity and fairness. Skills are now increasingly the key lever.' (p. 3, Leitch, 2006)*

The underlying assumption is that HE can provide individuals with the level of knowledge, and other skills, required to compete for knowledge intensive work on a global scale (DIUS 2008). The expansion of HE is seen as directly related to strategies to improve the UK's global competitiveness (Leitch 2006).

Whilst the idea of the Knowledge Economy and an instrumental view of HE as a means for economic growth are featured prominently in some policy documents, it is too simplistic to believe the expansion of HE was led entirely by policy visions. Another factor behind the expansion of HE in the late 1980s was the demand for HE by potential students rather than the demand for graduates by employers. Mayhew, Deer and Dua (2004) point out that a large demand for HE qualifications had already existed prior to the expansion of HE in the late 1980s and early 1990s. Acceptance rates for entrants to HE was around 50 percent in 1990 indicating an unmet demand for HE. This rate grew to 71 percent in 1998 after the dissolution of the binary divide (p. 70, Mayhew, Deer and Dua 2004). This demand may be attributed to both the increasing number of individuals staying in education beyond 16 and the demand from employers for post-secondary qualifications (HEFCE 2002). In either case we cannot understand the cause of the demand for HE from potential students without discussing the benefit it confers to the individual.

2.2.2 Private returns to higher education

It is important to distinguish between the personal and societal returns to HE. The private returns to HE, in terms of higher future earnings or other personal benefits for graduates, does not necessarily entail any societal returns. The latter may be measured by any growth in average earnings, or in other non-pecuniary benefits to society. Whilst the ability of HE to provide skilled workers and the ability of skilled workers to contribute towards the Knowledge Economy is a key argument in many policy documents, the societal return to HE is a topic that goes beyond the scope of this thesis.

Private returns to HE are repeatedly used to justify the shift of responsibility for funding HE from the state to students. Since individuals are expected to individually benefit from HE, as the argument goes, it would only be fair that they bore some of the cost of their education (Browne 2010). This is not to say that private returns are necessarily a cause of policy changes; after all the higher earnings of graduates compared to non-graduates is not a recent phenomenon. The causes of changes in tuition fees lies more in the demand for HE, and how increased student numbers exerted pressures on public funds through more students grants in the period prior to the introduction of tuition fees (Mayhew, Dua and Deer 2004).

Nonetheless consideration of the private returns to HE is important. The most obvious reason being that the financial benefits of HE qualifications (or their rates of return) are important to students because HE can be seen as an investment. Whilst students are studying for HE qualifications, they are forgoing opportunities to earn in the present. Many—if not most—students will opt to accept any lost earnings whilst studying in the hopes of greater lifetime earnings in the future.

There are numerous studies looking at the expected rate of return to HE qualification in the UK (e.g. Walker and Zhu 2003, O'Leary and Sloane 2005, Conlon and Patrignani 2011). These studies typically find that the estimated return to gaining a HE degree compared to A levels—the highest qualification that most new entrants to HE possess—can be substantial. For instance, Conlon and Patrignani (2011) estimate that gaining an undergraduate degree increases an individual's earnings by 27.4 percent compared to just possessing 2 A levels.

Rates of return are partly used as a justification for changes to tuition fees and student grants funding which have often proved unpopular in the past. These rates of return are also related to–and have often been at odd with–another motivation for the expansion of HE; the desire for greater equality of opportunity in society through widening participation in HE (NCIHE 1997).

2.2.3 Widening participation

Widening participation in HE refers to the policy of increasing opportunities to study in HE to groups, who either due to a lack of means or inclination, were previously underrepresented in HE. Given the impact of HE on future labour market outcomes, widening participation to HE also serves as a general means of increasing social mobility and equality of opportunities in society (DfES 2003, see next section). Equally one can also argue that if HE also confers other benefits to individuals, such as mental well-being or a better quality of life, then it stands to reason that all individuals ought to have equal opportunities to participate.

There is also an economic argument for widening participation; given the need for skilled workers in the economy, any obstacles that impede individuals from reaching their potential represents an inefficient use of resources. Diversity in academia, the student body, and within firms is also touted as an advantage in terms of fostering innovations and different perspectives (DBIS 2014).

At the same time there is a tension between the policy of widening participation and the expansion of HE in general. In order to fund the HE system, the system of student loans was introduced and expanded. The cost of tuition and living whilst studying have increasingly become the responsibility of individuals which potentially discourages those without the means to bear the cost of their studies from participating in HE. As mentioned before, changes to HE funding has often been unpopular in the past and there is substantial pressure to balance the funding needs of the whole HE system whilst ensuring fair access to HE.

2.3 The implications of higher education expansion in the UK

The aforementioned changes in Higher Education in the UK have interested many who are concerned the implications of HE expansion for inequalities and stratification in the labour market. Part of these concerns relate to differences in labour market outcomes between different groups of graduates. This includes differences along the lines of sex and socioeconomic origins. Research into differences in life outcomes between individuals on the basis of sex, socioeconomic origins and ethnicity has always been a core part of sociology of education (Lauder et al 2009). The role of education and training has been critical to the understanding of differences in labour market outcomes by ascribed characteristics, such as sex and ethnicity. For instance, it has been shown that much of the difference in labour market outcomes between individuals of different socioeconomic origins is related to differences in educational attainment (Blau and Duncan 1967). This lead to successive policies by governments across world to redress inequalities in outcomes between social groups through the expansion of the education system.

The expansion of HE in Britain, with its commitments to widening participation, is no exception (e.g. 'education is the best and most reliable route out of poverty and disadvantage' p.68, DfES 2003). Much interest has been focused on the impact that level of education, and access to education, has on labour market outcomes. With the expansion of HE, both in Britain and across the world, there has been further academic interest in differences in labour market outcomes between graduates. From the mid-1990s to 2009 the total number enrolled in HE across the world grew from approximately 76 to 179 million (Brown 2013). Academics have been interested in graduate labour markets within countries where there has been a transition from an 'elite' system to a mass system of HE (see Gerber and Cheung 2008 for a review). The underlying concern is over how this transition is affecting the state of labour market stratification amongst graduates.

2.3.1 HE expansion and stratification: The implications of an oversupply of graduates

Part of the underlying rationale for the expansion of HE assumes a growing demand for knowledge intensive work in the economy. However, there is considerable debates to whether there is unmet demand for the type of high level skills required in knowledge economy. The argument that a rapid expansion of HE can create an oversupply of graduates, with potentially troubling consequences, is not new (Arrow 1973). After the second expansion of HE in the 1990s, early concerns were centred on the lack of jobs requiring the skills of graduates in the UK. Further concerns were later added about the future of knowledge intensive work in Western Europe and America (Brown, Lauder and Ashton 2010).

First, there has been a rapid growth in the number of individuals with HE qualification and much of that growth has taken place in developing economies, such as China. In the past, routine manufacturing work migrated from western nations to these countries in part due to low labour cost. Now many of these developing economies are also upskilling their workforce. The ability of technology to connect workers across the world and the low cost of labour in these countries leads to concerns that knowledge intensive work will be outsourced to these nations, much like how manufacturing was in the past (Brown, Lauder and Ashton 2010).

Second, there is no certainty that many of the knowledge intensive jobs that currently exist will continue to do so in their current forms. The ability of new technology to undertake tasks on behalf of, or in conjunction with, human workers, can lessen the need for innovation, creativity and knowledge on the part of human beings. This can lead to previous knowledge intensive jobs becoming more routine and easily regulated in process referred to as Digital Taylorism (Brown 2013). This has two consequences; through Digital Taylorism the knowledge and skills required for many jobs goes down. This leads to the expansion of HE being potentially wasteful from an economic perspective as it produces too many workers with skills that are not needed. Furthermore regularisation and the increased surveillance of jobs leads to less bargaining power on the part of workers, leading to reduced earnings as skilled labour becomes more interchangeable.

The consequences of this is the potential that there will be a growing oversupply of graduate workers in the economy, relative to its needs, and many will be frustrated in their ambitions to find knowledge intensive work. The phrase opportunity trap has been coined to denote the lack of absolute mobility, from low skilled services and manufacturing work to knowledge intensive work, over time for workers in general (Brown 2010). Furthermore, if there is an oversupply of graduate labour, there is the potential for increasing competition amongst graduates and there has been interest, both in Britain and across the world, in the ‘winners’ and ‘losers’ of that competition. It has been argued that with increasing competition, the impact of factors, such as work experience and extra-curricular activities, on labour market outcomes has increased as well. This may be in part because employers have included these factors as part of their considerations in the formal recruitment and selection process (Brown and Hesketh 2004). Furthermore, the opportunity to acquire these resources can differ for different groups of graduates. For instance, students from more privileged backgrounds may have the necessary culture or social capital to both understand what is advantageous in the labour market and the resources to acquire these advantages (Bathmaker, Ingram and Waller 2013, Brown and Hesketh 2004).

Evidence of an actual increase in the proportion of graduates relative to the demand for graduate skills has been mixed. Looking at both the qualifications *and* skills required to do a job, there is some evidence of a mismatch between the supply of and demand for graduates in the labour market after the expansion of HE in the late 1980s and 1990s (Chevalier and Lindley 2008). If there was a relative ‘oversupply’ of graduates then we would expect the difference in earnings between degree holders and non-degree holders to reduce. However Walker and Zhu (2008) find that the difference in earnings between recent graduates and individuals with two A levels has remained consistent after the expansion of HE between 1994 and 2006.

2.3.2 Stratification amongst graduate and the implications for widening participation in HE

Knowledge of the factors that contribute towards labour market success, or an individuals’ employability, is of obvious interest to students. This is further compounded by policy discourses that firmly places one’s employability as a responsibility of the individual (Moreau and Leathwood 2006). Critics have argued that this position overemphasises the power of individuals to change their employment prospects, and ignores the role that supply and demand has on one’s employability (Tomlinson 2008, Moreau and Leathwood 2006).

If the goal of widening participation was to introduce greater equality of outcomes between individuals then increased competition for work amongst graduates can undermine this goal. When competing for jobs, graduates with the necessary advantages to get ahead may still be relatively successful even as the number of graduates increase. For example, in the past those from advantaged background may have sought to enrol in HE in order to improve their future labour market outcomes. With the expansion of HE, and the removal of barrier to participation in HE, these groups of individuals can seek to retain their past advantage through the acquisition of valuable resources, such as internships (Bathmaker, Ingram and Waller 2013). In addition, as the amount of education that people receive increases, advantaged groups may seek to compete by acquiring a better quality of education rather than more education (Lucas 2001). For instance, individuals from advantaged groups seek to study at more prestigious universities.

In either case the relative advantage that these individuals enjoy is maintained: people from more advantaged backgrounds will have better outcomes than others. However the amount of effort and investment expended by everyone is far higher in the latter scenario; more individuals would have HE qualifications but relative social mobility would remain the same. For society, this process incurs wasted resources on the part of both individuals and the tax payer. In short, stratification between graduates in the labour market can serve to undermine societal attempts to increase opportunity for individuals through widening participation to HE.

There have been numerous studies looking at stratification by sex, socioeconomic background and so forth amongst graduates as a whole. However the literature usually treats all graduates as one homogenous group. In reality whilst all graduates are educated to the same *level* of education, they do not necessarily all receive the same *type* of education. Graduates in different field of studies have different skills, aspirations, and career opportunities. As such, there are many reasons to believe that the state of labour market stratification between graduates will also vary across field of study. One reason is that increases in student numbers have not been uniform across all subjects areas. Other reasons are discussed in the next chapter.

2.3.3 Stratification and fields of study

There have been numerous UK studies looking at stratification by sex, socioeconomic background and so forth amongst HE leavers as whole (e.g. Bathmaker, Ingram and Waller 2013; Tomlinson 2008; Ramsey 2008; Macmillian, Tyler and Vignoles 2013; Chevalier and Conlon 2003 and so on). In the literature field of study is considered a significant factor in determining labour market outcomes. There is evidence that those who studied subjects related to the arts and humanities do comparatively badly in the labour market compared to other graduates. In contrast those studied medicine or subject related to medicine do well compared to other graduate (Chevalier 2011; Walker and Zhu 2011; O'Leary and Sloane 2005).

In these studies field of study is not expected to mediate the relationship between factors like sex and socioeconomic background, and labour market opportunities. In this regard graduates are treated as a homogenous group: the effects of getting a higher degree classification or going to a prestigious university is assumed to be same irrespective of what a person studied. However, in reality, whilst all graduates are educated to the same level of education, they do not necessarily all receive the same type of education. Graduates in different field of studies have particular sets of skills, aspirations, and career opportunities. Individuals aspiring to become nurses or radiographers select course relevant to their future career ambitions. Employers wishing to hire statisticians or economists will seek to hire individuals who studied more numerate subjects over those that studied the art or humanities. In short, the career trajectories that graduate follow, and the opportunities open to individuals, will vary depending on field of study. As such, we may intuitively expect that the state of labour market stratification between graduates will also vary by field of study. Employers who are looking for researchers or scientists may be more impressed by an individuals' academic qualification compared to employers who are hiring for social workers. This in turn will affect the state of stratification by factors like degree classification amongst graduates who studied different subject areas. I will formally elaborate upon these points in the next chapter.

While it is plausible that there are variations in stratification by sex, degree classification and so forth across field of study there are few studies that address this topic area. Aside from furthering our understanding of stratification amongst graduates in labour market, there are some practical implications as well.

There have been perennial concerns by policy makers, and in the public sphere, about a lack of STEM workers in the economy. STEM skills and innovations are thought to be essential to meet the demand of the knowledge economy in Britain (Sainsbury review 2007). At the same time, there is an estimated annual shortfall of 40,000 STEM workers (Broughton 2013) and concerns over the lack of student studying certain STEM subjects at HE (Purcell et al 2008).

There are several theories as to the cause of this deficit. Whilst there are not necessarily unfavourable attitudes towards STEM subject at school, there is a narrow perception of STEM careers by children that is likely to be exacerbated in many families by a lack of acquaintance with people working in STEM (p. 10-11, CaSE 2014). Furthermore, males are far more likely to study STEM courses at university than females, with the exception of subjects allied to medicine or health, and the biological sciences. For the academic year 2013/2014, 52 percent of full time male undergraduates were studying STEM subjects compared to 40 percent of females (HESA 2015). This could be down to several factors, such as gendered perceptions of careers by parents (CaSE 2014). Further reasons include the problem of retention in STEM jobs, whereby STEM graduates are leaving to pursue careers in non-STEM jobs. This problem is known to be more severe for female STEM graduates who are far less likely to be working in STEM subjects after graduation. The reasons for this are not fully known but there is speculation that STEM jobs may be less accommodating to the needs of women (Purcell and Elias 2009). Nonetheless there are some who have raised doubts about the extent of the 'leaky pipeline' problem in STEM. Chevalier's (2012) analysis of destinations data for recent graduates found that only a small minority of employed STEM graduates are actually in non-STEM careers. In a similar vein, there are also concern about the under-representation of people of black Carribean, Pakistani, and Bangladeshi origins in subjects like chemistry and physics (Elias, Jones and McWhinnie 2006).

The supposed deficit, and the lack of diversity, in STEM workers has not gone unnoticed by successive governments, who have sought increase the amount of STEM workers in the economy via various initiatives (see CaSE 2014). The rationale behind the drive to attract more STEM students is partly economic and partly down to a desire for greater equality. Given the deficit of STEM workers, it is argued, removing previous barriers for individuals to enter STEM careers both meets the needs of demand and promotes greater equality in the labour market. With regards to the latter, graduates with STEM degrees earn more than graduates who studied most other fields of study (Chevalier 2013). As a consequence it is possible to reduce the earnings gap between men and women by encouraging more women to study STEM jobs.

However if the UK government seeks to boost graduate numbers across certain fields of study, and in particular to attract previously under-represented groups of students to those field, then it makes sense to look at the state of inequalities within these fields of study. These inequalities may be as a result of differing rates of return for different groups of individuals. For example, if the rate of return to studying engineering compared to modern language was higher for men compared to women then we should not be surprised to see relatively fewer women engineers compared to men. Even if in absolute terms some may be better off economically studying engineering, the economic benefits may not outweigh other non-economic considerations. In the latter scenario, the relative rewards for choosing engineering is simply higher for men. Whatever the causes of these inequalities may be, they represent challenges to overcome for initiatives which aim to encourage higher participation in certain subjects by underrepresented groups. This is additional to any desires to promote equality and fairness across all fields of study in general. Levels of inequality in a particular field of study may concern prospective students. Since different fields of study are linked to different occupations and industrial sectors, higher levels of inequality may signal different rates of employer discrimination in hiring or promoting employees across occupations and sectors. In such cases, the perception that one is disadvantaged relative to others may discourage certain individuals and affect their choice of studies.

This chapter looks at the history and current state of HE in Britain, and current concerns and debates about HE. I have also highlighted the relevance of studying stratification in the graduate labour market—both in the context of broader policy aims to encourage fairness and social mobility, and current academic interests about the state of competition in the graduate labour market. However little research has been done on whether levels of labour market stratification between graduates varies across different fields of study. I will continue this argument in the next chapter where I will explain what is currently known about the causes of labour market stratification, and why stratification may vary across fields of study.

Chapter 3

Stratification in the graduate labour market

Labour market stratification may vary across fields of study but to understand why this might be the case we must understand why there are differences in labour market outcomes between similar groups of graduates in the first instance. This chapter serves as a review of the theory and empirical evidence looking at labour market stratification amongst graduates. In particular it will describe in detail the evidence for the existence of any variations in stratification across fields of study. Whilst there are various reasons to suggest that levels of stratification may vary by fields of study there is currently little empirical literature exploring this topic—particularly in the UK. What little evidence does exist comes from a diverse set of studies which have focussed on different types of stratification across several different countries. Despite efforts to explain the phenomena, there does not seem to be any clear patterns of stratification across fields of study in the literature. For instance, looking at the results of several studies, it is not clear that stratification by socioeconomic background is greater in the arts and humanities compared to the sciences as suggested by some researchers (Hansen 2001; Hällsten 2013; Jackson et al 2008). In order to advance our understanding of the topic, I will present an alternative explanation as to why levels of stratification fluctuates across fields of study based on levels of competition in the graduate labour market.

3.1 Why does labour market stratification exist?

Stratification studies are interested in explaining how differences arise between groups of people in a social system. To this end, figure 3.1 displays the theoretical relationship between ascribed characteristics (A), education prior to HE (B), tertiary education (C), and labour market outcomes (D).The figure is a simplified but useful representation of the processes underlying labour market stratification and I will continue to refer to it throughout the thesisl. Arrow A-B indicates the direct influence that ascribed characteristics have on pre-tertiary educational outcomes (and other related characteristics, such as type of school). Arrow B-C indicates the influence that pre-tertiary education has on education at the tertiary level. For example, someone's gender may influence what subject they studied at school (A-B) and subject of study prior to HE affects what subjects an individual is eligible to study at university (B-C). Arrow C-D indicates the influence of education at the tertiary

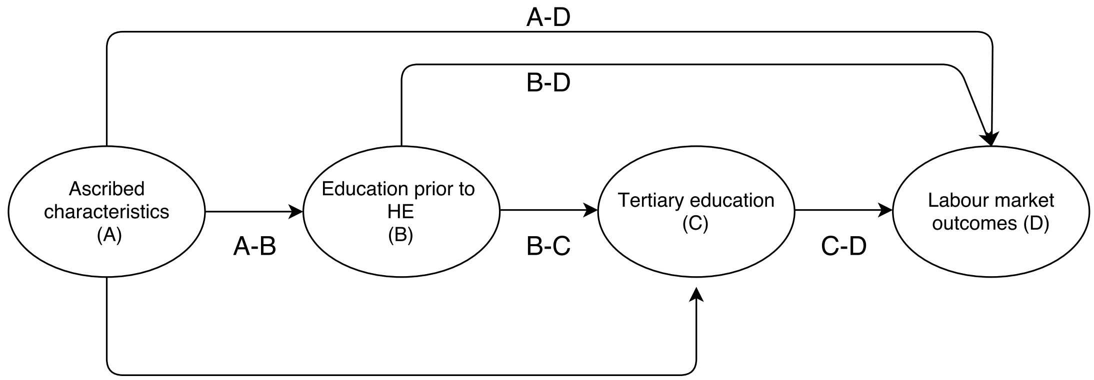

Figure 3.1: The theoretical relationship between ascribed characteristics, education, and labour market outcomes

level on labour market outcomes. Arrow B-D indicates the influence that pre-HE education has on labour market outcomes, *net of the influence of tertiary education*. For instance, if employers considered an individual's pre-HE qualifications alongside their HE degrees when making hiring decisions then this influence would be captured by B-D. Furthermore if a worker's sex or ethnicity had a bearing on their wages net of their education, due to discriminatory employment practises or other factors, then this effect would be captured by arrow A-D. This is sometimes referred to as the direct relationship between labour market outcomes and ascribed characteristics. In contrast, ascribed characteristics may have an indirect relationship on labour market outcomes through their relationships with educational attainment (and other education related factors) (A-B and A-C).

Some stratification studies start by looking at differences in outcomes between groups of people by characteristics such as sex or family background (i.e. component A). These studies would then continue to try to 'explain' how stratification comes about as a result of different influences. For instance, Chevalier (2006) decomposes the earnings difference between male and female graduates into several components. One component is the direct relationship between a worker's gender and their earnings (A-D) as a result of factors like employer discrimination. Another component is the relationship between gender and choice of degree subject (A-C) which indirectly affects labour market outcomes since earnings for graduates vary by field of study (C-D). However many studies choose to focus on one influence (e.g. just A-D or C-D; see Goldthorpe and Jackson 2008). The majority of this thesis falls belongs to the latter category, and looks at how the relationships captured by A-D, B-D, and C-D varies across fields of study.

To develop some points from the previous chapter; much of the earnings inequality between groups of individuals in society (by ethnicity, sex and so forth) is believed to be down to differences in educational attainment and its resulting effects on labour market outcomes (i.e. A-B and A-C in figure 3.1) (see Blau and Duncan 1967). These beliefs have lead successive government across the world to increase to access education in order to address these social inequalities (Teichler 1988). In the UK, successive governments have attempted to widen participation in HE by targeting groups who would have previously been unlikely to attend university. At the same time these governments have also made efforts to increase participation in other types of training and qualifications as well (McQuaid and Lindsay 2005). This link between education, inequality and employability, along with assumptions around the Knowledge Economy, has been one of the drivers behind the expansion of HE in the past two decades.

Yet educational qualifications and achievements do not explain all the difference in earnings between groups of individuals. There are differences between similarly qualified graduates in terms of their labour market outcomes by sex (Purcell, Elias and Wilton 2006), ethnicity (O'Leary and Sloane 2005) and socioeconomic background (Naylor, Smith and McKnight 2002). In short, amongst graduates there exists a non-negligible A-D relationship. There are numerous explanations for these differences in outcomes and a common point of departure for these competing explanations is human capital theory.

3.1.1 Human capital theory

Human capital theory has had—and continues to have—a profound influence on economic and education policy throughout the world (Becker 1975, Mincer 1958, Schultz 1971). It underlies much of the rationale for the expansion of HE and other policies aimed at upskilling the British workforce (e.g. UKCES 2010; Leitch 2006). Human capital theory posits that a person's skills, ability, and creativity—collectively referred to as their human capital——directly affects their productivity in the workplace. An increase in human capital is expected to subsequently increase a person's productivity. Consequently a person's human capital is also connected to their earnings: all things being equal employers want more productive workers and will seek to better compensate these worker for their labour (Becker 2006).

Education is thought to increase a person's human capital through imparting additional skills, abilities, and knowledge (Becker 1975). As mentioned previously, education can be thought of as a private investment in human capital that people undertake in order to obtain higher earnings in the future whilst forgoing potential earnings in the present. As a result, we would generally expect to see better educated workers to be in occupations with higher salaries or with more benefits. We may also expect people who have had a better quality of education or who possessed better educational attainments, such as higher course grades, to have better labour market outcomes. It is assumed that this relationship will exist so long as educational achievements are associated with higher levels of human capital.

It is easy to see how the relatively straightforward relationship between earnings and learning has influenced educational policy in HE. However human capital theory has also attracted numerous criticisms and influenced a number of other explanations regarding the causes of differences in people's labour market outcomes.

3.1.2 Signalling theory

One criticism of human capital theory, as it was originally formed, is that of imperfect information on the part of employers. For example, when hiring for a particular job, an employer would ideally wish to know how productive a person will be in that job. All else being equal, employers want to hire workers who are more productive and to offer them comparatively higher wages than less productive workers. However an employer cannot know for certain how productive a person will be before hiring them. In some cases, information will be directly available to the employers about a persons' productivity. For instance, if potential job candidate undertook a work trial, or if an individual held a similar role previously and detailed information was offered by that person's former employers. However, in general, these means of assessments are rarely available or used by employers (Bartram, Lindley and Foster 1992, Bartram et al 1995).

Another example is the problem of how to compensate current employees. In any moderately complicated production process it can be hard to judge worker productivity. For instance, in the case where one worker's output is dependent on others, it can be very difficult to set a monetary amount to the contributions of a particular person. As such it would be difficult to compensate individuals for their labour according to their productive output.

In these situations, employers lack direct knowledge about a person's productivity. It is argued that in these cases employers look for things that would indirectly signal a persons' productivity: educational qualifications, work experience, and so forth. These signals would help employers make judgements about who to hire and what to pay their current employees (Spence 1973). It is important to note that if employers did use educational qualifications as a signal for productivity then we would expect more educated individuals to be in higher earning jobs. This will hold true *irrespective* of whether gaining educational qualifications actually increases a person's productivity or not. For example, individuals with more patience or an innate ability to learn new things—both factors which may have a positive influence on productivity——may also be more likely to have HE qualifications. There may be various reasons for this: individuals with these traits might do particularly well in school for instance. In this example the association between productivity and educational qualifications partly exists as a result of selection effects. Another possibility is that individuals have a better information about their own abilities (and hence productivity) compared to their potential employers. Given that employers are willing to reward more productive employees, it is in these workers' interest to invest in things that would signal their productivity to employers—as long as the investment costs do not outweigh any potential benefits (Stiglitz 1975).

This has some relevant societal implications: more educated workers may be more productive and earn more but this does not necessarily mean that education increases productivity. In the extreme case, if education has no effect on productivity then educational qualifications are still likely to be beneficial for individuals due to their reputational value. However increasing participation in education would be an inefficient use of resources for the economy as a whole: more people might have expensive university degrees but workers would be no more productive than they were before (Arrow 1973). The role of education as a screening device for general ability or productivity could be cheaply replaced by other methods, such as cognitive tests and personality questionnaires (Schmidt and Hunter 1998). In general supporters of signalling theory do not subscribe to the strong theory of signalling whereby the effects of education on labour market outcomes is entirely caused by signalling and not due to any productivity enhancing powers that the education system may have. Instead most subscribe to a weaker theory which emphasises the signalling value of educational qualifications but does not deny that education can increase productivity as well (Bill 2003, Psacharopoulos 1979). Whilst I have used educational credentials as an example, employers may use a range of signals to screen for productivity including 'how an individual dresses, his accent, his socioeconomic, his race or ethnic group [which] may all provide bases for screening' (p. 292, Stiglitz 1975).

Another concept related to signalling is the idea of statistical and taste-based discrimination which has mainly been used to explain the existence of labour market stratification by ascribed characteristics such as sex and ethnicity. With a lack of knowledge about a *particular* person's productivity, employers may be tempted to infer this information from looking at other *similar* people in the labour market. For instance, employers may infer the productivity of *one* university graduate by looking at the average productivity of *all* university graduates in their firm or across the whole labour market. In essence, statistical discrimination occurs when employers rely on information about whole groups of workers to make judgements about the characteristics of particular individuals. Statistical discrimination refers to the process by which employers make these judgement but it does not imply that the information used is either accurate or used sensibly.

Taste based discrimination refers to preferences on the part of employers or potential customers for certain groups of workers (Becker 1971, Arrow 1998). In the context of ethnicity, personal racial preferences on the part of employers may lead to workers of a certain ethnic group receiving lower wages irrespective of their actual productivity. In these cases, employers may personally dislike working with certain groups of individuals leading to conscious or unconscious discrimination. On the other hand, potential customers may have prefer to deal with workers from certain ethnic groups and employers may respond to those preferences in their hiring decisions (see Holzer and Ihlanfeldt 1998).

3.1.3 Positional competition theories

The relationship between earning and learning in human capital theory is a relatively straightforward one: people who increase their skills and gain credentials are expected to yield better rewards in the labour market. The direction of human capital effects is fixed——more human capital is better than less——but many critics have argued that the size of these effects may fluctuate under certain circumstances (Brown and Hesketh 2004).

The argument goes that skills and qualifications may be important for gaining employment and doing a job. However, their value in the labour market is relative to the skills and the qualification of other competing job seekers, and the supply and demand for labour. When the labour market is tight, and there are relatively few skilled workers and many unfilled vacancies, those with previously inadequate skills and qualifications will suddenly become more employable as firms seek to fill those vacancies. Conversely when the labour market is loose and the proportion of skilled workers to unfilled vacancies is high, firms are able to be more selective and those who were previously employable can become unemployable. In short, the impact of factors, such as credentials and skills, on one's employability is relative and dependent on the conditions of the labour market (Blaug 1976; Thurow 1972, 1975).

Another related argument is that things like educational qualifications are positional goods: part of their value to workers lies in their relative scarcity (Hirch 1977). For instance, in a hypothetical system where only a minority of the brightest individuals receive higher education, a degree itself can be a powerful signal of raw ability to employers. However, if more individuals from a wider range of abilities acquire higher education degree the signalling value of such degrees diminishes (Arrow 1973).

With respect to higher education, this leads to a conundrum whereby getting a higher education degree increases the potential future earnings of individuals. However, as more and more individuals gain higher education degrees, the individual rate of return to these qualifications is expected to decline if the demand for graduate labour was held constant. This is irrespective of whether degrees are associated with labour market outcomes due to their signalling value or due to their effects on people's productivity.

Following the example of HE qualifications, once these qualifications become more widespread amongst workers, and assuming that the demand for graduate skills remain unchanged, employers may look for other signals of productivity. In a loose labour market for graduates we might expect those individuals who do relatively well to be those who can distinguish themselves through their extra-curricular activities, work experience and such like (Tomlinson 2008). This also increases the potential for one's socioeconomic background, sex, or ethnicity to affect one's chances of obtaining employment. As the numbers of graduates who hold the same levels of formal qualifications and training increases, employers may be tempted to use statistical discrimination in order to help them screen suitable job candidates.

When there is a large pool of seemingly acceptable candidates for a role, for the same wages employers are able to expect more from a successful job candidates compared to a scenario where are few candidates. Under these circumstance employers may simply to choose to raise the minimum required qualifications that applicants must have in order to screen the most able candidates. Successful graduates will need better qualifications to obtain the same labour market rewards resulting in credential inflation. Another possibility is that employers may seek out other additional traits——such as work ethic or reliability——that are not essential to a role but are otherwise desirable. These traits may include so-called soft (or personal) skills which are 'skills, abilities and traits that pertain to personality, attutide and behaviours rather than to formal or technical knowledge' (Moss and Tilly 1996; quoted in Nickson et al 2011, p. 66). Many of these traits are not directly observable and this increases the temptation for employers to rely on other things as potential signals. In the job interviews, employers may look for factors, such as one's style of dress or manners of expression, alongside one's formal credentials when assessing candidates. Furthermore knowledge of these aspects of performance is often tacit and cultural, reflecting one's upbringing and background (Hesketh and Brown 2006).

3.2 Stratification across fields of study

Whilst the three theories discussed above provide explanations as to *why* there is a relationship between certain characteristics and labour market outcomes there are still on-going debates as to whether the strength of these relationships vary across different cultural and institutional settings (Bills 2003; van de Werfhorst 2011; Jackson, Goldthorpe and Mills 2005; Goldthorpe 2014). Even in the earliest writings on signalling theory it was acknowledged that 'a characteristic may be a signal with respect to some types of jobs but not with respect to others' (p. 359, Spence 1973). Many of these debates have focused on the relationship between education and labour market outcomes across different industries and countries (Psacharopoulos 1979; van de Werfhorst 2011a, 2011b; Di Stasio, Bol and van de Werfhorst 2015). In addition, factors such as one's personality or aesthetic sense can contribute more to—or is more strongly associated with—workers' productivity in some occupations compared to others. For example:

> *'[...]in the case of professionals, technicians or workers in skilled trades, it could be supposed that employers are primarily concerned that the individuals they employ do possess a particular range of knowledge and see appropriate qualifications as adequately certifying that such human capital has been acquired. In contrast, with non-technical managerial positions or with various 'people processing' occupations in, say, sales or personal services, where what constitutes relevant knowledge and skills is less easily defined and likely to be more firm-specific, employers may be more concerned with non-observable characteristics for which educational attainment could help them screen.' (p. 273-274, Goldthorpe 2014)*

The above quote proposes that the relationship between education and the labour market (B-D and C-D in figure 3.1) varies for different types of workers. These differences in hiring preferences are present in studies looking at job adverts and employer preferences (Jackson 2007; Di Stasio 2015; Nickson et al 2012). Looking at hiring preferences for frontline retail assistants in the UK, Nickson et al. (2011) found that only 4.6 percent of employers thought that qualifications were very important or essential to the role. In comparison 79.7 percent and 68.2 percent placed a strong emphasis on a persons' personality and appearance when hiring.

If the relationship between different characteristics and labour market outcomes differs across different setting then this creates the possibility that labour market inequalities by sex or educational attainment amongst graduates may vary by fields of study. As I mentioned in the last chapter, broadly speaking, while all degree holders receive similar levels of education, we do not expect them all to have received the same type of education. There is a greater degree of specialisation in HE compared to other levels of education. Until recently, in the UK, all children were required to study English, Maths and Science——plus a wide range of other subjects——until they were 15 or 16. The existence of a compulsory national curriculum up to that age ensures a certain degree of homogeneity amongst people that have graduated from the secondary education system.

In addition, degree holders from different fields of studies will have distinctly different labour market opportunities after graduation. Some opportunities will be explicitly open to degree holders from some field of study and not others: employers will not hire doctors without medical degrees or engineers without engineering qualifications. Employers, depending on the type of role offered, may also prefer graduates from some field of study over others (see van de Werfhorst and Kraaykamp 2001). For example, professional statisticians do not necessarily have statistics degrees. However employers, such as the government, usually require statisticians to possess degrees in fields of study with some statistical content such as economics, psychology, or geography (GSR 2015). In the case of entry level marketing jobs, Wellman (2010) examined 250 advertisements and found that 48.8 percent specified that applicants must have a degree. Of these 74.8 percent required applicants to have a degree in marketing or another related subject area, such as public relations or psychology. Graduates themselves may also differ qualitatively in their preferences and career ambitions by field of study as well. As a result we should expect different types of graduates to be competing for different jobs in different sectors of the labour market.

These differences have led some researchers to consider the possibility that some factors thought to affect labour market outcomes may be far more important for some degree holders compared to others depending on their fields of study. For instance, after accounting for their abilities and previous educational attainments, an individual's socioeconomic background may have more of an impact on labour market outcomes for graduates in the arts compared to the sciences (Hansen 2001). This will subsequently results in greater differences in earnings (and other outcomes) between similar workers by family background (A-D) in some fields of studies compared to others. Research into this topic has mainly focus on ascribed characteristics, such as sex and socioeconomic background. However a number of studies have also explored stratification by educational attainments, such as degree classification, across different fields of study (Feng and Graetz 2015).

Most of these researchers have had similar underlying expectations about how stratification and fields of study are related. These may be broken down into expectations based on the characteristics of degree holders or the nature of the qualification itself (supply side explanations), and those based the characteristics of employers (demand side explanations).

Supply side explanations for variations in stratification

Employers may discriminate between different groups of employees in the labour market on basis of ascribed characteristics. This may be due to statistical discrimination or taste based discrimination, which in turn could be conscious or unconscious (Becker 1971). However it is thought that graduates with degrees in fields of study where the contents str well-defined are less likely to face such discrimination. An example of this would in fields where there is strong consensus around the core knowledge base (i.e. those with a single paradigm) (Biglan 1973). I will refer to these as hard fields of study. In contrast, soft fields—-such as humanities and some social sciences—-will have a range of fundamentally different theories on the same topic. In these subjects there may be no common consensus on about what the core body of knowledge in the discipline is and what skills practionioners are actually expected to possess.

Since the expected knowledge and skills of individuals with degrees in hard fields are relatively standardised it is arguably easier for employers to compare these graduates based on their formal educational qualifications. This ability to compare lessens the extent to which employer discrimination may affect the hiring process. This is also likely to be true for applied fields where the subject matter is more directly related to particular occupations. Individuals who receive better grades in their nursing degrees will, on average, have more of the skills and knowledge needed to become better nurses. For hard and applied fields, the nature of the qualification may give also greater power to potential candidates to question unfair hiring decisions (Roska 2005).

For fields of study where the skills gained are less well defined or professions where the skills used are less easily captured by a formal qualification (i.e. a weaker B-D and C-D relationship), there exists less potential for transparency in the hiring process. This in turn leads to a greater potential for employer biases to go unchallenged (resulting stronger A-D relationship). Researchers have often expected differences in labour market outcomes based on ascribed characteristics to be smaller in hard and applied fields of study, such as STEM and medicine, compared to other subjects (Hansen 2001).

Another related supply side explanations involves the indirect effects of factors, such as socioeconomic background, on labour market outcomes through educational attainments. Individuals from certain backgrounds may find it easier to succeed in certain fields of study as a result their upbringing. Their background may provide them with tacit knowledge or an advantage in their chosen field of study which translates to greater gains in human capital and higher course grades (Hansen and Mastekaas 2006, captured by stronger A-B and B-C relationships in figure 3.1). Furthermore, the indirect effects of these factors can extend to pre-HE achievements which will affect opportunities later on in life: children from advantaged backgrounds go to better schools, better schools help children get into better universities, better universities help people get better jobs and so forth.

Demand side explanations for variations in stratification

One type of demand side explanation posits that variations in stratification by fields of study are a result of the relationship between productivity and personal (or social) skills across different occupations. These personal skills may encompass things that we would normally think of as character traits, such as empathy or morality (p 384, Jackson 2007) rather than skills that are achieved (but also see Hochschild 2013). For some occupations, skills such as one's mode of presentation, aesthetic sense and manner of speech may be of great importance to a role.

Jackson's study looking at newspaper job advertisements in the UK (N=5021) found that personal and social skills, such as managing employees and verbal/written communication skills, were more likely to be requested for roles related to sales and personal services. In contrast, these skills were less likely to be in job adverts for technical roles and this relationship is somewhat apparent across for all occupational positions (e.g. managerial, intermediate or routine/semi-routine, p. 380 Jackson 2007). In these industries and occupations, an individual's upbringing, acquired tastes or manners of expression can be easily transformed into potential human capital, and can contribute towards one's productivity over and above the skills gained from one's education (resulting in a substantial A-D relationship) (van de Werfhorst and Kraaykamp 2001; Jackson, Goldthorpe and Mills 2005).

As previously mentioned, these qualities may also be poorly captured by one's formal academic qualifications and as such employers may give greater weight to other factors when hiring and promoting staff. In contrast, more technical professions may give much greater weight to formal academic qualifications. Furthermore, an individual's personal and social skills may contribute little towards one's productivity in these profession compared to an individual's technical abilities and subject-specific knowledge. As such, it is thought that there will be less stratification between graduates along the lines of socioeconomic background in fields of study that tend to lead to technical professions compared to those that lead to careers related to personal services and sales (Jackson, Goldthorpe and Mills 2005).

Table 3.1: Estimates of percentage of UK workforce in the public sector by industry (2012-13) (Source: Cribb, Disney and Sibieta 2014)

Industry	Percentage
Education	74.5%
Health and social work	50.7%
Public admin. And Defence	85.9%
Hotels, restuarnts and retail	1.1%
Real estate and business activities	3.0%
Other	9.0%

Another demand side explanation focuses on how hiring practises across different sectors may also affect stratification. The majority of workers in education (74.5%), health and social work (50.7%), and public administration and defence (85.9%) are emloyed by the public sector (table 3.1)[1]. As a consequence, the public sector is likely to be a major employer of graduates with degrees related to education and healthcare. Public sector organisation, such as the NHS, are likely to have more transparent hiring policies than those employers in the private sector. This is because the level of bureaucracy, also associated with the size of the firm or company, plays a factor in reducing inequalities (Weber 1968). Bureaucracy in this context refers to the existence of rationally determined rules that govern decision making in an organisation. Organisations with a higher level of bureaucracy may implement more stringent guidelines around hiring and promotions, and deploy standardised means of assessments which lessens the power of individuals to discriminate during the hiring process. The close relationship between the government and the NHS may also exert additional pressures on the organisation to practise and promote equality.

Finally the importance that employers in different sectors place on factors, such as the prestige

[1] These are rough estimates derived from Cribb, Disney and Sibieta (2014). Estimates are based on the proportion of public and private sector workers in certain industries as reported by the UK Labour Force Survey. The information is taken from table 5 in Cribb *et al* (2014). The same paper reported that 21 percent of the UK workforce were in the public sector in 2010. Assuming a very low proportion of third sector employees or self-employed individuals are in the workforce in these industries, it is possible to derive the statistics shown in the table using Bayes' theorem.

of one's university or degree classification, may simply vary for reasons unrelated to productivity or their formal hiring policies. In these cases, employer preferences may be down to entrenched practises and norms that have accumulated over time rather than for any explicit reason (Strathdee 2009).

In practise, both the supply side and demand side explanations predict roughly similar patterns of stratification across fields of study. Hard and applied fields of study are those thought to have the lowest levels of stratification between graduates based on ascribed characteristics. Furthermore, subjects related to professions contained mainly within the public sector are thought to also have low levels of stratification by sex, ethnicity and socioeconomic background (Hällsten 2013). Turning to the empirical literature, I will argue that there has been little evidence to support the aforementioned patterns of stratification across fields of study; both in the small number of studies looking at the UK as well as other countries. Furthermore I will offer an alternative explanation for the patterns of variation seen in the literature. For the sake of convenience I have chosen to focus on stratification by socioeconomic background, sex, the type of HEI graduates attended, and their degree classification.

3.3 Research on labour market stratification amongst graduates

3.3.1 Socioeconomic background

Blasko (2002) made use of the British subsample of a major international survey to assess the impact of one's family background on labour market outcomes. The estimates were obtained using multiple linear regressions on cross-sectional data. Although Blasko had access to information about graduates' parental occupations, this information was not used in her analysis. Instead parental educational background was used as a proxy measure for one's socioeconomic background. Blasko found that graduates whose parents had lower levels of education tended to earn less than those whose parents had achieved higher levels of education. Male (female) graduates whose parents had both achieved HE degrees earned around 16 percent (5.7%) more per year than those graduates whose parents only had received compulsory education or had no qualifications at all. However, when various factors (such as age of entry, HEI attended, and field of study) are accounted for, this gap drops to around 9-10 percent. A later analysis using the Destination of Leavers from Higher Education survey using a similar analytical strategy and set of controls reaches a very different interpretation about the direct effects of background (Ramsey 2008). Using parent's occupational class as a measure, Ramsey finds an earnings gap of around 3 percent between male graduates from professional and managerial backgrounds, and those from routine occupational backgrounds. This lead Ramsey to interpret that socioeconomic background had a significant yet small impact on earnings. Another analysis conducted using similar data and methods also support the size of Ramsey's results (Naylor, Smith and McKnight 2002).

There are various reasons why studies may come to very different conclusions. First both Ramsey and Blasko used different measure of socioeconomic background. While parental education is correlated with occupational status this relationship is not perfect, which would have therefore contributed towards their somewhat different interpretations of the data. Second the two datasets used are different: Ramsey looked at destinations for a graduate cohort in 2004 while Blasko had information on graduates from a 1995 cohort. Ramsey's study had information on graduate destinations 6 months after graduation whilst Blasko had information for graduates 4 years after graduation. This probably contributed a substantial amount to the analysis as it is known that a high portion of graduates are likely to be in temporary jobs that are unrelated to their later careers shortly after leaving university (ONS 2012, Purcell, Elias and Wilton 2006). This is in part due to the fact that many young graduates will have limited work experience or may be taking a career break (to go travelling, to save up money for PG education etc.) during this time (Sage, Evandrou and Falkingham 2012). Furthermore graduate from different backgrounds might accrue different rates of return for the years they spend in the labour market. Those from managerial or professional backgrounds may earn more over time as their line managers may seek—consciously or unconsciously—to promote people like themselves into higher positions (Brown and Hesketh 2004).

Macmillian, Taylor and Vignoles (2013) took graduate destinations data from individuals who graduates in 2006/07 cohort in the UK in order to look at the association between socioeconomic background, private schooling, and entry into high status occupations three and a half years after graduation. The analysis was once again using cross-sectional data and used a similar research design to Ramsey and Blasko. Their interest in private schooling arises from the fact that in the UK pupils in private schools make up a small percentage of all the students in the education system (7.2% in 2012, Bolton 2012). However a disproportionate amount of individuals in elite and high status occupations, such as judges and members of parliament, were privately educated (Milburn 2014). Since attendance at these institutions is partly based around the ability to pay, although some bursaries may be available, private schooling is often seen as being associated with social status and economic advantage. Much like Ramsey's study, Macmillian et al found that there was only a minor difference in outcomes between those from advantaged and disadvantaged socioeconomic backgrounds in obtaining high status occupations (2013). However they found a more substantial difference between privately educated graduates and state educated graduates. Privately educated graduates were more likely to be in high status professions, especially in law and in managerial positions, compared to their state educated counterparts. This is after taking into account factors such as educational achievements at HE and prior to HE, which are very different for these two groups of graduates (HEFCE 2013; Smith and Naylor 2005).

The idea that there are variations in stratification by socioeconomic background across fields of subject is often referred to as the differential advantage hypothesis. The concept originates in a series of analyses looking at labour market outcomes for graduates in Norway (Hansen 1996, 2001; Jackson et al. 2008). Hansen's (2001) analysis of Norwegian graduates aged 31-40 used tax returns data. Hansen expected that one's socioeconomic background had less of an impact for graduates from hard subjects (i.e. STEM) compared to graduates from soft subject (i.e. humanities and the arts). Hansen's paper argued that some support was found for the differential advantage hypothesis in her analysis. This claim may be slightly over-exaggerated since the analysis fails to account for multiple comparisons, an issue that I will discuss further in the next chapter. Her results show that these variations are only statistically significant for men, and only when we look at a measure of income that includes stock returns and any income from self-employment. The rationale behind this choice of income measure stems from the fact that many individuals in high earning and status occupations may earn additional income from consulting or receive part of their earned income through stocks. However Hansen concedes that the possession of stocks may be a result of investments made with wealth and savings, and therefore her measure of income may conflate labour market rewards with inherited wealth (p. 215, 2001).

Jackson et al's (2008) study made use of the general household survey (1991 and 1992) to test whether the association between graduates' class backgrounds and class destinations differed across different fields of study. Unexpectedly, for the UK, they found that the link between graduates' class backgrounds and destinations was stronger (for men) in technical and applied subjects, and not the humanities. In the same analysis, they also find mixed evidence of any variations in stratification by field of study in other European countries. A recent analysis done by Hällsten (2013) looking at individuals over 30 using Swedish Census data however seems to support the differential advantage hypothesis. Aside from the Jackson et al analysis, there is no other analysis looking at variations in stratification by socioeconomic background across fields of study using UK data.

3.3.2 Sex

Female workers earn on average less than their male counterparts and this difference is often referred to as the *gender earnings gap*. The gender earnings gap exists for graduates as well: men with bachelors' degrees earn on average 6.4 percent more than their female counterparts three and a half years after leaving university[2] (table 11a, HESA 2014). There are many explanations for the gender wage gap amongst graduates. Women, for example, are more likely to enrol in fields of study that have lower average salaries than men (Purcell and Elias 2006). Men are also overrepresented in the higher earning STEM subjects. Furthermore women graduates are likely to hold different attitudes towards their careers than men. Interviews with women graduates suggest that they are more likely to prioritise moral concerns in their careers; they may be more interested in working in jobs that give back to society or respects ecological concerns than men (Thomas 1990, Smetherham 2005). This in turn may lead to some women to opt for work in areas, such as the public sector or in social care, that tend to pay less (Purcell, Elias and Wilton 2006). Likewise, women may adopt different career expectations compared to men. For instance, two-thirds of women graduates expected to take a career break due to family commitment in the future compared to only 12 percent of men (Chevalier 2006).

Machin and Puhani (2002) made use of the British Labour Force Survey (1981-1995) to explore the gender earnings gap among graduates of all ages. Machin and Puhani made use of the Oaxaca-Blinder decomposition to estimate the gender gap in mean wages into two components: one component that can be explained by observable factors, such as difference in their fields of study, and another components that is unexplained. The latter can be due to unobserved factors or processes as well as employer discrimination (Oaxaca 1973, Blinder 1973). For instance, getting better course grades may be beneficial for graduates from both sexes but it may provide more of a benefit to men than women for unknown reasons.

Whilst men initially earned 21.5 percent more than women, this gap reduces to around 8.6 percent after accounting for other factors. In the analysis 62 percent of the initial gender earnings gap could be explained by differences in fields of study and job characteristics, such as sector of employment and industry, between male and female graduates. Subject of study alone was estimated to account for around 25 percent of the reduction in the initial gender earnings gap between male and female graduates in the UK. Chevalier's (2006) analysis follows on from Machin and Puhani's study, using information on graduates who completed their degrees in 1995. The dataset contains information on graduate destinations three and a half years after university, and includes survey information on graduates' career attitudes—information that Machin and Puhani did not have access to. This included information on whether individuals were prepared to take a career break for family and the characteristics they

[2] Full time mode of study based on median salaries from the 2008/09 Longitudinal DLHE

looked for in a job. The initial gender earnings gap was 12.6 percent, however a model accounting for subject studied, job characteristics and career attitudes accounted for more than 80 percent of the gender earnings gap. In the statistical model used, field of study, job characteristic and career attitudes all seem to make roughly equal contribution towards the explained gender earnings gap: each contributed to around a quarter of the explained gap. A similar set of explanations for the gender wage gap amongst graduates was also found by Purcell and Elias (2008).

From the evidence it is not possible to discount either job characteristic, career attitudes or subject studied as an explanation for the gender earnings gap. However the direction of explanation is unclear: women's career aspirations could account for their lower earnings or anticipated lower earnings could account for their career aspirations. The importance of fields of study in explaining the gender earnings gap is also reflected in studies done in other countries which quote very similar values for the portion of the gender wage gap explained by field of study (~20%, Gerber and Cheung 2008).

There have been few studies looking at variations in the gender wage gap by field of study, both in the UK and other countries. Purcell and Elias (2006) examined the difference in earnings between men and men for UK graduates in Law, Humanities and Engineering seven years after leaving Higher Education. In their sample, the gender earnings gap was less in Engineering compared to the other two subjects. Male graduates earned 10 percent more than female graduates in Engineering whilst the difference was 20 percent in Humanities and 22 percent in Law. In a more recent study of graduate destinations roughly 2 years after leaving HE, Purcell et al (2013) found some variations in the size of the gender wage gap across a wider range of fields of study. Their analysis only looked at descriptive statistics. Purcell et al found that the gender wage gap was practically non-existent for those who studied subjects allied to medicine and education. In constrast, full-time employed male law graduates earned on average around £8,000 more than females (£28,000 compared to £20,000). Roska (2005) used data from the US to look at the gender earnings gap across fields of study. The analysis looked at labour market outcomes in 1998 when the respondents were roughly 37 years old. The analysis looked at whether the gender earnings gap was smaller in female dominated fields of study and found some support for this in her analysis. Furthermore, the analysis also looked at the probability of obtaining a managerial/professional occupation across fields of study by gender. Roska's interpretation of her results is that '(i)ndividuals who are employed in the public sector are more likely to gain access to the top of the occupational hierarchy when they majored in female-dominated fields' (p.224, Roska 2005). However, since her interpretation was based on the results of interaction terms in a logistic regression model, her latter statement is not strictly correct as I will explain in the next chapter (and in the appendix).

3.3.3 Type of institution

The prestige and quality of one's higher education institution (HEI) is one factor thought to contribute towards a person's employability. In terms of policy, the argument that certain HEIs can provide better returns for their graduates has often been implicitly accepted by successive governments as a rationale to allow tuition fees to vary more across HEIs (Browne 2010). From a human capital perspective higher quality HEIs may improve their students' learning experience and, as a consequence, enhance their students' human capital. Other approaches argue that HEIs influence their graduates' employability through institutional prestige and not just through their added value to graduates' human capital. HEI prestige can serve as a signal to potential employers regarding the quality of a job candidate, irrespective of their actual abilities (Spence 1973). Brown and Hesketh's (2004) work on the hiring practises of graduate recruiters suggest that HEI serves an important screening device that employers use to filter potential job candidates. Likewise HEIs may have better connections to certain companies or alumni may be part of larger social networks that may help improve one's chances of finding work. In addition HEI quality may be an important indicator of unobserved characteristics associated with people's productivity.

Chevalier and Conlon (2003) made use of data from 3 graduate surveys (1985, 1990 and 1995) to derive the statistical association between HEI and earnings. They derive their estimates using propensity score matching although their estimates do not appear to differ much from results obtained by unmatched linear regression, especially after taking into account the precision of their estimates (Table 5 and 6, p.34-35, 2003). They found mixed evidence for the association between HEI prestige and earnings. In their analysis HEIs were grouped into three categories: Russell group universities—which is a group of prestigious research universities; non-Russell group universities—whose Royal Charters predate 1992 but are otherwise not part of the Russell group; and Post-1992 universities (see previous chapter for more details). Whilst going to a Russell group university was found to be associated with higher earnings, there was little difference in earning between graduates from older non-Russell group universities and more modern post-1992 HEIs. Chevalier and Conlon also point out that there are signs of a growing premium to HEI for younger cohorts, providing tentative support for the argument that educational differentiation has become more important as participation in HE rises. However, this pattern only seems to hold for men and curiously the opposite holds for women (table 6, p. 30-31, 2003). In addition, the effects of HEI on wages are actually very modest (~2%-11% for Russell group depending on cohort) and should be interpreted with caution especially once the accuracy of their estimates are taken into account.

Other studies have produced similar result to Chevalier and Conlon's study suggesting that HEI prestige has a significant but rather small effect on earnings (e.g. Naylor, Smith and McKnight. 2002). For instance Ramsey (2008), using OLS regression to account for other characteristics, finds that graduates from Russell group university earn only around 3.5 percent more than their equivalents from post-1992 modern universities. Overall the weight of evidence therefore suggest that HEI prestige has a statistically significant—but substantively small—association with graduates' earnings.

Wilton's (2011) study of business and managements graduates also looked into the effects of HEI on employability. In that study Wilton took graduates from both pre-1992 and post-1992 universities, and used data on graduates' self-rated skills to test for the presence of a prestige effect for HEI. If HEIs influenced career success as a result of the quality of their teaching then we could arguably expect graduates from more prestigious universities to do better in labour market, and to have on average higher levels of self-reported skill and knowledge. [3] Surprisingly graduates from the new universities actually had higher levels of reported skills. Yet, at the same time, graduates from the new universities, on average, did far worse in the labour market. One clear downside of Wilton's study is the reliance on reported self-rated skills development as well as its focus on just business and management students.

The relationship between HEI and labour market outcomes across different field of study is unclear. One expectation is that across different sectors of the labour market, HEI prestige may hold different weight. Some HEIs specialise in particular fields of study and thus their reputation will be stronger in some areas than others. This reputation can benefit some of its graduates by association depending on field of study (Strathdee 2009). However, it is also plausible that quality of education may

[3] This is assuming that more prestigious institutions have better teaching quality.

vary by field of study. To clarify, some fields of study have accrediting bodies that ensure standards whilst others may not. Furthermore, in these fields of study, professional bodies may accredit some degree courses and not others. For instance, only a proportion of all psychology are accredited by the British Psychological Association and accreditation is a prerequisite for other professional advances such as chartership status or registration as a professional psychologist (BPS 2014). As a result, there exists greater potential for differences in the quality and utility of psychology courses compared to some other fields of study.

Rumberger and Thomas (1993) used information from a US graduate cohort survey and looked at labour market outcomes less than two years after graduates had received their degrees. They test for heterogeneity across HEI using separate random effect model for six fields of study, where individuals were clustered by HEI. Looking at wages as the outcome, they find that the variance in wages between graduates from different HEI was relatively low to negligible for those who studied engineering and health (*ibid*, table 5 p.10). However, this result may be slightly hard to interpret as not all HEI offer courses in every field of study. Non-existent variations between HEI for engineering may only indicate that the quality or prestige of HEIs offering this field of study does not vary. This may be because only very well-funded or prestigious HEIs offer this subject to begin with. Smyth and Strathdee (2010) make use of student administrative data linked with tax returns data to explore relationship between HEI and labour market outcomes in New Zealand. Despite the quality of the data, the analysis only made use of descriptive statistics and only looked at four fields of study.

3.3.4 Degree classification

Degree classification is another factor that is thought to impact employability for a variety of reasons. For instance, the majority of new graduates with bachelors' degrees are under 24 (table D, HESA 2014). These graduates are a fairly homogenous group, compared to the general working population, with respects to their previous work experience and level of education. Employers may therefore resort to using degrees classification as a way of distinguishing between graduates. Studies looking at both graduate recruiters and graduates themselves have noted that an upper second class degree is often used as a minimum benchmark criterion by employers for various jobs (Brown and Hesketh 2004; Tomlinson 2008). A higher degree class may also reflect greater human capital and ability which in turn would be related to higher earnings and career success over time. Likewise degree classification may affect one's employability because it signals information to employers about a person's potential productivity and ability (Spence 1973, Stiglitz 1975).

There is more substantial evidence for the association between degree classification and labour market outcomes compared to HEI (Ramsey 2008, Blasko 2002). Over average first class degree holders are expected to earn around 18 percent more than those with a third class degree. This gap reduces to 8.2 percent after accounting for other characteristics. Achieving a higher degree classification is also associated with higher job satisfaction levels and occupational success (in terms of class destination) for both male and female graduates (Blasko 2002). The positive relationship between degree classification, wages and occupational status also seem to hold true for individuals of both genders across a range of degree subjects (Walker and Zhu 2011, Smetherham 2008).

Much of the literature mentioned so far has tried to estimate the rates of return using some sort of regression model (or matching) on cross-sectional data. If one were interested in looking at *differences* in outcomes between individuals who are otherwise broadly similar, as I am in this thesis, then the results of these studies are useful. If one were interested in estimate of causal effects then we need to be more cautious with regards to interpretation. The aforementioned methods can only estimate the casual effect of factors, such as the effects of degree classification on labour market outcomes, under a specific range of circumstance (see Heckman 2005; Heckman and Vytlacil 2007). One necessary, but not sufficient, condition is that relevant factors are account for in the statistical model (or are otherwise unrelated to our predictors of interest). Since we often do not observe all the relevant factors, estimates using non-experimental data are likely to be biased to an unknown extent—although any results obtained may still prove useful. Feng and Graetz (2015) used a different research strategy: they make use of regression discontinuity to estimate the effects of degree classification on labour market outcomes.

Feng and Graetz used information on graduates from one single UK institution and looked at their destinations 6 months after graduation. Their research design takes advantage of the fact that degree classification is a rough indicator of total course grade in the UK. For example, say a degree classification was determined by average course grade, which runs from 0 to 100, and students with averages of at least 70 were awarded first class honours degrees. The two groups of individuals achieving average course grades on the borderline (i.e. 69 and 71) will be almost identical in their abilities: assuming a 2 point difference reflects a negligible difference in ability. In addition, they would be similar with respects to all unobserved characteristics as well. However, graduates in one group will have a first honours class degree and graduates in the other group would not. As a result any observed differences in labour market outcomes between the two groups can be explained by the degree classification awarded and not by differences in ability or other unobservable factors. Furthermore since this difference does not capture differences in ability—or human capital—one plausible interpretation is that any difference between the two groups captures the impact of degree classification on labour market outcomes due to signalling[4].

Using regression discontinuity, those with an upper second class honours are estimated to earn 7.4 percent more than those with a lower second class honours. Those with a first class honours are estimated to earn 3.6 percent more than those with an upper second class honours. Interestingly their estimates do not differ significantly—both in a practical and statistical sense—from estimates derived using a linear regression model (see table 5 and 6, p.27-28, 2015). Since the estimate derived from the linear regression models also capture differences in ability and human capital, one interpretation of the results is that the majority of effects of degree classification on labour market outcomes in graduates' early careers is due to signalling.

Feng and Graetz's analysis also goes further and looks at these effects by field of study. Since the institution they studied only offered courses in the social and economic sciences, as well as some humanities, they could not investigate the effects of degree classification across a wider range of fields. They group fields into those requiring a qualification in mathematics as a pre-HE requirement and those which do not. The estimated rates of return to an upper second class honours, compared to a lower second class honours, was 14.6 percent whilst the returns to a first class honours was 6.5 percent compared to an upper second class honours for fields requiring mathematics. The estimated returns to higher degree classifications were much smaller and not statistically different from zero for those in fields not requiring mathematics.

[4]The actual design that Feng and Graetz used was similar but more complicated as the institution studied had a less straightforward means of allocating degree classification.

3.4 Evidence of variations in stratification across fields of study?

As mentioned previous, many researchers have expected labour market stratification by ascribed characteristics, such as sex and socioeconomic background, to be lower in hard and applied fields of study, after accounting for other relevant factors. However studies have generally found weak evidence of lower stratification by socioeconomic background amongst graduates from these fields of study (Hansen 2001, Hällsten 2013), no evidence of any such variation at all, or even greater stratification for graduates from hard and applied subjects (Jackson et al 2008). The evidence looking at gender disparities across fields of study also does not support this pattern (Purcell and Elias 2006). However, there is some support for the theory that labour market stratification based on ascribed characteristics is lower for those in fields of study connected to employment in the public or non-profit sector (Hällsten 2013, Jackson et al 2008, Roska 2005).

These mixed results have made it very hard to draw any definite conclusions about any variations in stratification by field of study. One reason for such disparate results could be due to technical issues, such as lack of statistical power, over-fitting the data, and failure to adjust statistical tests to take into account when making multiple comparisons of results by fields of study. There are a number of ways in which the methods used to assess variations by fields of study could be improved. This issue will be discussed in the next chapter.

Another unexplored explanation for these patterns could come from examining the extent of competition in the labour market for graduates across different fields of study. This idea was also briefly explored by Rumberger and Thomas (p.16, 1993).

Whilst higher education participation has risen in general over the past few decades these increase have not been uniform across all subject areas. Table 3.2 shows leavers with qualifications at bachelors level who graduated in the academic year 2002/3 compared to 2012/13. Whilst total undergraduate numbers have risen for the Biological science and Subjects allied to medicine have grown by 79.5 percent and 75.9 percent each between 2002/3-2012/13, the number of student enrolled on computer science courses actually fell during that time period. The specialist nature of higher education means that graduate workers are not easily interchangeable: a company cannot replace computer programmers with biologist and nurses, and still expect productivity to stay the same. As such, student enrolment numbers in higher education can act as a limit on the supply of potential new entrants into the labour market for some sectors. There are also different levels of demand for worker across different sectors of the economy as well.

Changes in supply and demand for graduates in the labour market over time can lead to conditions where the growth in demand for new graduates outpaces supply and vice versa. According to positional competition theories, in the latter scenario, we may expect employers to be more discriminating when screening candidates and for factors other than formal education to play a bigger part in distinguishing one degree holder from another. This could mean greater stratification between graduates in the labour market based on their socioeconomics background, sex or ethnicity (Brown and Hesketh 2004). This would also mean that a greater emphasis may be placed on degree classification or possessing a postgraduate degree as well. Since graduates from different subjects will tend to enter different sectors within the labour market, it could explain some of the variations in stratification between different degree subjects. This could explain some of the inconsistent patterns of variation of stratification

Table 3.2: Number of leaver with bachelor's degrees by subject area (2002/03 and 2013/14) (Source: HESA)

Subject area	Academic year 2002/03	2013/14	Percentage change
Combined*	9,990	4,415	-55.81%
Computer science	18,240	16,080	-11.84%
Languages	20,025	24,160	20.65%
Engineering & technology	19,455	25,870	32.97%
Agriculture & related subjects	2,150	2,950	37.21%
Physical sciences	12,480	17,300	38.62%
Historical & philosophical studies	13,285	18,645	40.35%
Architecture, building & planning	6,555	9,435	43.94%
Law	11,745	17,925	52.62%
Medicine & dentistry	6,175	9,780	58.38%
Business & administrative studies	40,310	64,000	58.77%
Veterinary science	560	900	60.71%
Creative arts & design	26,465	43,645	64.92%
Mass communications & documentation	7,415	12,350	66.55%
Mathematical sciences	5,100	8,605	68.73%
Social studies	25,315	42,720	68.75%
Subjects allied to medicine	23,665	41,625	75.89%
Biological sciences	23,725	42,580	79.47%
Education	9,730	18,865	93.88%
Total	282,380	421,850	49.39%

*Combined category was subject to many reclassifications between this period

that we find in studies that look at different countries (Hansen 2001, Jackson et al 2008, Hällsten 2013). Different countries all have potentially very different labour market conditions, especially across different industrial sectors. A 'oversupply' of graduates in STEM industries in one subject may lead to credential inflation amongst STEM graduates. On the other hand there could be a shortage of these graduates in another country leading to less stratification by course grade or HEI attended for STEM graduates.

This raises the questions as to how competition affects labour market stratification. This has topic has implications for more general debates about HE expansion. Much of the concern over the expansion of higher education has been centred around the idea that an oversupply of graduates would increase the importance of factors like socioeconomic background in determining labour market outcomes (Brown and Hesketh 2004; Tomlinson 2008; Moreau and Leathwood 2006; Strathdee 2009). Furthermore the literature on variations in stratification by HEI and degree classification (or overall course performance in other countries) in different fields of study is underdeveloped, especially with respects to the UK. The rest of this thesis aims to test for the existence of these variations by field of study, and to examine the various explanations for the existence of any variations using UK data.

This chapter sets out to look at the various theories explaining stratification between graduates in the labour market. I have also introduced and presented literature that argues that this relationship could vary by fields for study for a number of reasons. Upon a review of the literature, the evidence base for any such variation is lacking and is primarily based on data from other countries. In following chapters, I set out to examine and test the theories outlined in this chapter using interview data collected from UK graduates across different fields of study, and two cohorts of a UK graduate destinations survey. The next chapter discusses the data used in this thesis and sets out some of methods used in the following chapters.

Chapter 4

Data collection and methods

This chapter describes the two main sources of information used in this thesis: an exploratory qualitative study using interviews with recent graduates, and the Destination of Leavers from Higher Education (DLHE) survey. The latter is a survey collected by HEIs and administered by the Higher Education Statistics Agency (HESA). I will also briefly explain some methodological issues and statistical techniques that are used in subsequent analyses. Any interested readers—who may want to check the fine details or replicate the analysis—can find in-depth explanations and formal proofs in the appendix chapters.

4.1 Interviews with recent graduates

In chapter 5 I make use of repeated interviews with 21 graduates from three different HEIs in Wales to discuss graduates' experiences after leaving higher education. All the respondents had left higher education with bachelor's degrees. Fourteen respondents out of the 21 had received their degrees from the same institution. The respondents had usually graduated one or two year prior to data collection; the least recent graduate received their undergraduate degree four years prior to their interviews. The question used in the interviews cover events in a similar time period after graduation, six months to three and a half years, to the DLHE survey data mentioned later in this chapter. Most respondent were interviewed 2-3 times over a period of about a year although two had dropped out after one interview. In total 44 different interviews were collected; on average each interview lasted an hour long. The shortest interview lasted 20 minutes and the longest lasted almost 2 hours. Almost all of the interviews took place in 2012 and 2013.

Ethical consent was sought from the Cardiff University board of ethics to conduct the interview research. Each participant was given an information sheet detailing what the research was about and what was expected of them. Participants gave either written or verbal consent prior to the interviews. Consent was sought for each wave of interviews and participants were given the opportunity to drop out of the study at any time. Each participant was given a pseudonym, and their interview recording and contact details were stored in encrypted hard disks.

The respondents were recruited with the help of their universities and their careers services, as well as through snowball sampling. Alumni newsletters and circular emails were sent on my behalf and four respondents were recruited from an earlier pilot study whilst in their final year of study (Zhang 2011). Ultimately the method of sampling was not random or purposeful as I lacked direct access to a sampling frame of potential participants and information about their characteristics. Instead the sampling strategy was mostly opportunistic which nonetheless still makes it sufficient as means of exploring the research area in preparation for other methods. The interview structure and questions used were created with reference to previous studies done on graduates' careers and experiences. In particular Smetherham (2005) and O'Reagan's (2010) research were useful resources for developing the questions and interview structure. The second wave of interviews began in May 2013 and took place around roughly 6-9 months after the first wave.

The interview design changed from being semi-structured, for the first wave, to unstructured interviews in the second wave. The unstructured interviews used a design based on the Biographic Narrative Interpretative Method (BNIM) interview method (Fischer-Rosenthal and Rosenthal 2000, Wengraf 2001). The BNIM method is designed to elicit narratives from individuals and, in contrast to semi-structured interviews, involves less verbal intervention from the interviewer. Instead interviewees are positioned as storytellerd narrating events and thoughts from their own biographies rather than being a participant in a conversation. Biographical narratives have a distinctive structures with a beginning and end, and as sense of causal connection between events. The advantage of biographical narratives is that they convey conscious and unconscious assumption of an individual. To this end the interviews were structured in two stages. In the first interview stage individuals were asked only a single question aimed at inducing a narrative:

> *'I would like you to tell me the story of what has happened since we last met, including all of the events and experiences which were important to you. Start wherever you like. Please take all the time you need, we have plenty of time. I'll listen first and I won't interrupt. I'll just take some notes for afterwards.'*

Non-verbal cues and encouraging remarks were made if participants felt hesitant to start speaking (see Appendix B). However it was important not to provide direction as to how participants should structure their stories or to interrupt their narratives once they had started. This includes not stopping participants to ask about unfamiliar terms or to pose follow-up questions. Instead individuals were free to talk about whatever topics that were relevant to their narratives and during the first stage was used to write down notes about particular phrases or events that would be used to generate further narratives in the second stage. Typically the graduates would speak for around half an hour or more in this first stage.

In the second stage, I would repeat back interesting parts of the narrative that individuals spoke about in the first stage. The parts would be repeated back in the order that they were first mentioned in the original narrative. Once again the goal here is to get individuals to elicit more narratives and stories—there is no effort at this stage to try to get the participant to clarify unfamiliar terms. Instead meaning and thought processes can be inferred from the way the content or structure of the stories that participants tell. Once there are no further narratives to elicit then I would ask participants to clarify any unfamiliar terms, elaborate on key events or to ask them unanswered questions about what has happened to them. However, at this stage there is usually little need for further clarification as participants would have already answered these points themselves much earlier in the interview.

The practical decision to change from semi-structured to unstructured interviews was motivated by two things. First it was potentially off-putting to use unstructured interviews in the first wave as much of the information sought could be found be asking structured questions—such as participants' previous job history and how did they found their current jobs. The open and conversational nature of the interviews also made it possible to explore and investigate other topics that the participants may have wanted to bring up (Warren 2002).

Unstructured interviews are aimed at eliciting long narratives and encouraging free-flow introspection: this type of interview requires a very specific performance on the part of the interviewer to pull off. Unstructured interviews involves active listening and encouraging participants to speak without directing the topic by using cues, such as leaving long silences to give the other party time to respond, which are rare—and very awkward—to have in normal conversations (Wengraf 2001). The interview experience may therefore seem a bit jilting to respondents and discourage individuals from staying in the study. In short, it was simply more suitable and less time consuming to use semi-structured interviews for the first wave of interviews.

Second I felt that participants did not elaborate much about their own personal circumstances outside of their careers in their first interviews. Much of this could be due to the importance of careers in their lives and future plans, as evidenced by previous studies (e.g. Tomlinson 2005). However this could be a methodological artefact created by a combination of the style of interviewing, participants' expectations about the research, and the type of questions asked. In order to explore other issues further and to allow any relevant pieces of information to emerge, a more unstructured interviewing strategy was used for the second wave. Given that a rapport had already been established with participants and that detailed information about each graduate's career history had already been collected, there was little to lose by adopting a new interviewing strategy. A new interviewing technique can also overcomes the risk of interviewee fatigue in longitudinal research—where respondents become tired of being asked the same question at each wave of interviews—and can offer a new way to elicit more data (Farrell 2006).

The set of repeated interviews with respondents were used to order to build cases studies which were then used to explore graduates' experiences and circumstances over time. The aims are similar to other longitudinal designs which have become increasingly popular in research for the public and third sectors as a means of evaluating interventions over a longer time period than conventional qualitative research (e.g. Holland, Thomson and Henderson 2006; Farrall 2006; Molloy, Woodfield and Bacon 2002). Many researchers choose to study individual cases longitudinally across a period of time that is full of transitions and developments, such as the transition from education to the labour market, to explore changes and continuities (Hodkinson, Sparkes and Hodkinson 1996).

By taking data across a longer time period, qualitative longitudinal research is thought to be 'particularly useful if one is studying a process which has a notion of a "career" of some sort or which involves a developmental process' (p. 2, Farrall 2006). It is this aspect of qualitative longitudinal research that makes it so pertinent for the investigation of individuals' trajectories after graduation. It also allows researchers to capture people's thoughts in the present rather than ask about them in retrospect in order to avoid participants imbuing them with a rationality that they did not have at the time (Farrall 2006).

4.1.1 Qualitative data analysis

Qualitative researchers commonly state to their ontological stance when presenting their work. A researcher's stance invariably impacts upon the way they analyse their research material. At the fundamental level, these ontological stances relate to issues around how language works, and the relationship between language and thought.

A simple realist account of language is that speech (and written language) is simply a reflection of events in the real world or a person's thoughts. Assuming this is the case it would be relatively straightforward to gain insights into people's thoughts and actions—we simply have to just ask people and take their accounts at face value. This view of language is not widely held for a number of reasons, instead many researchers subscribe to an anti-realist account of language. All these accounts question whether information about reality can somehow ever be communicated with any certainty.

Some researchers draw upon Wittgenstein's private language argument as a foundation (see Billig 2006); any language must be inherently learnable otherwise it would fail to continue to exist. As such, words must be related to physical external objects that all speakers of a language can objectively refer to. Words cannot refer to things like abstract concepts or inner mental states because, whilst these things may exist, it would be impossible for two speakers agree upon what is spoken about. Instead when we speak of things like mental states, for example, we are really referring to external behaviours or people's outward expressions. In principle therefore, it would be impossible to understand one's inner mental states through qualitative research. Furthermore, following the work of philosophers like Searle and Austin (Searle 1969, see Potter et al. 1990), researchers are also sensitive to the fact that words do not merely describe some facet of reality but that they have some performative element to them. Words are used to greet, apologise, demand, comply, ask, question, affirm, defend and so forth. When a student arrives late to a lesson and a teacher utters 'you're late': we do not take this utterance as a statement of fact—it is a demand for apology or explanation. In this example language is not used as a simple descriptor of reality at all.

Other researchers may be opposed the realist account of language due to the influence of post-structuralism. Post-structuralists generally do not hold the view that we can sufficiently define the meaning of utterances and people's actions. Any conditions or context can always be copied for different ends—two actors can exchange rings and vows in a church but no one would consider that to be a legitimate act of marriage (Derrida 1988). Since we cannot guarantee the meaning of any human act, the reliability of language as means of information gathering can be questioned.

The summary of anti-realist accounts given here is by no means exhaustive: some researcher rely on arguments from psychology (Vygotsky 1986) or sociology to make the case that a) language does more than just describe reality and b) that there is always some uncertainty or unreliability involved when interpreting qualitative data. There is no argument that can guarantee that we can interpret actual events, meanings or infer people's thoughts from qualitative data with certainty—debates about the matter often generate far more heat than light (see Edwards, Ashmore and Potter 1995; Hollway and Jefferson 2005a, 2005b; Wetherell 2005). However, despite these arguments, most researchers aim to prove plausible (yet fallible) accounts of these things through the use of various methods in their research. This includes paying attention to alternative interpretations of qualitative data, triangulating the data with other sources, being aware of their own positioning (and possible interpretative bias), looking what actions are being achieved by talk and so on (Silverman 2014, see Hesketh and Brown 2006 for an example). My own approach is no different; despite the challenges it is useful to understand graduates thought processes and their account of events after they finish their studies. To achieve plausibility in the analysis of the interview material, I took a number of steps.

First the interviews were then transcribed and managed with the help of the Atlas.ti computer package. I then read and re-read the interviews whilst coding sections of talk along the way. The goal of coding to generate possible interpretation of what is being achieved and what is being expressed in the interviews. These possible interpretations are related to the different ways that we can interpret talk and language that I mentioned earlier. For example, this involves asking questions such as what events are being described; what does the respondent's narrative tell us about their thought process or perceptions; what is being achieved in talk—are they describing particular events in order to justify an account or moral stance. These interpretations are not mutually exclusive and each piece of talk may be coded with several possible interpretations.

Then I revisited the coded interview material, and tried to find recurring idea or themes that appeared across the interview material. This may be recurring perceptions of employability, attitudes towards the labour market, similar pathways to work after graduation and so forth. In addition, I also used the longitudinal nature of the interview to explore whether graduates' perceptions and careers developed in particular ways over time. The process of creating themes is to aggregate and condense the large amount of qualitative material available, and involves constantly reworking particular themes. In particular, this involves constant comparison between codes in a theme to judge whether all the ideas being expressed are actually similar, and between different themes to judge whether there exists substantial differences between them.

Since a large goal of the qualitative data is exploratory and designed to supplement analysis of the DLHE survey, there is little in the way of generalisation. I cannot guarantee that any experiences or opinions held by graduates in this sample exists in the same proportion as in the general graduate population. Small sample sizes are an obstacle to generalisability in general—although some argue that generalisability can be achieved with small qualitative studies (see Mason 2010 for a short review). However, the small sample size is not necessarily so much of an issue if one is concerned about collecting as wide a range of themes in order to present them. This may be useful if one's research question was 'what are the range of opinions that graduates have on employability?' or 'how many different types of ways do graduates find work?'. In these examples the researcher is interested in creating an exhaustive (or near exhaustive) description of a phenomena. This is similar to the idea of saturation in qualitative research (and in particular grounded theory)—where researcher collect data until no new cases or phenomena appear.

Usually the exact number of cases that one should collect for saturation is never stated; this makes it difficult to judge the effectiveness of a study. However, the problem of achieving saturation is analogous to the classic problem of picking out coloured balls from an urn (with replacement). Say we wished to collect information about graduates' perceptions of employability and, for the sake of argument, that these perceptions fit several broad themes. Assuming that theme A is prevalent 10% of the population, what is the probability that in a random sample of X individuals we will have at least one case of theme A? The probability is given by $1\text{-}0.9^{X}$. We can see that even in small sample we have a reasonable chance of finding at least one expression of theme A. For instance, with 21 individuals (as in this study), the chance of finding at least one occurrence is 89.1%. In short, it is still possible to use small sample sizes to study the range of phenomenon present in a social system—assuming random sampling[1]. Whilst I did not employ random sampling I did draw upon a range of sampling sources and different ways of recruitment which may have served to diverse rather than narrow the range of participants that I finally collected.

[1] In this example I talk about the probability of finding a relatively rare example of a theme given a particular sample size. This is related, but not equal, to the probability that we would be able to find at least one example of every theme given a particular sample size. The latter is a more accurate statement of the problem but is rather cumbersome to calculate (and to express as an example).

Since the sample was so small, it is tempting to fit patterns to the data that simply do not exist in the actual population of graduates. Therefore any findings from the interview data is only presented as being suggestive—requiring support from other sources—or used as illustrative examples for arguments which are also backed by other sources. As mentioned before, the analysis is exploratory and mainly used as grounds for further investigation.

4.1.2 Why conduct an exploratory qualitative study?

There were three main reasons for doing an exploratory qualitative study. First I wanted to find out what graduates were doing after leaving higher education. In particular I wanted to hear the stories respondents told about how they got to where they were and the choices they made along the way. Exploratory qualitative research can offer the researcher an opportunity to refine their research questions and get a *feel* for the phenomena under the study. In addition, the qualitative data allows me to explore another aspect of the research topic: whether graduates' perceptions of employability and stratification varies across fields of study.

There was also a more pragmatic reason for doing exploratory research. Information from the Destination of Leavers from Higher Education survey is not publically available and HESA does not usually give out the complete survey to researchers. The process of requesting data from HESA requires one to specify the information required and there is a cost incurred for each dataset request. For a small research project, such as this one, the cost of the survey data alone might take up a substantial amount of the research budget. In short, I couldn't afford to make any mistakes in ordering the data—such as neglecting to order any information that would be crucial to the analysis later on. This also meant that a rough analysis plan for the survey data had to be decided upon before any data could be obtained. The qualitative study, along with previous literature, helped guide the analysis plan and the DLHE data request.

Finally I use information from the case studies—–as well as other sources—–to defend the way that some of the statistical analyses have been conducted. It is not unusual for many quantitative pieces of research to make key assumptions that are backed up by recourse to theory, qualitative data or other sources of information (Acemoglu, Johnson and Robinson 2000; Angrist and Krueger 1991). In particular, the method I use to adjust for sample selection bias relies on the assumption that where graduates were domiciled *prior to* HE has an effect on their chances of being employed *after* graduation (see appendix A). The assumption is grounded by appeals to intuition, other studies, and information gained from the qualitative interviews.

To further clarify this final point: researchers in the social sciences commonly make use of non-experiment data to answer their research questions. Often when these research questions are about causal effects, such as the effect of degree classification on wages, researchers exploit natural experiments or other quirks to estimate the effects of interest. For example in the last chapter, I described how Feng and Graetz (2015) exploited a rule in how degree classifications are awarded to estimate the effects of degree classification on graduates' wages. Angrist and Krueger (1991) exploited the relationship between month of birth and compulsory school entry laws to estimate the effects of years of schooling on people's earning. Acemoglu, Johnson and Robinson (2001) exploited the relationship between pre-20$^{\text{th}}$ century European settler mortality rates and early institutions in colonial nations to estimate the effects of modern day institutions on GDP per capita in different countries.

All the examples given above have analysis strategies that rely on some key assumption. For

Table 4.1: Qualitative study partcipants' background information

Name	Gender	Education	Latest Activity	Rough SOC(HE) 2010 category
John	Male	Civil Engineering (BEng)	Graduate engineer outside the UK	Expert
Monica	Female	Maths and Philosophy (BA)	Employed in HR	Non-graduate
		Human Resources (MSc)		
Danny	Male	Music (BA)	Freelance conductor	Expert/ Non-graduate
		Musicology (MA)	Other non-graduate part-time work	
Lucy	Female	History (BA)	Studying for a Social Work (MA)	NA
Helen	Female	Geography and Planning (BSc)	Employed as a Planner	Expert
		Town and Country Planning (MA)		
Lana	Female	English Literature (BA)	Hostel Manager	Orchestrator
Amanda	Female	Psychology (BSc)	Employed as a teaching assistant	Non-graduate
Carly	Female	Social Science (BSc)	Studying for a Psychiartry (MSc)	NA
Poppy	Female	Civil and Environmental Engineering (MEng)	Scheme project manager	Expert
Gemma	Female	Diagnostic Radiography and Imagining (BSc)	NHS radiographer	Expert
Jake	Male	Business Management (BA)	Sales and marketting manager	Communicator
Owen	Male	Physiology and Psychology (BSc)	Continuous improvement manager	Orchestrator
Tina	Female	Biology (BSc) Optometry (BSc)	Optometrist	Expert
Rachael	Female	Psychology (BSc)	Assistant psychologist	Expert
Diane	Female	Criminology (BSc)	Studing Criminology and Criminal Justice (MA)	NA
Sally	Female	Law (LLB)	Paralegal	Non-graduate
Andy	Male	Fine Art (BA)	Freelance artist	Expert/ Non-graduate
			Other non-graduate part-time work	
Domnic	Male	Graphic Communications (BA)	Graphic designer	Communicator
Steve	Male	Business Management (BA)	Customer service team manager	Non-graduate
Rhiannion	Female	Graphic Communications (BA)	Graphic designer	Communicator
Liz	Female	Mechanical Engineer (MEng)	Graduate engineer	Expert

instance, Angrist and Krueger (1991) assume that children born in December will received almost one extra year of schooling compared to those born in January (p. 980). It is also assumed that children's month of birth are otherwise uncorrelated with inherent ability and family background. These assumptions have to be justified; if they are simply not plausible then we would have no reason at all to believe the rest of the analysis. More often or not these assumptions are justified through appeals to intuition (p. 12, Chevalier 2012); anecdotes (p.7, Feng and Graetz 2015), historical documents (p. 1373-1377, Acemoglu, Johnson and Robinson 2001) and so forth. Ultimately these assumption have to be persuasive and the role of other sources of data—including qualitative data—can be very important in this regard.

4.2 The Destination of Leavers from Higher Education survey

The Destination of Leavers from Higher Education (DLHE) survey is a graduate survey that is sent out to all those who have left higher education with a qualification from a UK university in a particular academic year. The survey does not cover graduates from further education colleges—unless their courses were franchised out by a university—or graduates from most private HE providers. Most graduates receive the survey roughly 6 months after they graduate and the data is collected either by universities themselves or outsourced to private agencies on their behalf.

For this project, I obtained access to DLHE survey data for two graduate cohorts; one graduating in the academic year 2006/07 and the other graduating in 2008/09. I focus on individuals who have left HE with bachelors' degree in this thesis. For the 2006/07 cohort DLHE responses pertain to their activities on 16th April 2007 (if they graduated before 1st January 2006) or 14th January 2008 (if they graduated between 1st January-31st July 2007). Similarly the reporting periods for the 2008/07 cohort are 20th April 2009 (if they graduated before 1st January 2009) or 11th January 2010 (if they graduated between 1st January-31st July 2009). The survey is collected as a part of HESA's goal to gather accurate official statistics about leavers of HE for its statutory customers, of whom include the various devolved HE funding agencies in the UK. Given the importance of the survey data, HESA sets target response rates for universities. For both years, the target response rate was 80 percent for full-time UK domiciled leavers and 70 percent for their part-time equivalents.

Table 4.2: DLHE response rates for all UK domiciled graduates

Population	Valid returned responses	Total population	Response rate
Full time 06/07	258,845	328,250	78.9%
Part time 06/07	65,665	92,340	71.1%
Total 06/07	324,510	420,590	77.2%
Full time 08/09	275,910	339,100	81.4%
Part time 08/09	71,635	95,835	74.7%
Total 08/09	347,545	434,935	79.9%

Source: HESA 2008, 2010. Frequencies rounded to nearest 5

Responses were initially collected by a postal or online survey. Subsequent follow-ups for non-responders used telephone interviews and other types of contact to boost response rates. As results of efforts to reach targets, the response rates to the DLHE are particularly high for a survey of this type with 77.2 percent for all UK domiciled leavers responding to the survey in 2006/07 (79.9% for 2008/09) (table 4.2). In later chapters, I assume that responders to the DLHE are roughly representative of the overall population of leavers from HE. Descriptive statistics from the DLHE are also commonly used without any weighting for non-response in official HESA publications. The implications of any sample selection bias and missing data for statistical analyses are discussed later.

A follow-up survey, the Longitudinal Destination of Leavers from Higher Education, is conducted every other academic year. The Longitudinal DLHE aims to sample a subset of respondents to the original DLHE, and collects data about graduates roughly three and a half years after they have received their qualifications. The survey is collected by an independent research company, IFF research, on behalf of HESA. Contact details were passed to IFF research from universities themselves.

The sampling strategy used for the Longitudinal DLHE is more complicated compared to the initial DLHE. The Longitudinal DLHE aims to oversample certain populations, such as ethnic minorities and graduates from non-English universities. To do this a sample was constructed (Sample A) that deliberately oversamples individuals with these characteristics. The individuals in Sample A were contacted by email, telephone and post (as well as SMS text messages for the 08/09 cohort). Those who were not in Sample A, but still responded to the original DLHE, were contacted through their email addresses or SMS messages (Sample B). It is clear to see the data collection strategy for respondents in sample A is more aggressive compared to sample B. This is reflected in the response rates; 42.1 percent for sample A compared to 7.7 percent for sample B for the 06/07 cohort (43.9% compared to 11.1% for 08/09). Overall response rates are also much lower compared to the initial DLHE survey (table 4.3, see IFF 2011, 2013). This could be due to a number of reasons: outdated contact information, respondents being less inclined to respond to a surveyed conducted by a private company (as opposed to their alma mater in the DLHE), and so forth.

As a result of the sampling strategy and non-response bias, descriptive statistics from the Longitudinal DLHE are usually weighted using a system devised by IFF themselves. The sampling and data collection strategy of the Longitudinal DLHE is worth noting as I will exploit it to explore the impact of any sample selection bias due to attrition in later statistical analyses (see later in this chapter and the appendix). Descriptive statistics about the DLHE and Longitudinal DLHE samples used to conduct all the analyses in this thesis are contained in tables D.2 and D.3. The data used was stored and encrypted in accordance with HESA's regulations on data protection.

Table 4.3: Longitudinal DLHE response rates for all Bachelor's degree holders

Sample	Eligible sample	Contactable	Total response	Response rate
Sample A 06/07	41,740	40,293	17,576	42.1%
Sample B 06/07	173,280	104,009	13,361	7.7%
Total 06/07	215,020	144,302	30,937	14.4%
Sample A 08/09	51,298	47,027	22,498	43.9%
Sample B 08/09	175,881	143,538	19,609	11.1%
Total 08/09	227,179	190,565	42,107	18.5%

Source: IFF technical report 2011, 2013.

The DLHE survey can be linked to administrative information held by UCAS and the HEIs themselves. This is an extremely useful resource: administrative data about a graduates' educational achievements prior to and after HE is generally of good quality with little missing information. Information about parental social class is also provided by UCAS but this measure was self-reported by graduates themselves prior to their studies. As others have noted (Wakefield 2009, Feng and Graetz 2013), this information about socioeconomic background is often missing, particularly in the case of older or non-traditional students who entered HE from employment. Furthermore, for students 21 and over at the beginning of their course the DLHE survey records *their* socioeconomic status, and not that of their parents or main caretaker. Due to these—and other—issues, all the analyses in this thesis only looks at students who were under 21 at the beginning of their studies.

Fields of study are categorised into 12 broad groups according to their Joint Academic Coding System (JACS) codes—a system for classifying subjects used by HESA themselves. There groups were Biological science; Business; Creative arts; Education; Engineering and Computer science; Humanities and languages; Law; Medicine; Other STEM (including mathematics and the physical sciences); Social Studies; Subjects allied to medicine; and a grouping of other subjects could not be put into the categories. This grouping of subject is comparable to groupings used in other studies (e.g. Hällsten 2013; Hansen 1996, 2001; van de Werhorst 2002; Hansen and Mastekaasa 2006). I only look at results for ten fields of study; graduates with degrees in medicine, and other hard to categorise subjects (e.g. agriculture) are dropped from any analyses. The analysis looks at graduates who have at least two thirds of the taught component of their degree scheme in one broad field of study group. This drops a very small minority of respondents from subsequent analyses who did joint qualifications in a range of disparate subjects.

Specifics details of about the analysis of the DLHE and Longitudinal DLHE are given in the findings chapters. However some general methodological issues are common to all the analyses in these chapters and require some discussion here. This includes the measure of skills utilisation used in the analysis; why the partial correlation coefficient is used to compare the relationship between characteristics and skills use across different fields of study; how I account for multiple comparisons of results across fields of study; missing data; and how sample selection bias was dealt with. A general description about each issue is given here and interested readers can find more details in the appendix. All analyses and simulations were done in R version 3.2.0 (R Core Team 2015).

4.2.1 Measuring skills utilisation using the SOC(HE)2010

Graduates' occupations are recorded in both the DLHE and Longitudinal DLHE in the form of Standard Occupational Classification (SOC) codes. Many academics and policy makes are interested in graduate underemployment (or overeducation) and this commonly captured by the proportion of graduates working in roles that do not make use of their skills (Elias and Purcell 2004). One measure of underemployment is the SOC(HE)2000 and SOC(HE)2010. Both SOC(HE) are recoded versions of the SOC codes used by the ONS.

The SOC(HE)2000 reclassifies the SOC2000 into 4 different groups of 'graduate' occupations (Traditional, Modern, New and Niche) plus an additional non-graduate group. The classification was based on two sources; nine quarter of the Labour Force Survey (LFS, Spring 2001 to Spring 2003); and a special file from the ONS containing job titles, job descriptions, and the qualifications required in an occupation compiled from more than 65,000 employed individuals from the 1996/7 LFS (Elias and Purcell 2004). The latter included material that was also used to create the initial SOC2000 and SOC90 codes (Elias and Purcell 2013). The SOC(HE)2000 aims to sort occupations into graduate and non-graduate job based on whether having a bachelor's degree was a *requirement* of a job.

The classification method itself involved a mix of looking at the proportion of graduates within an occupation and looking at the detailed file of job descriptions to decide whether a degree was typically required. Job descriptions were used to avoid classifying occupation as 'graduate' jobs purely based on the proportion of graduates already working in them. This is because in some occupations having a degree may not be a requirement but, perhaps due to oversupply, graduates have crowded out individuals with lower educational qualifications. Validation of the SOC(HE)2000 using self-reported information given by graduates in the DLHE survey shows that the SOC(HE)2000 classification of graduate jobs largely corroborates with graduates' own self-assessments about their jobs (HEFCE 2011).

The SOC(HE)2000 allows academic researchers and statistical agencies to determine the extent to which graduates were being employed in jobs that required a HE qualification. Nonetheless, the SOC(HE)2000 classification itself attracted criticisms because its fundamental aim was to capture the minimum qualifications required by employers, not whether the skills and knowledge acquired as part of a degree was actually being used in a job. Employers could respond to an increased supply of graduates in the labour market by increasing the minimum level of qualification required for a role (James et al 2011). In the worst case scenario a degree can be used as a signal for other characteristics or personal attributes by employers who then subsequently makes no use of the knowledge or skills that graduates acquired from HE (Arrow 1973, Spence 1973). Conflating qualification required with knowledge used in a role distorts the extent to which the labour market actually makes use of graduates' skills.

The SOC(HE)2010 was created to update the measure and overcome criticisms initially levelled at the SOC(HE)2000 (Elias and Purcell 2013). The SOC(HE)2010 uses the SOC2010 as its basis and aims to capture the degree to which the skills and knowledge acquired from HE is actively *used* and *developed* in a role. Three separate domains of knowledge and skills were identified: specialist expertise (I will refer to this as just Expertise from now on), Orchestration skills and Communication skills. Expertise skills refer to specific expert knowledge and skills that graduates are expected to acquire in HE. Orchestration skills refer to leadership and organisational skills, and Communication skills refer to writing, verbal presentation and other personal (or soft) skills. The classification procedure used detailed descriptions of the typical tasks performed in each occupation by their SOC2010 code——using information contained in Volume 1 of the SOC2010 manual——to score the level of skill required in an occupation. The scores for each of the three domains goes from 1 to 9 (lowest to highest). If any of the three skills score was 6 or higher then occupations in that SOC code are deemed to be 'graduate' occupations (Elias and Purcell 2013). One point of note is that whilst Expertise skills are usually gained exclusively in HE, Orchestration and Communication skills could be acquired from experiences outside of HE. Furthermore SOC codes were divided into three groups of graduate occupations (Expert, Orchestration and Communicator)—plus one non-graduate group—based on the skill domain that is most crucial to a role.

Comparisons between the SOC(HE)2000 and SOC(HE)2010 using the same datasets shows large overlaps in the occupations regarded as 'graduate' by either measures. However, the SOC(HE)2010 tends to be more conservative and many occupations previously classified as 'Niche' graduate positions under the SOC(HE)2000 are regarded as 'non-graduate' positions in the SOC(HE)2010. This is perhaps not surprising as the two measures are defined using different, but related, criteria: one is based on the qualification required for a job and the other is based on the skills required for a job.

The fact that the SOC(HE)2010 scores occupations by the knowledge and skills used in a role, and not the qualification required, is useful. Furthermore, the SOC(HE) skills scores can be used to examine claims that the skill demands of particular occupations influences inequalities in certain sections of the labour market (see Jackson, Goldthorpe and Mills 2005; Jackson 2007; see chapter 9).

However, the occupations of employed graduates in the 2006/07 and 2008/09 DLHE are coded using the SOC2000. This presents an issue as the SOC2000 cannot be straightforwardly converted into the SOC2010 (and from the SOC2010 to the SOC(HE)2010). Nonetheless it would be useful to do this in order to make use of the SOC(HE)2010 skills measure in further analyses. Fortunately the main major discontinuities between the SOC2000 and SOC2010 lie in the re-categorisation of several major occupational groups (Elias and Birch 2010). For instance, nursing occupations were moved from major group 3 to 2. More fine grained classification of occupations remains mostly unchanged across both the SOC2000 and SOC2010. This makes it relatively easy to convert the SOC2000 into the SOC2010. To this end, I make use of a comparisons work done by the ONS using the SOC2000 and SOC2010 to add the SOC(HE)2010 skills measure to occupations coded using the SOC2000. The exact details of how the SOC2000 codes were converted into SOC2010 codes in order to produce the SOC(HE)2010 skills scores are explained in appendix A.

4.2.2 Using partial correlations coefficients to compare results from logit/probit models by fields of study

In many instances in this thesis, I am interested the relationship between certain factors, such as sex or degree classification, and the extent to which graduates are using their skills in the labour market. In particular I am interested in whether the relationship between certain characteristics and skills utilisation varies by field of study. Whether a graduate is underemployed or not is a binary outcome, and it can modelled using probit or logistic regression.

One may be tempted to first estimate separate probit or logistic regression models for each field of study and then compare the parameter estimates in these models to test for any variations in results by field of study. Similarly one may estimate one model using all the data, and include interaction terms between certain predictors and field of study to achieve the same goal (e.g. Roska 2005). However, it is problematic to compare parameter estimates from different logistic or probit regression models in the same way that we compare parameter estimates from linear regression models (see Allison 1999). The same issues arise when we are using ordered response models, and for interaction terms in logistic and probit regression model.

The key issue is that whether a graduate is underemployed or not is simply an imperfect indicator of the level of skills used in a job (or skill utilisation). Skills utilisation is a potentially continuous measure, and whether a graduate is underemployed or not is simply a binary outcome. Some graduates can be more underemployed than other. If a graduate is not underemployed we assume that he or she is in a job has skills requirements beyond a certain threshold but we do not know much else. This introduces some ambiguity in how to interpret the relationship between skills utilisation and characteristics, such as sex, using the results of a logistic or probit regression model.

Instead of comparing parameter estimates from these regression models I choose to compare the partial correlation coefficient between skills utilisation and different predictors across fields of study using a method proposed by Breen, Holm and Karlson (2013). The partial correlation coefficient can be derived from either a logistic or probit regression model of graduate underemployment. The partial correlation coefficient can be interpreted as the strength of association between one predictor and an outcome after accounting for other predictors. The values are interpreted in the same way as the standard Pearson's correlation coefficient: a value of 1 or -1 represents a perfect positive or negative relationship, and 0 represents no relationship at all. Say for the sake of example that I found a partial correlation coefficient of 0.3 between being male and skills use in my analysis. This would indicate that there is a moderate positive association between being male and levels of skills use, after accounting for other factors. A more in-depth explanation of the problem and how the partial correlation coefficient was derived is given in appendix A.

4.2.3 Adjusting for multiple comparisons of results by field of study

In many studies looking at stratification across fields of study, researchers commonly use interaction terms to test for the existence of any variations across fields (Hansen 2001, Roska 2005, Hällsten 2013). Another common strategy is to run separate regression models for each field of study and compare the parameter estimates for the same predictors across models (Hansen 1996). The two methods are related since estimating a separate model for each field of study is akin to estimating one model with all the data and including interaction terms between field of study and all the other predictors in the model (plus dummy variables for field of studies itself).

In the case of running separate regression models, researchers argue that there is evidence for variations across fields of study if parameter estimates for the same predictor seem to differ across at least two different fields of study. For instance, if earnings differences between graduates from different socioeconomic background was higher in economics graduates compared to social graduates (Hansen 2001). Whether any two parameter estimates are different from each other is usually determined by a simple t test or through visual inspection of standard errors (Hällsten 2013). In this case, the chance of finding at least one statistically significant result increases exponentially as the number of fields increases. When there are K fields of study, the researcher can end up making $\frac{K(K-1)}{2}$ pairwise comparisons. The chances of making a Type 1 error greatly increases and most researchers in the literature do not take this into account in their analyses.

When using interaction terms it is possible to test for the significance of any interactions by using a test of model fit (i.e. F ratio, AIC etc.) to compare two models: one with interaction terms and one without. However when we have two interaction terms in a model—for example one between sex and fields of study, and another between socioeconomic background and field of study—things become more complicated. We can test if both interaction terms jointly increase model fit. We can also see if one interaction term improves model fit when the other is also included in the model; in this case we can compare one model containing one interaction term with another model containing both interaction terms. However this test is dependent on the order in which we enter the interaction terms (i.e. does the first model feature interactions with sex or socioeconomic background?).

I adjust for multiple comparisons and test for variations in results by field of study using a chi-square test with critical values derived from Monte Carlo simulations. The overall aim is to test for any differences in the relationship between certain predictors and labour market outcomes by field of study whilst at the same time accounting for the fact that I am making multiple comparisons. Further explanations and an example of the method using Hansen's (2001) results are contained in the appendix A.

4.2.4 Missing data in the DLHE and Longitudinal DLHE survey

Cases with missing information on relevant items of interest are omitted in later analyses. This approach to missing data is known as case-wise deletion. For example some information could be missing because a respondent did not fill out a question on the survey. If this information is used in *any* analysis then any cases with missing information will be excluded from *all* of the analyses unless stated otherwise. This can cause a substantial loss of information and statistical power. However, this does not necessarily cause bias in the results.

I will comment here on the case where data is missing completely at random (MCAR) and missing at random (MAR) using Rubin's terminology (1976). Section 4.2.5 deals with the case when data is missing not at random (MNAR).

When the data is MCAR, case-wise deletion will not yield biased estimates but will be less efficient than other techniques for handling missing data. If the data is MAR, then case-wise deletion will not yield biased estimates for regression models *unless* the values of our outcome can predict missing-ness in our predictors (Allison 2001). Estimates from regression models are known to be unbiased in the case where one of our predictors can predict missing-ness in the other predictors.

So to clarify, if Y was our outcome and X_j were our predictors where we have J numbers of predictors (i.e. $j = 1 \dots J$). $Missing(Y)$ and $Missing(X_j)$ denotes that our values of Y and X_j are missing. The results of a regression model will be not biased if the probability if Y or X_j is missing is some function of the other predictors in the model:

$$\Pr\left(\text{Missing}\left(Y\right)\right) = f(X_j)$$
$$\Pr\left(\text{Missing}\left(X_{j=i}\right)\right) = f(X_{j\neq i})$$

In both cases the data is MAR but this type of missing-ness will not bias any regression model results—assuming that we only care about the parameter estimates. Results will be biased if either of the following is true:

$$\Pr\left(\text{Missing}\left(Y\right)\right) = f\left(Y, X_j\right)$$
$$\Pr\left(\text{Missing}\left(X_{j=i}\right)\right) = f\left(Y, X_{j\neq i}\right)$$

The first case is an example of MNAR (i.e. values of Y predicts missing-ness in Y even after accounting for X_j). In the second case data is MAR and regression results will be biased unless something is done to rectify the situation.

There are several popular methods for dealing with missing data. One is dummy adjustment whereby missing values are replaced with a dummy variable indicating missing-ness. Macmillian, Tyler and Vignoles' (2014) analysis of graduate destinations mentioned in chapter 3 uses this type of technique (p. 11). This method is easy to carry out and it is also flawed: it is known to produce biased parameter estimates even when the data is MCAR (Jones 1996).

Another technique is mean imputation and one example of its use if the Feng and Graetz (2015) study mentioned in chapter 3. Feng and Graetz (2015) replaced information about graduates' salaries from the DLHE survey with information from the UK Labour Force Survey. In their analysis, graduates' earnings were replaced by the mean hourly wages of other similar workers in the same occupation. This circumvents a lot of the issues around the DLHE survey and how earnings are reported (see section 4.2.5). However, there are two downsides to their analysis. First, it cannot capture any earnings differences between similar individuals within the same occupation. These differences can be quite substantial (see chapter 9). Second, mean imputations underestimates standard errors by eliminating all the variation in earnings for similar individuals in the same occupation (Allison 1999). The latter is a technical issue that can be partly resolved by randomly replacing graduates' earnings with the earnings of similar workers in the same occupation instead of the mean.

Another popular way of dealing with missing data is multiple imputation, which is generally a robust and efficient method when dealing data that is MAR (see Rubin 1996). One major issue is that multiple imputation is not robust when the data is MNAR—a very plausible concern for any analysis using the DLHE data.

It may be possible to account for both MAR and MNAR data in the analysis if one were willing to specify exactly what the missing data generating mechanism was. Unfortunately, this would involve manually programming the entire imputation routine for every analysis. This is likely to be a lengthy and error prone process which may be an interesting methodological exercise for a statistician *but* is well outside the ambitions of this thesis. Given that MAR data only produces biased estimates under certain circumstances, case-wise deletion seems to be the best general approach to dealing with missing data. This study assumes that results obtained by case-wise deletion are not biased (or at least not to a substantial degree) and deals with MNAR data using the approach outline in the next section.

4.2.5 Sample selection bias in the DLHE and Longitudinal DLHE

The problem of sample selection bias in regression models is well known but there is often little empirically that can be done about it. Typically we wish to know the answers to questions such as 'how large is the earnings difference between graduates who have a first and those who have an upper second class honours degree'. However, we only observe earnings for individuals who are employed. In this case, a simple regression of earnings on degree classification has the potential to produce biased results.

There are two situations in later chapters when sample selection bias can affect the results of the analyses. The first situation is caused by a quirk in how earnings are reported in the DLHE and longitudinal DLHE; only employed graduates report their earnings and earnings are measured in terms of annual salary. However, until recently, the DLHE survey did not record how many hours people worked. As such, earnings between full-time and part-time workers cannot be reliably compared. The second situation is caused by sample attrition. As mentioned earlier, overall response rates to the Longitudinal DLHE are low and it is possible that non-responders are systematically different to those who responded to the Longitudinal DLHE.

In order to explore the impact of sample selection bias on my results I make use of control functions—this approach is also more commonly known as the Heckman correction. James Heckman (1979) first proposed a solution to the problem of sample selection in linear regression models. Heckman's initial proposal has since been extended to discrete response models and there are non-parametric estimators as well (van de Ven and Van Praag 1981; Ahn and Powell 1993; Bourguignon, Fournier and Gurgand 2007).

I use the original Heckman two-step correction and a result from path analysis to explore the impact of sample selection bias. The entire technique is explained in appendix A. I use information about where graduates were domiciled before their studies to adjust for any sample selection bias that may occur as a result of only using earnings for full-time employed graduates in the analysis. To correct for attrition in the longitudinal DLHE I exploit IFF's sampling and data collection procedure. As mentioned before, all respondents to the initial DLHE were placed into one of two sample (A or B). Response rates in the longitudinal DLHE were far higher for individuals in Sample A compared to Sample B. However, after accounting for certain characteristics, DLHE respondents were placed into Sample A and Sample B randomly. This randomisation can be used to adjust for sample selection bias as a result of attrition.

4.3 Correlation not causation

In most of the chapters I look at whether there are difference or inequalities in labour market outcomes between graduates along the lines of sex, socioeconomic background and so forth. For example, this is done by comparing average earnings for male and female graduates who are otherwise similar with respects to their educational qualifications or other characteristics. As mentioned before, I refer to these systematic inequalities between graduates as examples of labour market stratification. Stratification refers to differences in outcomes and not causation. In the previous example, stratification by sex does not imply that if an individual were to—with great difficulty—change sexes then they would expect to earn more in the labour market. This is the distinction between what is meant by stratification and rates of return. The latter ought to refer the causal effects of getting a degree, going to a prestigious university, or such like. Whilst all other things being equal causation necessarily implies correlation, the reverse is not true. It is easy to conflate the two because many studies looking at rates return in the graduate labour market have used research designs that simply involved looking at differences in outcomes between similar individuals (e.g. Chevalier 2011; Chevalier and Conlon 2003; Ramsey 2008; O'leary and Sloane 2005; Rumberger and Thomas 1993; Walker and Zhu 2008, 2011; Blasko 2002 and so on). Whether such research designs are produce reliable estimates of causal effects is debateable (Holland 1986, Heckman 2005).

This thesis focuses exclusively on stratification and not on rates of return. The only causal effect of interest in this thesis is discussed in chapter 7 where I attempt to estimate the effect of increased competition on labour market stratification.

This chapter has outlined the two main data sources used in this thesis. It also discusses a variety of recurring methods and analytical techniques used in the analysis. The next chapter deals with the findings of the exploratory study with recent graduates. It looks at graduates perceptions of employability and their experiences after leaving higher education.

Chapter 5

Graduates' experiences after leaving higher education

This chapter discusses findings from an exploratory study looking at how graduates across different fields of study perceived employability, and how they found work. It also explores the stories that they presented about their experiences and their choices after leaving HE. The motivation behind such a study and its relationship to subsequent chapters is stated. Then I present selected findings and discuss the implications of these findings for any subsequent analyses of graduate destinations.

5.1 Purpose of the chapter

There were several motivations behind the current qualitative study. Many of these were elaborated upon in the previous chapter. In general, qualitative studies can serve as a basis and inspiration for further quantitative studies in a number of ways. In addition, the findings from this qualitative study are of interest in their own right.

The focus of chapters 6 to 8 is on stratification in the graduate labour market across fields of study. The statistical analysis using graduate destinations data does not tell us if graduates themselves have different *perceptions* of the labour market depending on their fields of study. These are two separate research questions but both can yield useful insights. For instance, graduates may underestimate or overestimate the relative importance of some factors, such as degree classification, compared to others in terms of their relationships with labour market outcomes. Furthermore it remains to be seen whether graduates' perceptions of the labour market varies by field of study. The qualitative study also gives me a chance to explore the graduate job search process, which has been given little attention in previous studies.

As mentioned previously, the employability of graduates can roughly refer to the ability of graduates to find, obtain and retain work. [1] This topic has received much interest from academics, policy makers and the general public in the past two decades (Moreau and Leathwood 2006, Hillage and Pollard 1998). There have been numerous studies looking at employability and, in particular,

[1] There are alternative critical definitions of graduate employability that differ from the one offer (Hinchliffe and Jolly 2011).

graduates' perceptions of employability (Purcell and Elias 2004; Brown and Hesketh 2004; Smetherham 2005, 2006; Tomlinson 2005, 2008; Wilton 2011; Bathmaker, Ingram and Waller 2013; Tymon 2013).

However much of the UK literature in relation to graduate employability, and employability in general, has paid scant attention to the job search process (see Keep and James 2010 for a recent review). Across the labour market, it is known that many workers have found their current jobs through informal means. By informal means I refer to personal contacts, direct applications to firms, or any such methods used by workers to gather information about job vacancies which may not be openly advertised and thus not knowable first hand to many potential applicants (Grannovetter 1974). In contrast, formal means refer to job adverts in newspaper or online, through job centres, and other such means which makes vacancies publically known.

Companies themselves may use informal means as a way to find applicants for vacancies. A UK survey of large employers (>1000 employees) shows that 30 percent of large employers used word of mouth and agencies to recruit candidates (p. 27, LSC 2008). Furthermore small and medium sized firms, who make up a significant proportion of graduate employers, may be more likely to use informal means as part their strategy to recruit as they have less money to spend on recruitment (Carroll et al 1999, Marsden and Gorman 2001). Employers may elect to take referrals from current employees, pick applicants from pools of previous CVs, or use intermediaries such as recruitment agencies. This is also not to mention the role of internal labour markets whereby employers seek to fill vacancies with current employees, as opposed to external candidates. In addition to having better access to information about vacancies internal candidates will have comparatively better information about a firm and may be trusted more by some employers (p. 24-26, LSC 2008). Looking at the graduate labour market, nearly a third of entrants into well paid graduate fast track scheme have previously worked in the firm or had done an internship with the company whilst at university (p. 13, HFR 2015).

The use of informal means to recruit on the part of employers has a concomitant impact on the careers of graduates. Franzen and Hangartner (2006) report that over 31 percent of workers in the UK found their current jobs using informal means. They found that the use of informal contacts amongst graduates was also associated with obtaining a better skills match in their current jobs but not with increased earnings. Greenberg and Fernandez (2016) examined all job offers received by two cohorts of MBA graduates in the US. They found that job offers that came via informal means had on average *lower* starting salaries however graduates were *more* likely to accept job offers that came via informal means. A large proportion of graduates accepted these offers due to a greater potential for growth in these jobs. Gaby and Purcell (2010) found that is some variation in the ways that UK graduates looked for work across fields of study. Informal means such as friends and family, or speculative applications to employers are used less by graduates who studied education or subject allied to medicine. On the other hand, graduates in these two subjects are far more likely to use specialist websites to find work. A short discussion about how graduates find work is also found in Purcell et al (2005).

Within the literature on graduates and employability, aside from the examples above, there is little mention as to how graduates find information about available work. There are several areas where further work can be done to elaborate our understanding of the job search process. First, while informal contacts are a common means that people use to find work, there is some ambiguity over *how* it helps people obtain work. For instance, do informal contacts improve outcomes through increasing one's access to information about vacancies or is it the case that informal contacts are important because these contacts help recommend candidate for certain roles (Fevre 1989). Furthermore, little is known about the relationship between job seekers and their contacts. Finally, do these processes differ for graduates depending on their fields of study. The last question is particularly relevant to the overall theme of this thesis. Lee's study of workers in the media industry suggests that these workers do make extensive use of informal contacts and recommendations as a way of finding work (Lee 2011). Employers across other industries may vary with respects to their recruitment practises (Keep and James 2010). The importance of informal means in some industries and sectors of the labour market may disproportionately disadvantage graduates with smaller or less power social networks in some fields of study and not others.

The general research questions explored in this chapter are as follows:

1) What are graduates' perceptions of employability and does this vary by field of study in the sample?

2) How do graduates search for—and obtain—work? Do experiences of the job search process vary by field of study?

5.2 Graduates' perceptions of employability

Questions were asked in order to explore what factors graduates perceived were important to obtaining employment and, in particular, in obtaining graduate jobs (Elias and Purcell 2013). In the first wave of interviews, the respondents were asked what qualities they thought employers were looking for, both generally and for specific jobs that they had applied for in the past. In addition they were asked to reflect on how they acquired their current jobs and any work in the past. Where applicable, graduates were asked about what recruitment strategies their current employers used and if they had any experiences in hiring individuals themselves.

The factors that graduates identified as being important for their employability are very similar to those found in a multitude of other studies (Hinchlliffe and Jolly 2011; Brown and Hesketh 2004; Purcell, Elias and Wilton 2004; Smetherham 2005; Tomlinson 2008; Tymon 2013).

Almost all graduates responded that employers were looking for previous work experience. This was, in turn, hard to acquire for some respondents who were younger and had no previous work history prior to university. In such cases, individuals would often attempt to augment a perceived lack of work experience with volunteering. Another factor seemed to be personal traits, such as 'reliability' or being a hard-worker. Such traits also include the ability of a potential candidate to 'fit' into a firm.

Around a quarter of graduates mentioned postgraduate qualifications, in particular a masters degree or a PhD, as another factor that would help improve their employability. It was this perception that led some graduates to pursue postgraduate studies after leaving their undergraduate degrees. In these cases, individuals felt that the influx of other candidates with postgraduate degrees had put them at a disadvantage when applying for some jobs, despite it not being a formal requirement. Degree classification, and in particular acquiring an upper second class honour degree, was mentioned as important and it was often an explicit requirement for particular roles.

Looking across fields of study, there seemed to be little difference in the things that graduates thought employers were looking for. For instance, work experience and personal traits were mentioned by all the graduates as being important. This could reflect the size of the sample and an inability to find consistent patterns within small groups of individuals. Nonetheless there are some slight differences in how graduates across different fields of study perceived the labour market.

It is worth noting that the majority of the graduates had received their undergraduate degree shortly after the onset of the 2008 recession. Graduates who studied subjects allied to medicine and engineering had more positive perceptions of the labour market—at least in hindsight—compared to other graduates. The graduates in other subjects, such as the humanities or social science, seemed to have a more pessimistic outlook on the labour market. In general these individuals also took longer to find work after finishing their undergraduate degrees. For instance, the experiences of Diane and Jake reflect common perceptions that respondents had about the graduate labour market.

> *'I don't know if it's just London or if this applies to the whole of the UK but it doesn't seem like there's much out there for graduates. If companies are looking for graduates then it doesn't seem like they're making it known. It's almost like it is too competitive, like there's loads of graduates but not enough jobs. So there's a serious imbalance there that needs to be addressed.'*
>
> [Diane, BSc Criminology, Doing postgraduates studies]

> *'Well I think it was all very much doom and gloom. I graduated in 2011 so the recession had hit 2009 properly and we were studying the recession basically because it had come at the perfect time. Particularly the third year, I was writing a load of essays on the recession and the impact it was having economically. So it was very doom and gloom and everyone was thinking 'Oh crikey' you know. [Other students] weren't that hopeful for their prospects you know.'*
>
> [Jake, BSc Business Management, Currently a sales and marketing manager]

On the other hand Gemma's account presents a counter-narrative and quite a different experience of the labour market:

> *'I was interested in taking part [in this study] because my story is really straightforward and I want a balanced perspective [laughs][. . .] 'cause there's a lot of graduate unemployment and all of that rubbish. I did a degree for a specific job and I managed to get a job doing that straight away [laughs] [. . .]I thought I was going to be unemployed for ages 'cause there's all this hype and this feeling that it was going to be difficult and because obviously there's cuts to the NHS. There's not much funding for new jobs so we all thought it was going to be terrible but we're all sorted now. I think pretty much everyone else on my course has got a job now.'*
>
> [Gemma, BSc Radiography, Radiographer]

Chapter 7 presents statistics that support the idea that graduates from different fields of study may have different experiences of the labour market. Graduate from first degrees in STEM, subjects allied to medicine and education subject areas are much more likely to be working in graduate jobs than those in other subjects (see table 7.1). Furthermore, for those with degrees in subjects allied to medicine, the recession did not seem to have as large an effect on graduate underemployment compared to graduates in other subjects.

Graduates in STEM subjects also expressed the opinion that a postgraduate qualification in the same field of study was a necessity for obtaining jobs or promotions in their field. This was either due to the large number of other applicants who had postgraduate degree qualifications or explicit formal requirements for advancing in their professions (i.e. the case of becoming a chartered engineer, Engineering Council 2014).

> *'They said there was a lot of masters and PhD students applying for the position. They're more likely to get it than I would which is why I thought maybe I should do a masters sooner rather than later and change my plans a little bit.'*
>
> [Carly, BSc Social Sciene, Commenting on feedback received for a research assistant role]

Graduates from other subject areas also talked about getting postgraduate qualification. In these cases, the reason for getting a postgraduate qualification was only loosely framed in terms of employability—if employability was mentioned as a factor at all.

> *'I did a masters and I always thought "Well I would be able to buy myself some time by continuing to study in exactly the same way as I was doing before" [...] I thought I would buy myself some time and stay in this university environment that I enjoy with the people around me that understand me—people I understand, and I don't actually have to go out into the world of work and start to make a career before I feel ready to do that. I didn't feel ready at that point to make some big decisions about my life.'*
>
> [Danny, BA Music MA Musicology, Freelance conductor].

Furthermore, across the interviews, the economic downturn was cited as an additional incentive for individuals to undertake postgraduate studies shortly after finishing their undergraduate degrees.

5.3 The job search process

In the interviews, graduates were asked about occasions when they tried to look for work in order to gauge the range of methods they used and their experiences of searching for jobs. In addition, for each period of employment, questions were also asked about how graduates first found out about their jobs and how they came to acquire that position. Several types of experiences came through; almost all had tried to use the internet to find work. Many found work through channels that they were not actively using. For the sake of presentation I'll separate the findings into two section detailing the method that graduates used to search for work and how they actually *found* work.

5.3.1 How graduates searched for work

The overwhelming majority of job searches conducted by respondents were done through the internet. There was little variation in its prominence across all 21 case studies. However there was some variety amongst respondents with regards to the type of web resources they used.

Specialist job websites for particular industries or sectors were used by graduates from specific disciplines. In the case of graduates in subjects allied to medicine, and to a lesser extent psychology, the NHSjobs website was almost exclusively used to find work. This may be due to recruitment policies within many NHS organisations requiring them publically advertise vacancies on NHSjobs (see Henry and Fleet 2011 for an example). As a result graduates from subject allied to medicine have very similar stories about their transition from work to employment. This is also reflected in statistics from the DLHE survey.

Table 5.1: Proportion of employed individuals who found their current jobs through informal means (6 months)

Field of study	Percentage
Medical and veterinary sciences	5.55%
Subjects allied to medicine	11.34%
Education	13.76%
Business	17.12%
STEM	18.34%
Social studies	18.95%
Law	20.33%
Biological sciences	20.70%
Humanities and languages	23.82%
Other subjects	25.87%
Creative arts	27.36%

Note: Informal means refers to speculative applications, and personal or professional contacts

Table 5.1 displays the proportion of employed graduates who found their current jobs through informal means 6 months after graduation. The figures combine respondents from both the 2006/07 and 2008/09 cohorts. Only around 11.3 percent of individuals who studied subjects allied to medicine had found their current roles through informal means; this proportion is almost double for other subject like the humanities and creative arts.

More general recruitment websites or online recruitment agencies were mentioned by graduates irrespective of their field of study; this type of method was used by graduates to find stop-gap or non-career related work as well as more traditional graduate roles. Websites for companies and institutions were also used by those who had a particular career in mind.

Other means were also used but were mentioned less often. Newspapers and specific professional publications—such as industry magazines—were mentioned by three graduates but it was sensed these respondents either used the online recruitment sections of these publications or used these sources infrequently. This is a significant change from past sociological studies of job searching, such Granovetter (1974) and Fevre (1984), as the internet seems to be have replaced much of the role that physical media played in formal job searches.

The Jobcenter, both the physical service and its accompanying website, was also mentioned by graduates but respondents were critical of the service. Perceptions were that the service is not well-catered for helping graduates to find the type of work that they desired. Graduates also expressed uneasiness about the actual experience of physically going to the Jobcentre to look for work.

> *'[. . .] They're friendly staff and you know in that sense its fine. They're lovely but they're not very helpful. I mean all anyone has to do is write two things they've done a week towards finding work and it could be something as simple as "I've updated my CV, I looked on the jobcentre website and there was nothing there". So for loads of people that's so easy and*

> *it's free money and they'll keep doing it and ride on in. In that respect I guess they're so used to handling people like that. They don't quite know how to handle the overqualified graduates who are getting nowhere because they don't know what advice to give. What can you do, you are overqualified and you're not getting anywhere you know.'*
>
> [Monica. BA Philosophy and Maths; MSc Human Resources. HR administrator]

Informal means, such as using word of mouth or speculative applications, were uncommon amongst the graduates interviewed—except in the case of graduates who did degrees related to the creative arts or design. All the graduates in these fields placed great importance on networking as part of the job search process. One reason may be the fact that these graduates are often engaged in freelance work, either exclusively or alongside their main jobs, and as such there is a lot of onus on graduates themselves to find new business. However, there are indications from graduates' experiences that this is how employers in these industries tend to recruit individuals as well. This could be as a result of the close knit nature of the industry or because employers find it hard to assess the skills of a job candidate by traditional means, such as by job interview or a CV. As such the opinions of trusted individuals, who can vouch for the applicant, may carry more weight.

> *'You know I can present to you a CV saying "I'm the best conductor in the world" and it doesn't say anything. If somebody is really rated as the best conductor in the world then you don't go looking for a CV. You just say "Can we afford them?" and, if you can, they will come in and conduct your orchestra. So at every step of the way in music it's about getting your name across and making sure that people know about you for the right reasons.'*
>
> [Danny, BMus Music, MA Musicology. Freelance conductor]

> *'I think it's quite easy to ignore someone that rings up or emails a CV or something because I did that with a design agency that I wanted to work for. I remember ringing them a few time and they said "Send us your CV. We'll keep it in mind if something comes up" and then I never heard from them again but I didn't push it and I didn't hassle them. I didn't turn up and send them examples of work and I feel like I should have done more. I was just kind of waiting for them to get back to me whereas now I've actually met a lot of people from that company and made friend with them [. . .] I said to one of them on the bus the other day "Oh you know if you need any freelancers, I'm around". I found out that he had told his boss that I was available for freelance work. So that's all kind of word of mouth and like indirect ways of work.'*
>
> [Rhiannon, BA Graphics Communications. Graphic designer]

Aside from those graduates in the creative arts or design, respondents did not seem to be attach a strong importance to the use of informal means. Graduates' efforts to use word of mouth mainly revolved around just letting friends and family know that they were looking for work and to 'keep their ears open'. This was usually done during what were described as everyday conversations, rather than through overt solicitations for help which were more uncommon. Three respondents said that they were uncomfortable in actively networking for career gains.

> *'I think some people are quite ruthless about and it shows and it doesn't really work [laughs]. With the art scene in [City] I think the best way to go about things is to get involved and*

make friends. I find some people can be quite blatant about it. They just want shows and they go around talking about themselves all the time and that doesn't work for me [laugh].'

[Andy. BA Fine Art. Freelance artist]

However, seemingly plain statements of fact indicating that one is looking for work could also be interpreted as solicitations for help regardless of the speaker's intentions. Consequent actions by respondents' personal and professional contacts seem to indicate that these statements may have been understood as subtle solicitations. A few graduates who previously did not make use of informal means in their initial job searches after graduation did gradually begin to stress the importance of these methods more in their later interviews.

There are two further things to note about the timing of job searches and the range of locations covered by graduates' job searches. Many graduates began their job searches, prior to graduation, around October or November, in their final year of study. In addition, recruitment for graduate fast-track schemes typically start one year prior to the start date of employment (Graduate Jobs 2015). For instance, for a scheme starting in September 2009, recruitment would have started one year prior. Typically, in their final year of study graduates stated that they had searched for work up to April, stopping around that time to concentrate on their final exams or assessments. This is similar to the findings of Gaby and Purcell (2010), who found that students usually started looking for work in the second half of their final year of study. By that point, for those graduates that had not secured worked before graduating, many had plans to move back into their parental homes to look for work. This was primarily due to lack of other plans and to save costs whilst looking for work. This pattern of graduate migration has also been supported by other studies (Tucker 2013; Sage, Evandrou and Falkingham 2012). It is interesting to note that for many returning back to their parental home was not ideal given their initial aspirations to leave home for higher education in order to leave and live independently. The implication of such migrations patterns for subsequent analyses was mentioned in chapter 4 and discussed further in the appendix.

5.3.2 How graduate found work

From the interviews with graduates, it is clear that the internet was an important part of their job search strategy. While it is hard to assess the exact amount of time and effort that each graduate spent using each method of job search, descriptions of the job search process by graduates seem to indicate that more effort is usually spent using formal methods compared to informal methods. However, when looking at job offers actually received, there is an almost even number of jobs offers that have come as a result of informal means and those that have come from formal means.

While there was much data on how jobs came to be acquired by *both* formal and informal means in the interview sample, I've restricted the current discussion to jobs found which were not stop gap or temporary work. These may be jobs that are entry level work to careers that graduates wanted, such as paralegal or assistant psychologists positions. Some of these jobs, such as hostel manager, may not be traditionally regarded as 'graduate' jobs and the degree to which they make use of skills developed as part of a degree course is debateable (see Chapter 4; Elias and Purcell 2013). These borderline cases are still included mainly for the sake of investigating how jobs are obtained. In addition, I will cover offers of work but these offers were not always accepted by respondents.

As previously mentioned, the use of word of mouth information was particular well regarded by those graduates with degrees related to the arts and design. Most of these graduates engaged in freelance activity either alongside their main jobs or as their main means of income. In order to generate business, these graduates often have a presence on job directories or their own website but mainly gained commissions through informal means. This may be through word of mouth referrals, or speculative enquiries to organisations or businesses. A key point for freelancers is raising one's profile and this includes a degree of networking with people in the industry at events. However networking as used in practise rarely referred to the activity of meeting people purely for career purposes, although those motives are acknowledged. Individuals who were 'professional contacts' that graduates met through networking at events were also likely to become personal friends or contacts.

> *'All the time you're finding people who interested or enthusiastic about music. They happen to go to concerts and you happen to see other people who are interested. Suddenly being seen in the right places or having the right conversation with right people just falls into place or slots into place. So it's not an exact art form, this kind of networking and [laugh] I hate it on the one hand but on the other hand you find things slot into place and become a lot easier when you do make friends with these people. It sounds very false in one sense and in another way you do make very good friends who've got some common values and common reasons for doing music'*
>
> [Danny, BMus Music, MA Musicology. Freelance conductor]

Outside of self-employed work, informal means were prominent in the events leading up to respondents acquiring their current jobs. For sake of simplicity I've sorted these accounts into cases where information about work has come from a personal or professional contact, academic contacts, speculative enquiries, from previous work placements or internships, and internal promotions. The latter two are not usually regarded as informal means of finding work however in many of those cases the jobs that were offered were not advertised—often not even to internal candidates—and the events leadings to a job offer relied heavily on the help of contacts. It is also worth noting that in reality there are overlaps between each type of case, not least because the event leadings up to a successful job offer may be long and involve many other individuals.

In the interview sample there was large amount of information about work from personal contacts ranging from family members, school friends, and friends from previous workplaces (or more commonly work placements). In the latter case, there is a blurry distinction between a professional and personal contact as many graduate often kept in touch on a personal level with people or mentors that they have met on work placements. Offers of information related to work were almost always unsolicited; it was usually the case that the contacts themselves had known beforehand that the graduates themselves might be looking for work. It is therefore no coincidence that contacts got in touch with graduates usually just before or shortly after graduation. As mentioned before, offers of help may not be explicitly sought by graduates but implicitly solicited by graduates in everyday conversations and contact with people. However there were cases where the contact has had little or no recent contact with graduate or had any idea that they were looking for work at all.

> *'Yes the company that I'm in now is owned by the father of someone I knew at college and he went off to university. I hadn't really contacted him and one day out of the blue he emailed me and said "My dad's company, they might have space for you. He's looking for*

business graduates." and I said "Well bloody hell give me his number!" and bit his hand off. This was back in the January before I graduated [...] [The dad] must have said to his son "Do you know any business graduates?" and he said "I don't know any graduates but I know one that's going to graduate soon" and that's when the dialogue started between us. '

[Jake. BSc Business Management. Currently a sales and marketing manager]

In the case of Jake, the reasons behind how the contact knew of the work and why they made contact with Jake may sound unusual but the events described in his story were not exceptional. Information about vacancies that graduates get passed on are usually as a result of a recent departure of an employee in a company and the contact will ask graduates to pass on their applications directly to the firm. However, unlike in Jake's case, contacts were usually employed (or were employed) in the same firm and as a result knew of a vacancy as soon as someone departed. In three cases this also meant that respondents were given information about job openings long before they were externally advertised—if they are advertised at all. In all case graduates still had to go through some sort of application and assessment process, usually a job interview. Often the competition for these vacancies consisted of other candidates who were also informed of the vacancy by informal means.

Academic tutors are sources of work information for graduates, although this is more uncommon. In the sample there are only a few instances of this and it seems to be dependent upon the graduate having a close relationship with their tutors. As in the account below, information offered to graduates come from tutors' links with industry.

'I think I understood a lot more about the importance of networking. I know it's awful but it does seem to really help to have some sort of personal connection with somebody. I was talking to my [academic] supervisor today and his friend is a director of a consultancy in London and he said "Well Helen if you wanted to work in London he was asking if I'd got any good students to recommend." But I think that it is quite important to have this kind of personal relationship.'

[Helen. BSc and MSc Planning. Planning assistant]

'I think when I graduated I had kept in touch with my tutor and I think she was the kind of tutor that had favourites. I was one of her favourites and she took me under her wing I guess. I emailed her several times asking her advice about various things and she knew I was in [City] and stuff. I think she knew my current boss and when she found out they were hiring someone she suggested that I apply.'

[Rhiannon. BA Graphic communications. Graphic designer]

Given that in both cases information about the vacancies were acquired through the academic tutor's professional contacts, we might speculate that the efficacy of tutors as a source of information may vary across subjects and universities depending on the links between academia and industry.

In many cases graduates have made speculative enquiries about vacancies directly to companies which are not externally advertised. In the interview sample there are broadly two types of cases where this happens, when the graduates speculatively applies but has heard about a possible opening from a contact and when the graduate directly applies with no information about a vacancy. Incidents where graduates have used the latter methods, quite obviously, yields fewer responses compared to the former as there is only a chance that an opening exists at the company. In the former case a potential vacancy is known about beforehand.

For those that had gotten their work as a result of speculative applications, based on a contact's information or not, the employers often did not have a vacancy at the time but contacted the graduate at a later date. This could be due to the contacts' imperfect information about that particular company—many contacts were not current employees of the company at the time. In some cases the events leading to a job offer are quite complicated. One graduate speculatively applied based on information from a contact (unsuccessfully) and was approached by the same company at a later date about a different vacancy.

From the interview sample there were graduates who received job information and offers from firms where they had previously done work placements or internships. In one case, a respondent had perceived that the firms have sought to fill their vacancies solely with graduates who had previously worked there before. In this case there was an understanding that employers regarded work placements as a kind of work trial for a role. In Poppy's example a job offer, without an application beforehand, was offered by a civil engineering consultancy before she had graduated.

> *P: I think I was sort of expecting it because they said while I was there on the work experience 'We would probably be taking somebody on' and two of the guys were going. I thought 'Oh they're definitely going to need to replace those two'. Actually by the time they rang me up and offered it to me.'*
>
> *M: So they do this once in a while do they—the smaller firm?*
>
> *P: Yeah I discussed it with them and they said it was basically a week long interview. They preferred it like that because one time they recruited a guy just through interview and after two weeks of him working in the office they thought 'God it was dull'. They didn't actually get on with him and being a small office it is quite important to all get along so I think they preferred recruiting people they'd already got to know .*
>
> [Poppy. MEng Civil and Environmental Engineering. Graduate engineer]

Finally, from tracking each participant longitudinally, it is possible to observe graduates' job changes both across different firms and internally within the same firm. The longitudinal design also makes it possible to track these changes in greater detail due to the minimisation of memory loss. Half of graduates had recently changed jobs or roles, or were in a situation where their current roles were coming to an end by the second interview. Graduate transitions in the second wave were usually upwards from a non-graduate or stop gap job (or entry level career job) to a role with more responsibility and higher salary. Five respondents moved upwards internally rather than through changing firms. Once again these proportions are not robust estimates that can be generalised to the entire graduate population but it is possible nonetheless to investigate the varieties of ways that these upwards shifts are negotiated.

In two cases this happened when an individual's employment contract ended. They were moved to a new role within the same organisation by their supervisors or managers. In the other cases, where promotions or a changes of role occurred, this was as a result of business expansion or through active negotiation. In three cases out of five, the roles changes occurred informally as a result of contact with management. There were no formal applications or assessment processes.

Owen's case is perhaps the most extreme example of this type of role change within an organisation. Initially after completing his psychology degree Owen had managed to obtain a routine plant worker role within his current company with some help from his father's professional contacts. Throughout the course of the project he has been promoted twice within his company: once prior to his first interview and once again prior to his second interview nine months later.

> *'What happened is I was part of the team that was looking after these machines. I mean to give you a background of sort of our business. It's a big company and our site is the biggest investment that [company] have ever made and so we have these brand new machines and they're brand new technology. We're learning a lot about it. So I was helping out with these things and a bloke came in to help us improve the process for about a month. He came sort of from November to December and because of what I was doing I started working quite closely with him. At the time our general manager sort of worked with the both of us to try and get some improvements which were needed. We needed to do them to basically get product out of the door to hit our rates and I started working quite closely with him. I was taking an interest and he started teaching me a bit more just off the back of it. There wasn't any sort of agreement it was just genuinely out of interest. Then one day he, our general manager, said "Is this something you enjoy?" and I said "Yes". He was "Well I'm looking to develop you further" and he sort of talked me through this role which is site continuous improvement leader and its run by sort of the global team. [..] I carried on doing what I was doing really and then I started applying for another job at another site in [city]. Then one day he pulled me into his office and he said "I hear you're applying for another job so would you like this job?", which is [Continuous Improvement] leader. He told me what it's about and what it entailed. He asked what I wanted to get paid and we came to an agreement and he offered me a job there and then. Pre-empting one of your questions again, I never went through an interview phase or anything. They were planning to advertise for the role but because they sort of offered it to me internally. So they sort of went around some of the loopholes and didn't post it and sort of gave it to me because obviously it was an internal post anyway.'*
>
> [Owen. BSc Psychology. Continuous improvement manager]

The story of Owen's first role change within his company shares features with other repondents' accounts of obtaining work in the internal labour market. First, while they were suggested or recommended to a role which was not created specifically for them. Second, there is usually an element of 'sponsorship' involved on the part of a more senior individual to help these graduates either in the form of directing them towards an upcoming role or giving them a recommendation directly for that role. In the case of Owen, where a person is senior enough, the individual is hired without any further application or screening process. The example below illustrates another attempt by managers to move graduates within the company internally.

> *P: [. . .] It's coming to a natural end point of the role so I started looking for other jobs internally and that got my manager's attention "Oh I'll make a job for you. I'll make a promotion, stay with us" and I'm just waiting to hear back from a job that I applied for internally which is also a promotion and tomorrow I'm going to go onto this new job that my boss has made and see how I like that [. . .]*

> *M: So because it's coming to the end you said you were starting to apply for jobs internally is that right [P: Yes] and your boss tried to make a new job happen for you because of that.*
>
> *P: Yeah they wanted to keep me in the team. [. . .]I sort of applied for a job internally yet my immediate manager gets notifications saying that I'd done so. I hadn't talked to him beforehand because we were so busy in the run up to finishing. We work 12 hour days most of the week. I never got a chance to talk to him and ended up applying for a job without discussing it but he obviously saw that anyway. So then his manager phoned me up and says "What about this job? Does it sound like something you would- could do?" I said "Yeah could do" and he says "Oh I strongly suggest that you apply because you'd be a very strong candidate".*
>
> [Poppy. MEng Civil and Environmental Engineering. Graduate engineer]

Once again, Owen's case provides some further insight into the sorts of motivations that managers may have. One motivation is to keep individuals that perform well and whom they work well with on staff. Speaking about his second promotion, another role which was not externally advertised, Owen says:

> *'I think the relationship we have for each other is part of it but also we know that I get results. He knows that I work hard to get results and it's very important to the relationship. He's also seen how I work and we work really well together both at a professional level. He respects my opinion and I think that earlier in the year, well possibly before that, we had a conversation about where I want to go in the next few years and he said to me "Well I don't want you to leave the business until I'm ready to leave the business and then you can do what you want". So that was in the back of mind and I'm sure that it was in the back of his mind as well. Our characteristics work really well.'*
>
> [Owen. BSc Psychology. Continuous improvement manager]

There were examples of individuals who were had managed to get work through the internal labour market of a company. In these cases the roles were all internally advertised through company newsletter or other internal sources of information. These roles were not open to external candidates and as such graduates identified themselves as being in a position where there were fewer candidates for a role. Unlike in the case of informally recruited internal candidates, there is an application and assessment process. However this process may be easier for those applying for a vacancy internally compared the process for external candidates. In the example below Lana gives her account of the interview assessment process for her current role as a hostel manager.

> *'Yeah it came up and I applied and I got it. That was fairly straightforward. The manager at [Hostel] actually already knew me from the initial recruitment day and so she remembered me. Then she said "Oh I've seen quite a few managers come up" and she's like "and it'd be nice to see you" and that all went very smoothly really. I would have been surprised if I hadn't got it."*
>
> [Lana, BA English literature, Hostel manager]

Given the prevalence of personal and professional contacts in helping graduates find work, some respondents had reflected on their own pathways into work. On the whole graduates who used contacts were aware of the moral aspect of this practise and dilemmas around their own participation in the practise. As a result graduates would present themselves as being apologetic and very lucky. However the same graduates would also present the case as to why, despite relying on contacts to find their jobs, they were nonetheless suitable or had deserved the role. This qualifier is usually made by an appeal to how much work they have into their jobs since being hired or the fact that they still had to pass a screening process.

> *'Sometimes I feel like I should be in the Tory party, in this sort of nepotistic Etonian sort of cabal where they all give each other little jobs and things but the funny thing is neither of my parents went to university. They're not what I would say professionally well connected people. They're not the kind of people who can smuggle me into these lovely big companies on a nice cushy job. That was never an option but ironically enough that was what happened as it turns out you know. So I do feel quite bad in some ways when I look at friends who've struggled through these incredibly competitive assessment days and things like that and I think "Oh god I never had to get away with that". Now I've started working and I try and work very hard and take pride in my work and those feelings of guilt have receded [laughs] as time has gone on.'*
>
> [Jake. BSc Business Management. Currently a sales and marketing manager]

> *'I don't feel that bad about it because I feel I was a good candidate. I really did want to work in planning. I really did want to work for the company I'm in. I think that having the contact with them has meant that I had an easier route through the process part but not actually once I got to the interview stage. It's entirely meritocratic and I was very fortunate to get it but I think what it meant was that I didn't have rounds of interviewing, being sifted out. Whereas I think, particularly in the big graduate schemes, you have so many rounds.*
>
> [Helen. BSc and MSc Planning. Planning assistant]

5.4 Discussion and conclusion

Across the small number of interviews in the sample, there has been little difference between graduates in their perceptions of employability. This is somewhat of a surprise given the emphasis that some researchers have placed upon the variations in the rates of return to factors, such as socioeconomic background or university prestige, by fields of study (e.g. Jackson 2007; Strathdee 2009; Smyth and Strathdee 2010). Whilst there does not have to be a close relationship between how graduates *perceive* employability and what *actually* affects their employability, it does seems plausible that the the latter ought to have some influence on the former.

A number of reasons may contribute towards the findings; the obvious reason being that the sample is small and unrepresentative. The analysis is mainly used for exploratory means and to support practical choices in later analyses. Another reason could be that whilst certain factors may affect employability differently by fields of study—and graduate perceive this to be true—these effects are relatively minor. Instead respondents may have mentioned only relatively important factors that employers look for which happen to be common for all roles. For instance, whilst researchers speculate that communication and personal skills affect the productivity of worker differently depending on their occupation, a minimal amount of these skills is likely to be a common requirement for almost all occupations (Jackson, Goldthorpe and Mills 2005).

Other explanations include the fact that the interview material may not have been sensitive enough to convey the degree of importance that graduates placed upon different factors. The interview guide, for both the semi-structured and unstructured interviews, also did not contain any questions to prompt graduates to compare their field of study and others. This was done in order to avoid leading graduates to favourable responses.

Respondents from subjects allied to medicine, and to a certain extent those in engineering, did however seem to view their employment prospects and experiences more favourably compared to other subjects. Whilst these individuals did express some concern about the state of competition in the labour market—bearing in mind many had graduated after a recession—there was in hindsight a perception that competition for work in their chosen areas was less fierce compared to others. Furthermore, graduates aspiring to get positions in areas related to STEM, such as psychology, also emphasised the importance of postgraduate qualifications.

In contrast to how graduates perceive employability, there was greater variety in the ways that graduates conducted their job searches and their career histories across fields of study. On the one hand, graduates who studied subjects allied to medicine exclusively used the NHS jobs website to find work. This is perhaps due to the strong association between their field of study and a particular employer. As such, these graduates did not use informal means to find work or to gain work placements in their field. On the other hand, respondents from the creative arts and design stressed the importance of informal means and networking for obtaining work. The role of contacts featured a lot in respondents' career histories.

The effects of networking, or social capital, on the labour market outcomes could vary by fields of study. This may be interesting avenue of research to pursue. However, the DLHE and longitudinal DLHE surveys do not contain information about the quality and extent of a person's social network. Instead, the surveys do record the means by which employed graduates first heard about their current roles. Unfortunately, this is not a sufficient amount of information to estimate the actual impact that social capital has on labour market outcomes—unless we were willing to make some assumptions about the data (see Mouw 2006 for a review).

Nonetheless, the impact of any network effects may be captured by other factors. For instance, suppose that socioeconomic background is associated with better social capital and the latter has a positive influence on labour market outcomes. In this case, if we omit social capital indicators from an analysis, then the positive effects of these networks will be captured in the relationship between socioeconomic background and labour market outcomes. For fields of study related to occupations and industries where recruitment is driven entirely formal means, we may expect see less of an influence of network effects on labour market outcomes. This lines of inquiry is explored further in chapter 8 where I use firm size as an indicator of bureaucratic practises which may include the use of formal means of recruitment.

The main finding from the qualitative data is that there may be a relationship between social networks and earnings that can vary across different fields of study. The differential effects of social networks may explain why the gap in outcomes between advantaged and disadvantaged groups of graduates varies by field of study in later chapters. The qualitative data also highlights an interesting phenomena regarding graduate migration that is later used to check for sample selection bias in the DLHE survey analysis.

Many respondents in the study had moved back to their parental homes after finishing their studies. This pattern of migration is also found in other studies (Tucker 2013). For instance, Sage *et al* studied the migration patterns of 963 individuals who graduated from the University of Southampton between 2001 and 2007 (2012). Their survey showed that 32.7 percent of first moves by graduates, after their degrees, were back to their parents' homes. Of those that returned, around half stayed for one year or longer. The main reason given in the survey for the move was similar to that found in the interview sample: to save money. Interestingly, the study also showed a boomerang effect as a substantial proportion of graduates' second moves were back to Southampton, the region where their university was based. In my interview sample, some graduates did express desire to stay or to relocate to the region where they did their degrees. Using information about graduates destinations, Ball (2015) also found that a substantial proportion of graduate return back to where they were domcilied prior to HE after finishing their studies. Looking at graduate migration pattern, 25 percent of graduates left their home regions in the UK to study at university and returned 6 months after graduation for work. However a substantial proportion of graduates studied and worked in the same region of the UK where they lived prior to HE (45.9%). Gaby and Purcell (2010) found that almost 70% of final year students had based their preferences about where they looked for work on where they lived prior to HE. Factors such as family members and costs of living constrained people's choices about where to look for work. Since regional economies across UK vary, graduates domiciled in regions of high unemployment may be less likely to be full-time employed 6 months after graduation.

However it is unlikely that an individual's domicile prior to HE will have a causal effect on their wages, after accounting for factors like education. This is because employers set wages that take into account factors such as the cost of living and local competition for work in the areas where their firms are based and *not* where in the UK their workers originally came from. Assuming this is the case, information about graduates' migration patterns and the local economy in different regions of the UK can be used to explore the existence of any sample selection bias in the DLHE survey. The full method, and the results of the analysis, are contained within the appendix chapters.

The current chapter explores the topic of graduates' perceptions of employability and how graduates' found work in the labour market using interviews with 21 recent graduates over time. In the small sample there appeared to be no strong patterns in graduates' perceptions of employability across fields of study. However, there seemed to be some patterns that suggests that the way that graduates found work differed across different fields of study. The possible implications of this on rates of return and labour market stratification across field of study are discussed. The next three chapters focus exclusively on labour market stratification across fields of study.

Chapter 6

Labour market stratification across fields of study

6.1 Introduction and research questions

This chapter examines whether the extent of labour market stratification by sex, socioeconomic background, and different educational characteristics varies across fields of study. These educational characteristics are the receipt of private education prior to HE, degree classification, and the type of university graduates attended. I examine results for two labour market outcomes: earnings and skills use. Whilst salary alone does not capture the full reward package received by a worker, for most employees, it will capture most of the compensation received by a worker for their labour. This makes salary a useful measure of labour market outcome. Skills use, whilst associated with earnings, is also another useful measure. As mentioned in chapter 2, the expansion of HE was linked to the anticipation of more knowledge intensive jobs in the UK economy. Skills use allows us to compare the extent to which different groups of graduates are able to participate in knowledge intensive work.

This chapter builds on and extends the previous body of research on this topic which was reviewed in chapter 3 (Hansen 1996, 2001; Roska 2005; Jackson et al 2008; Hällsten 2013; Purcell and Elias 2006; Feng and Graetz 2015; Rumberger and Thomas 1993; Smyth and Strathdee 2010). The two subsequent chapters will test the various explanations for the existence of variations in stratification by field of study. The analyses focus on individuals who left HE with a bachelor's degrees. In this chapter I focus on answering the following research questions:

1) Is the relationship between sex, socioeconomic background, and labour market outcomes mediated by education related factors? Does the indirect relationship between sex, socioeconomic background, and outcomes vary by field of study?

Differences in labour market outcomes between men and women, and students from different social economic backgrounds could be a results of factors related to education. For instance, students from advantaged backgrounds may achieve better grades at university or are more likely to study subjects that have high rates of return (Jackson et al 2008). In addition, studies done in the UK have shown that differences in subject of study explains a large proportion of the earnings gap between male and female graduates (Machin and Puhani 2002, Chevalier 2006). In both cases, we may say that socioeconomic background or sex has an indirect relationship with outcomes through education-related factors. However there are few studies available looking at whether this indirect relationship varies by field of study.

Hansen and Mastekaasa (2006) used information on Norwegian graduates to investigate whether individuals from certain socioeconomic backgrounds are likely to receive better grades depending on what they studied at university. In their study, they set out with no particular hypothesis but speculated that individuals from advantaged socioeconomic backgrounds may do comparatively better in soft and non-science subjects, such as the humanities. In these fields, the body of knowledge and standards of assessment are more ambiguous and less standardised (i.e. the relationship in figure 3.1 between A-C is stronger in some subjects) (Biglan 1973). Students from advantaged background can potentially draw upon their cultural capital—in the form of tacit cultural knowledge or familiarity with highbrow culture—to help them achieve better grades (Bourdieu and Passeron 1977). In their study, Hansen and Mastekaasa concluded that the difference in attainment between students with parents in professional cultural occupations, such as journalist or teachers, and those with parents in unskilled occupations were greatest in fields like Norwegian, and media studies. The difference was smallest in fields related to engineering. If the relationship between course grade and socioeconomic background was stronger in some fields compared to others then the indirect effects of socioeconomic background on labour market outcomes will also vary by field of study—assuming better course grades lead to better outcomes (i.e. there is a non-negligible relationship between C-D in figure 3.1). However, another study by Smith and Naylor using information on UK graduates concluded that the academic attainment gap between those from advantaged and disadvantaged backgrounds did not vary by field of study (p. 57, 2001).

2) After accounting for educational attainment and other background characteristics, is there less stratification by sex and socioeconomic background in hard and applied fields compared to soft or pure fields of study? Is there greater stratification by educational achievement in hard and technical fields of study?

In hard fields, there is greater perceived consensus about the body of expertise and knowledge that graduates are expected to possess compared to other fields of study (Biglan 1973). For graduates in hard fields, educational achievements could be a good signal to employers about the type of skill and knowledge that they possess. Furthermore applied or technical fields of study, such as engineering and nursing, are more vocationally orientated than other subjects. This theoretically creates a stronger link between academic qualifications and the skills used in a job. On the other hand employers who typically employ graduate with degree in non-applied or pure subjects—such as the humanities—may place more emphasis on personal skills and less relevance on formal qualifications (Jackson, Goldthorpe and Mills 2005; Jackson 2007).

3) Is there less stratification by sex and socioeconomic background in fields of study related careers in the public sector?

In the UK, education, medicine, and subjects allied to medicine are all fields linked to occupations that are predominantly in the public sector. Looking at graduate destinations 2 years after finishing HE, Purcell et al (2008) found that 77 percent and 73 percent of workers who studied subjects allied to medicine and education were employed in the public sector. In comparison, only 34 percent of all graduate workers were employed in the public sector. There are several reasons to believe that stratification along the lines of sex and socioeconomic background would be lower in these organisations. Public sector employers, such as the NHS, are large organisations and large employers are more likely to use more structured methods of assessment when hiring individuals (Bartram et al 1995). The use of structured interviews and psychological tests diminishes the impact that personal biases can have in the hiring processes. Public sectors organisations may also have more interest in promoting equality due to the large amount of scrutiny they receive from the media, government and the public. These issues are explored further in chapter 8.

4) Is there greater stratification between graduates in fields of study where the labour market is loose?

I wish to test the theory that variations in stratification by field of study can occur as a result of competition in the labour market. For example, the market for STEM graduates may be tight whilst the market for social science graduates may be loose. According to positional theories, a loose labour markets will result in greater competition for work, and therefore greater levels of stratification between workers (Brown and Hesketh 2004).

To answer the last question I need some measure of competition for graduates in different fields of study. One commonly used measure is the rate of unemployment (Williams 2004). This is typically very low for graduates and it is theoretically not very sensitive to the conditions of the graduate labour market. If the demand for graduate labour falls we would not necessarily expect unemployment amongst graduates to rise since these graduates could go on to find jobs that do not require degrees—displacing less educated workers in the process.

Another potential measure is the proportion of graduate employed in graduate jobs. As mentioned in chapter 4, occupations may be categorised as 'graduate jobs' if they may make use of advanced skills or competencies that can be acquired through HE (Elias and Purcell 2004, 2013).

Table 6.1: Individuals in full-time graduate jobs as a proportion of all employed graduates (Source: DLHE 2006/07)

Field of study (ranked by 6 month results)	6 months	42 months
Law	26.53%	86.82%
Biological sciences	28.62%	83.93%
Humanities and languages	35.74%	80.69%
Creative arts	37.20%	77.54%
Social studies	41.95%	83.31%
Other subjects	49.32%	90.30%
Other STEM	49.81%	88.21%
Business	52.28%	90.12%
Education	63.84%	84.78%
Engineering and computer science	65.19%	90.57%
Subjects allied to medicine	73.92%	89.87%
Medical and veterinary sciences	98.84%	90.67%

Table 6.1 displays the proportion of employed graduates who were employed full time in graduate jobs in the UK, as defined by the SOC(HE)2010 (Elias and Purcell 2013). This measure has its own potential drawbacks; it does not account for unemployed graduates or those that choose to do further studies. Nonetheless the table shows that graduates with degrees in Medicine, Engineering, Education

and Subject allied to medicine are the ones most likely to be in graduate jobs 6 months after leaving HE. This indicates that the labour market for these graduates is relatively tight. However all four are also considered to be hard and applied fields of study, and—with the exception of Engineering—are associated with employment in the public sector. This makes it difficult to answer research questions 2, 3 and 4 separately.

One solution is to compare levels of stratification in the Biological sciences with stratification in other STEM subjects. There is little doubt that the Biological sciences—including psychology, ecology and zoology—are natural sciences and is a hard field of study. However, graduates in the Biological sciences, in contrast to other STEM subjects, are amongst those who are most likely to be working in non-graduates jobs. This may be due to the fact that there has been a larger increase in student numbers in the Biological sciences compared to other STEM subjects over the past decade (see table 3.2).

The Biological sciences can be considered a test case; if competition does affect stratification then we ought to see greater stratification by sex, socioeconomic status and so forth in the Biological sciences compared to other non-applied STEM fields. The latter includes subjects such as physics and mathematics. This research design is far from ideal and I present a different strategy in the next chapter to test whether competition in the labour market affects stratification.

6.2 Analysis

6.2.1 Data

The information used in this chapter comes from the 2006/07 DLHE and LDLHE surveys. I look at graduates who left higher education with bachelor's degrees in the academic year 2006/07, and I focus on their destinations 6 months and 42 months later. Degree courses were grouped into 10 fields of study and these fields were then classified along two dimensions: hard/soft and pure/applied (table 6.2). This classification of subjects was based on Biglan's (1973) research into how academics grouped different fields of study. Other studies have sought to update Biglan's original classification by including newer subject such as the computer sciences into the framework (Stoecker 1993).

Table 6.2: Classification of fields of study (based on Biglan 1973 and Stoecker 1993)

Field of study	Hard/Soft	Pure/Applied
Biological sciences	Hard	Pure
Business	Soft	Applied
Creative arts	Soft	Pure
Education	Soft	Applied
Engineering and computer science	Hard	Applied
Humanities and languages	Soft	Pure
Law	Soft	Applied
Other STEM	Hard	Pure
Social studies	Soft	Pure
Subjects allied to medicine	Soft	Applied

6.2.2 Predictors

Only bachelor's degree holders who were in full-time paid employment 6 months (or 42 months) after graduation are included in the analysis. Characteristics such as sex, ethnicity, having a known disability, residence (or domicile) prior to HE, and socio-economic background are used in the models (see next section). Age is also included in the model to account for any previous labour market experience. Whilst there is detailed information about ethnicity in the dataset, due low sample sizes, ethnic groups are grouped into two categories: 'White' and 'Non-white'. Due to the broad categories for ethnicity, I avoid making conclusions about the relationship between ethnicity and labour market outcomes. Studies have shown that the relationship between ethnicity and labour market stratification varies between non-white ethnic groups (Blackaby et al 2005).

Pre-university UCAS tariff scores are used in the analysis as an indicator of pre-university achievement and ability. I have included the quartile that an individuals' tariff score falls into as dummy variables, rather than the raw tariff score. An indicator of whether or not an individual attended a state or a private school/college prior to HE is also included in the models. The institutions that where graduates received their degree from are grouped into three categories; Russell group institutions, Pre-1992 institutions and Post-1992 institutions. Graduates from small institutions that specialise in only a narrow range of subjects and the Open University are not included in the analysis. This does not substantially reduce the sample size in general although a significant minority of individual with degrees in the Creative arts graduated from these institutions (<10%). Analysis of labour market outcomes at 42 months also includes information about whether or not an individual had gained a postgraduate qualification since completing their undergraduate degree. Further analyses testing the sensitivity of the results to sample selection bias are reported in appendix A.

6.2.3 Statistical analysis

I look at two type of labour market outcomes in this chapter: earnings and the extent to which graduates make use of their skills in their jobs. I use logistic regression to model the probability of an individual being in a graduate job (as measured by the SOC(HE)2010, Elias and Purcell 2013). Then the use the results of the model to compute partial correlation coefficients (Breen, Holm and Karlson 2013). The partial correlation coefficients can be interpreted as the strength of association between a predictor and skills use, after accounting on other factors.

Logistic regression models are more prone to over-fitting compared to linear regression models (see Babyak 2004). Due to this issue, when I looked at results by field of study, I do not display any sub-group results for Law, Education and Subjects allied to medicine in order to avoid making inferences from over-fitted models using too few observations.

I use multiple linear regression to model the mean salaries of graduates who are working in the UK 6 months and 42 months after graduation. In the models, the natural logarithm of earnings is used as the outcome variable. Log earnings is usually used in research instead of raw earnings in part because, in human capital theory, an increase in human capital is thought to lead to a proportional increase in productivity (Mincer 1958). Studies using empirical data have also found that increases in human capital (or factors related to human capital) are associated with proportional increases in earnings (Heckman and Polachek 1974).

The DLHE survey contains information about self-reported the annual salaries of graduates recorded to the nearest £1,000. However there are some issues. The full-time salaries of some graduates seem to fall below the expected minimum annual salary of a worker in 2007, which was roughly £10,046[1], whilst the salaries of individuals earning over £90,000 are censored. Fortunately the proportion of graduates earning less than the minimum wage or over £90,000 in the DLHE is extremely low (>200 after case-wise deletion for cases with missing values on other predictors).

Due to the presence of some unusually low reported salaries and an upper limit to reported salaries values, I also compare the results from the OLS regression models to the results of a censored quantile regression models (Ahn and Powell 1993, Koenker 2008). The quantile regression model estimates the median salaries of graduates and account for the fact that salaries over £90,000 are censored. Furthermore regression estimates of the median are also more robust to the outliers—such as particularly low or high salary values—compared to the mean. Analysis of censored regression quantiles also have fewer assumptions than the commonly used Tobit regression model (Ahn and Powell 1993). The results of both the censored quantile regression and the OLS model were broadly extremely similar. I will report the results of the simpler OLS model with some confidence that any issues caused by outliers or censored reported salaries will not substantially affect the results.

I will present the results of the analysis of skills utilisation and graduates' earnings separately. In both analyses the underlying procedure is the same. In order to see whether the relationship between sex and socioeconomic background, and outcomes are mediated by education-related factors I fit a regression model using only age, ethnicity and socioeconomic background, disability status, sex and domicile prior to HE as predictors (i.e. A in figure 3.1). I will refer to this as the *Basic Predictors* model. Then I will include additional predictors for UCAS tariff and whether an individual had private education to the model (*Pre-HE Predictors*). These two predictors represent education-related factors prior to HE (B in figure 3.1). Finally I will fit a model with all the aforementioned predictors along with predictors for degree classification, type of university attended, field of study, and whether an individual has a postgraduate qualification—where applicable (C in figure 3.1) (*HE Predictors*). If the relationship between sex and socioeconomic background, and labour market outcomes is mediated by education-related factors (i.e. A-B and A-C) then we should see difference in outcomes by sex and socioeconomic background reduce after we account for predictors related to education.

In order to see whether stratification varies by field of study I fit regression models using information from all graduates first. In this model the relationship between our predictors (i.e. sex, socioeconomic background and so forth) and our outcomes of interest is assumed to be the same across all fields of study. Then I conduct separate analyses by field of study. This allows the relationship between all our predictors and the outcome to vary by field of study. I will then use the chi-square statistic to test whether differences in labour market outcomes between male and female workers, private and state school students, and so forth varies by field of study. The Wilcoxon-Mann-Whitney test is used to examine whether levels of stratification differ between hard and soft, and pure and applied fields of study.

[1]Minimum wage was increased to £5.52 for over 21s on October 2007. The expected annual salary for a full time worker on minimum is based upon a 35 hour working week.

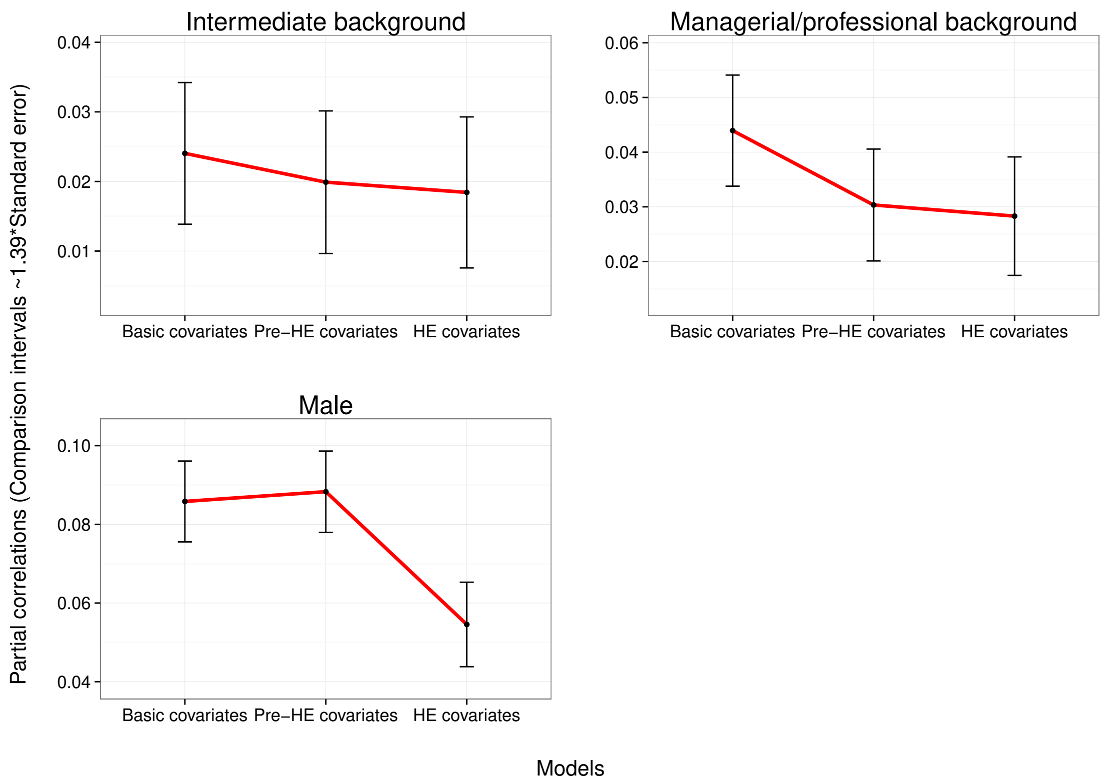

Figure 6.1: Partial correlations with skills use 6 months after graduation (all subjects) (2006/07)

6.3 Results

6.3.1 Skills use

Looking at the proportion of individuals in graduate jobs in table 6.1, it is clear that these figures vary across fields of study. Only 26.5 percent and 28.6 percent of employed graduate with degrees in Law and the Biological Sciences were employed in full-time in graduate jobs 6 months after finishing their studies. In contrast around 63.8 percent and 73.9 percent of all employed graduates with degrees in Education and Subjects allied to medicine were employed in full-time graduate jobs. It is also worth noting that STEM graduates are also more likely to be working in graduate jobs compared to other fields of study. We see a similar ranking between fields in the 42 month destinations data although the differences are not as stark as at 6 months.

The indirect relationship between sex, socioeconomic background, and skills utilisation

Figure 6.1 plots estimates of the partial correlation coefficient between socioeconomic background, and sex, and skills use at 6 months. The comparison intervals (CI)——not to be confused with confidence intervals—allows us to visually compare estimates between models. Non-overlapping intervals indicates that there is on average a statistically significant difference between two estimates (p<0.05, see Goldstein and Healy 1995).

The figures show that there is an extremely weak correlation between skills use and socioeconomic background even before we account for educational characteristics. The partial correlation is only

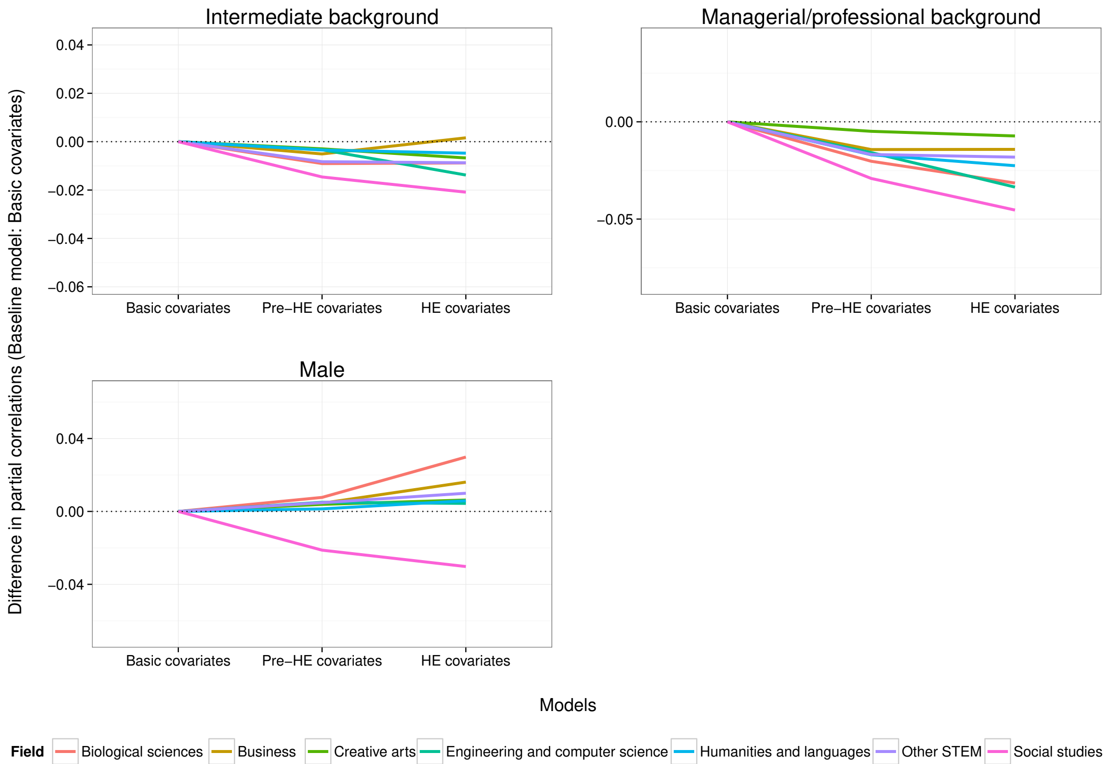

Figure 6.2: Difference in partial correlations with skills use across models and fields of study 6 months after graduation (2006/07)

0.02 and 0.04 for intermediate, and managerial or professional backgrounds. The reference group are graduates from routine and semi-routine backgrounds (table D.4). These results hold true for destination at 42 months as well (table D.5).

In contrast there is a stronger partial correlation between skills utilisation and sex in the *Basic Predictors* model, with male graduate being in higher skilled jobs than female graduates on average. This relationship weakens after educational characteristics related to HE are accounted for. As mentioned, this is likely due to the fact male and female graduates studied different subjects at university. This relationship also diminishes later on in graduates' careers. The partial correlation for males is 0.06 at 6 months compared to 0.02 at 42 months in model containing all education related predictors (tables D.4 and D.5). This suggest that there are early difficulties for women in finding a job that matches their skills compared to men which diminishes over time.

Since the indirect relationship between sex and socioeconomic background, and skills use may vary by fields of study, I also conduct the separate analyses for each field of study (Hansen and Mastekaasa 2006). The results are displayed as the difference in partial correlation coefficients across the three models for each individual field of study (Figure 6.2). Comparison intervals are omitted from the plot for clarity's sake. However there were neither any substantial nor statistically significant variations in the indirect relationship between sex and socioeconomic background across different fields for study.

Looking at graduates as a whole, since the *HE Predictors* model contains information about educational achievement prior to and at HE level, the results can be used to compare outcomes for graduates with similar educational backgrounds and abilities. There is only a very weak partial

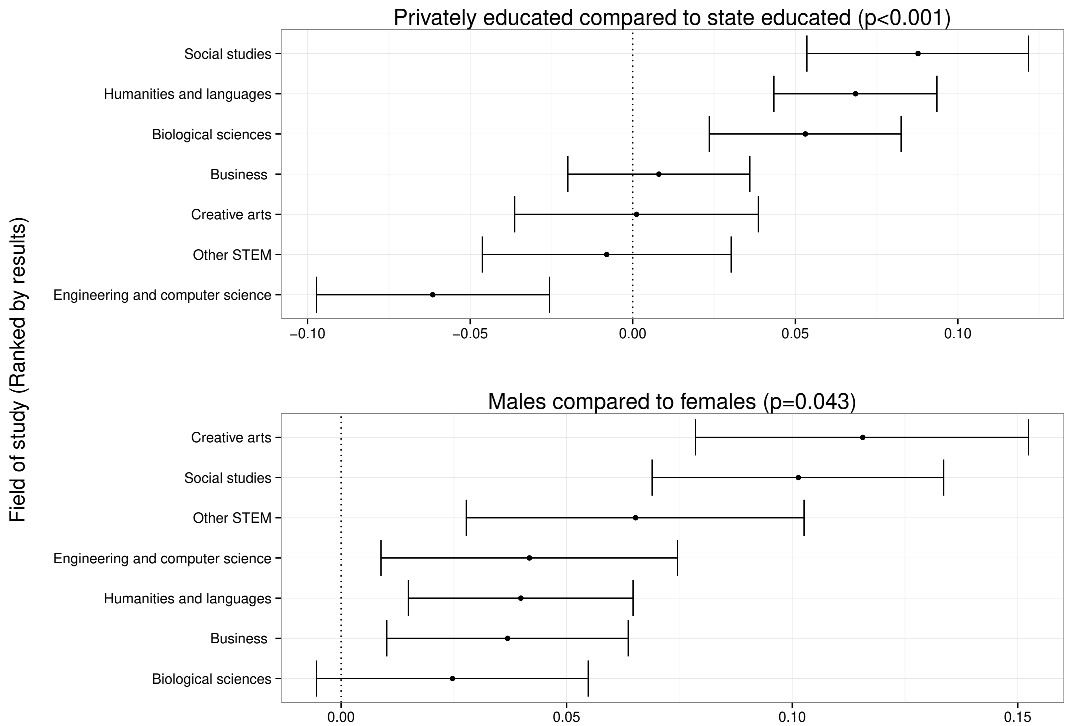

Figure 6.3: Partial correlations with skills use by fields of study: Private education and Sex (6 months) (2006/07)

correlation between socio-economic background and private schooling, and skills use for individuals 6 months after graduation (0.03). There are small positive partial correlations between type of HEI and skills utilisation (0.09 for Russell group and 0.08 for Pre-1992 universities). Similarly weak partial correlations exist for sex and degree classification. Moderate partial correlation coefficients exists for field of study. Individuals with degrees in all the STEM fields (including Engineering and computer sciences), Subjects allied to medicine, and Education have higher levels of skills use in their jobs compared to individuals in Law and the Biological sciences. The strength of this relationship remains roughly the same at 6 month and 42 months after graduation (see table D.4 and D.5)

Evidence for variations in stratification by fields of study

Next I turn to the results of the analysis for each field of study to see if any variations in stratification exists across fields of study after accounting for other factors. Table D.6 and D.7 reports the full results of the sub-group analysis for the model containing all education related predictors. Selected results are displayed in a more accessible way in figures 6.3, 6.4, and 6.5. Again, comparison intervals (CI) are displayed to facilitate comparisons of estimates across fields of study, non-overlapping intervals mean that the differences in estimates between fields are, on average, statistically significant (p<0.05, Goldstein and Healy 1995). The results of the chi-square test for variations in estimates by field of study are also displayed in the graph titles. I find statistically significant variations in the partial correlation coefficients for sex, private schooling, degree classification and type of HEI across fields of study (6 months). However only variations in the association between skills use and type of HEI across fields of study are statistically significant at 42 months.

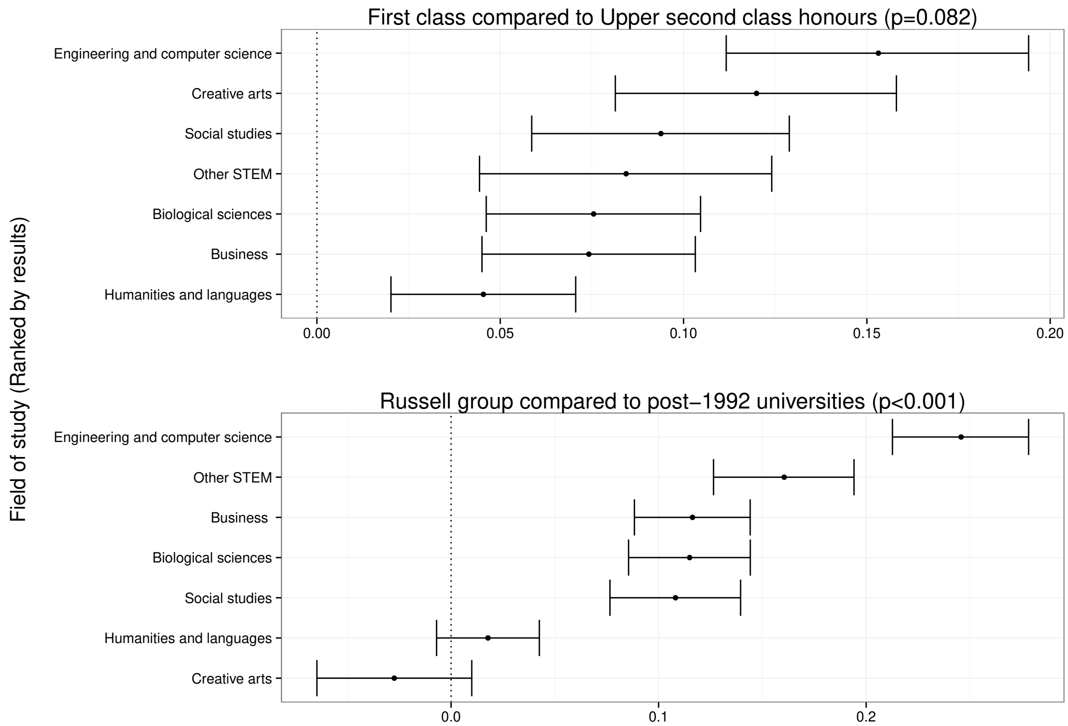

Figure 6.4: Partial correlations with skills use by fields of study: Degree classification and university type (6 months) (2006/07)

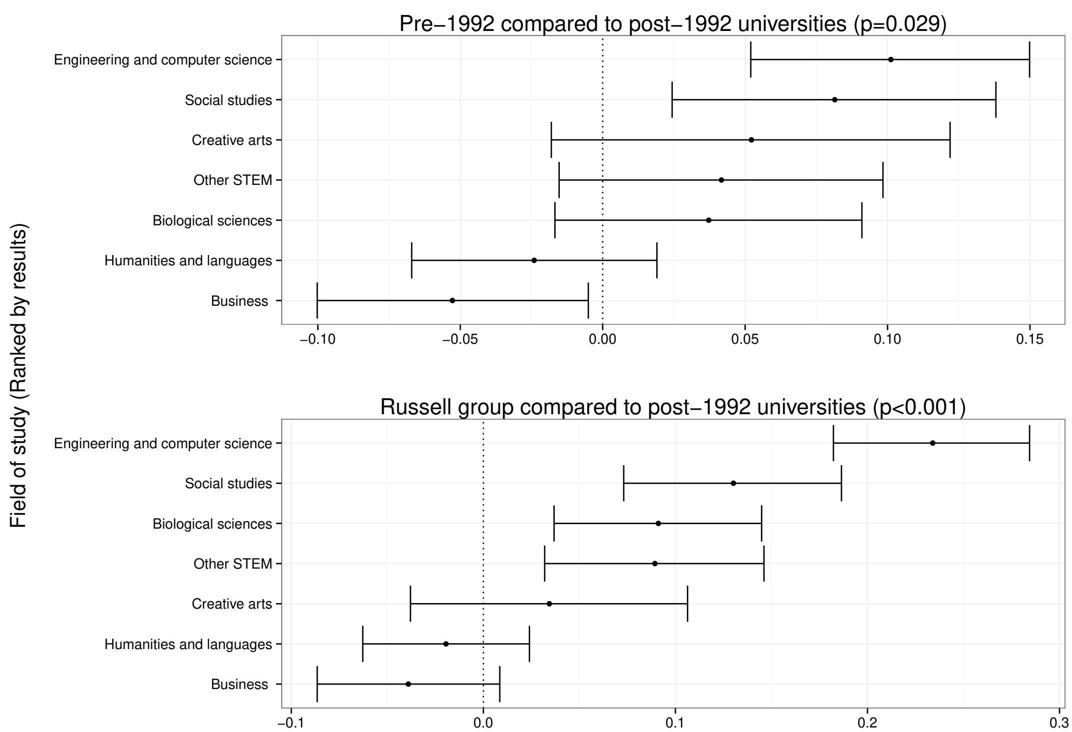

Figure 6.5: Partial correlations with skills use by fields of study (42 months) (2006/07)

The relationship between type of HEI attended and skills utilisation varied the most by field of study; there are moderate partial correlations between skills use, and attending a Russell group or Pre-1992 HEI for graduates with degrees in Engineering and computer sciences (0.25 and 0.20), and Other STEM subjects (0.16 and 0.15) 6 months after graduation. In contrast, there seems to be almost no correlation between attending a Russell group university and skills use for graduates with degrees in Creative arts, and Humanities and languages. A similar pattern also occurs for results at 42 months. The relationship between degree classification and skills utilisation seems to be stronger for Engineering and computer science graduates compared to Biological sciences and Other STEM graduates. The partial correlation for receiving a first class honours degree is 0.15 for Engineering and computer science compared to 0.08 for Biological sciences and 0.08 for Other STEM graduates. The weakest association exists for Humanities and languages graduates, where there is only a weak positive correlation between skills use and degree classification (0.05 for first class honours).

At 6 months there are also variations in the relationship between sex and skills utilisation by field of study. The association between sex and skills utilisation is strongest amongst Creative arts (0.12), Social Studies (0.10), and Other STEM graduates (0.07) with men being more likely to be employed in jobs with higher degrees of skills use than women. In contrast, there are very weak partial correlations between sex and skills utilisation for graduates who studied the Biological Sciences. The associations between sex and skills use are much weaker in the 42 month results but the overall pattern of variation by fields of study remains broadly the same—although these variations by fields are no longer statistically significant.

Finally there are differences between degree holders who attended private schools/colleges and those who attended state schools/colleges by field of study. I find no statistically significant partial correlations for private education for those who studied Creative arts, Business, and Other STEM subjects 6 months after graduation. However, I do find weak partial correlations for graduate who have degrees in Social studies (0.09), the Biological sciences (0.05), and Humanities and languages (0.7). The rankings are similar for the 42 month data as well although these variations are not statistically significant. Contrary to expectations, I do not find any significant variations in the relationship between socioeconomic background and skills utilisation by field of study.

I use the Wilcoxon-Mann-Whitney test to evaluate whether the relationship between skills use, and the predictors mentioned above—sex, HEI type, degree classification and private/state education—differs between pure/applied and hard/soft fields of study. Given that there are only 7 fields of study, the statistical power of the test is fairly low. I do not find any strong evidence that the relationships between skills use and these predictors differs systematically between pure/applied or hard/soft fields of study. In the next section, I report results using earnings instead of skills use.

6.3.2 Earnings

The indirect relationship between sex, socioeconomic background, and earnings

I adopt the same approach for estimating the indirect relationship between sex, socioeconomic and earnings as I did for skills use in the previous section. The results of each model are contained in tables D.8 and D.9, and are displayed in figures 6.6 and 6.7. The results are largely similar to those for found for skills utilisation—apart from a few exceptions. Differences in earnings between those from managerial or professional backgrounds, and those from routine or semi routine backgrounds seem to

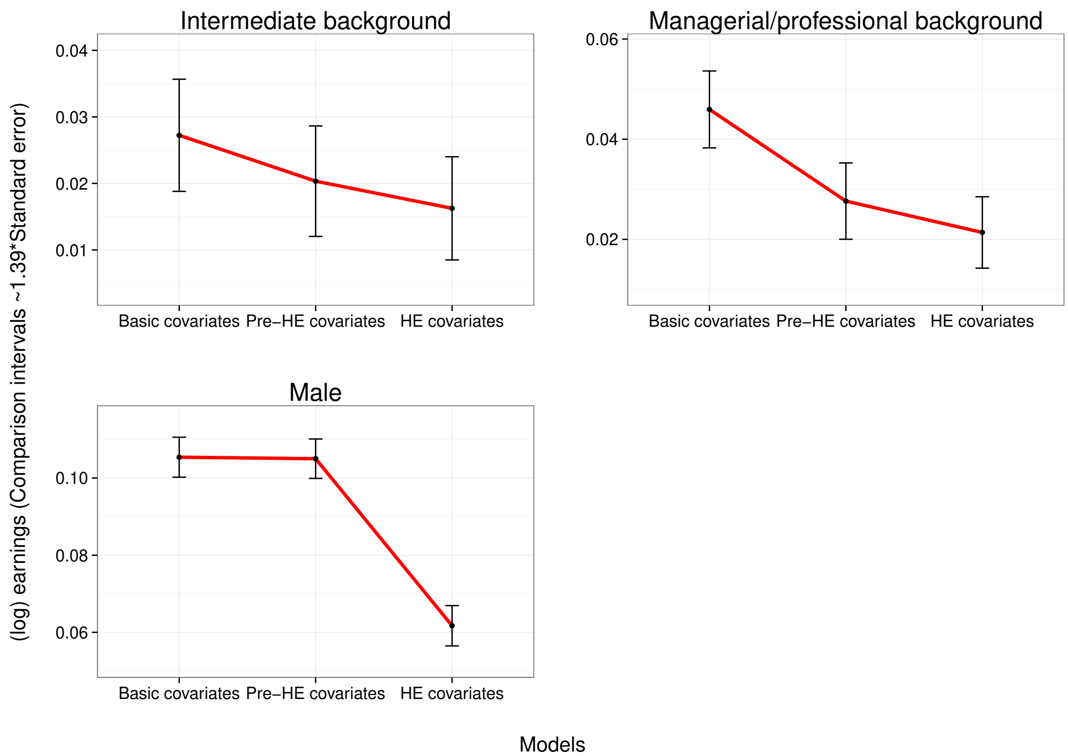

Figure 6.6: Difference in (log) earnings 6 months after graduation (all subjects) (2006/07)

be largely mediated by differences in education prior to HE. This is true for earnings 6 months and 42 months after graduation. This could be because people's educational choices and attainments prior to HE can affect what they study for their degrees or where they choose to study, which in turn can affect earnings.

The relationship between earning and sex is substantially mediated by education predictors related to HE. As mentioned before, this could be down to differences in what men and women choose to study at university. Whilst the relationship between skills use and sex greatly diminishes as time passes, the earnings gap between men and women does not decrease over time. In the *Basic Predictors* model, which does not include any education related predictors, men are estimated to earn around 11.1 percent more than women 6 months and 11.6 percent 42 months after graduation. In the model with all education related predictors (*HE Predictors*), the difference is 6.4 percent at 6 months and 8.1 percent at 42 months. Additional analysis by fields of study show that, as in the case of skills utilisation, the indirect relationship between sex and socioeconomic background, and earnings does not by fields of study (figure 6.8).

Looking at the results for model with the all predictors, I find that individuals from intermediate and manager/professional backgrounds earn more than those from routine/semi-routine background. Whilst the differences are statistically significant, they are also substantively small (1.6% and 2.1% respectively at 6 months). There are modest effect sizes for sex, degree classification, and type of HEI. These seems to be a large difference in earnings between graduates who studied different subjects. STEM and Education degree holders earned the most 6 months after graduation, and individuals with degrees in the Biological sciences and the Creative arts earned the least. This ranking remains broadly similar when we look at earnings 42 months after graduation as well.

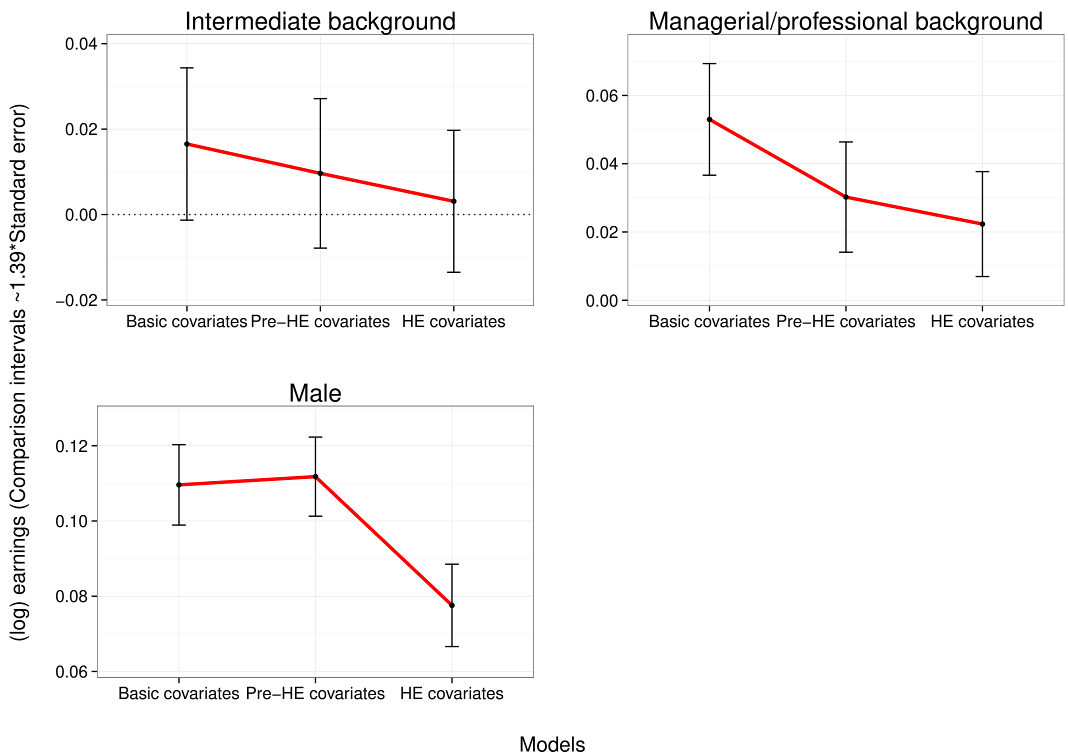

Figure 6.7: Difference in (log) earnings 42 months after graduation (all subjects) (2006/07)

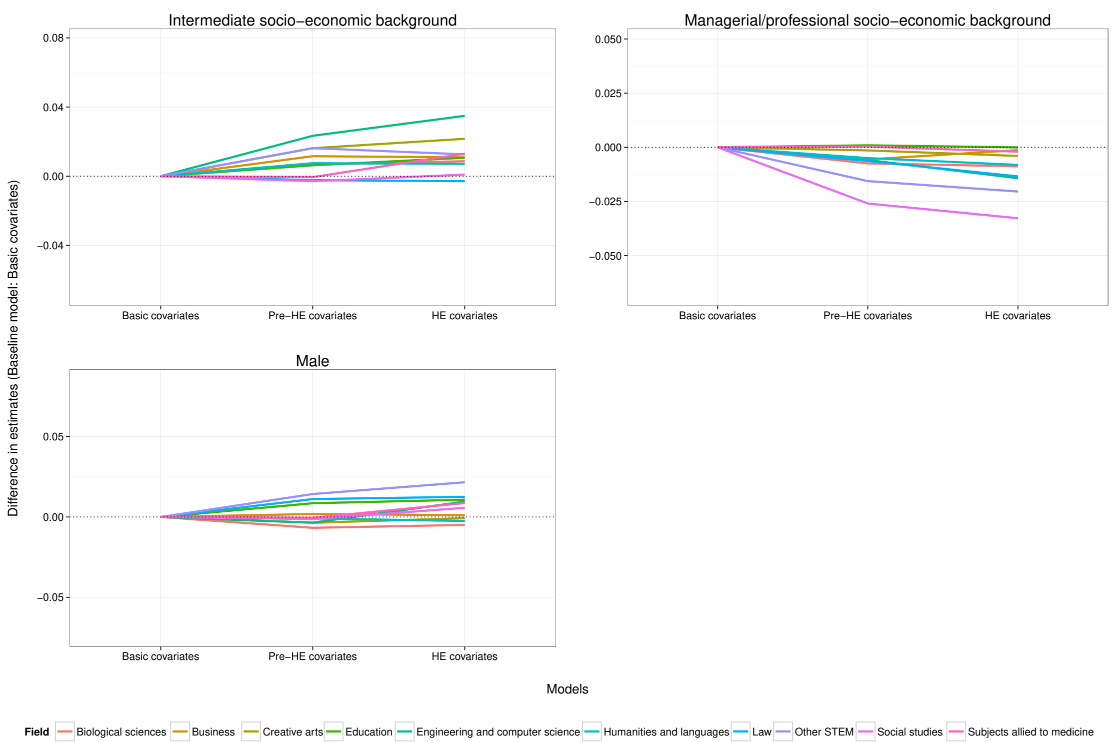

Figure 6.8: Partial correlations with skills use 6 months after graduation (all subjects) (2006/07)

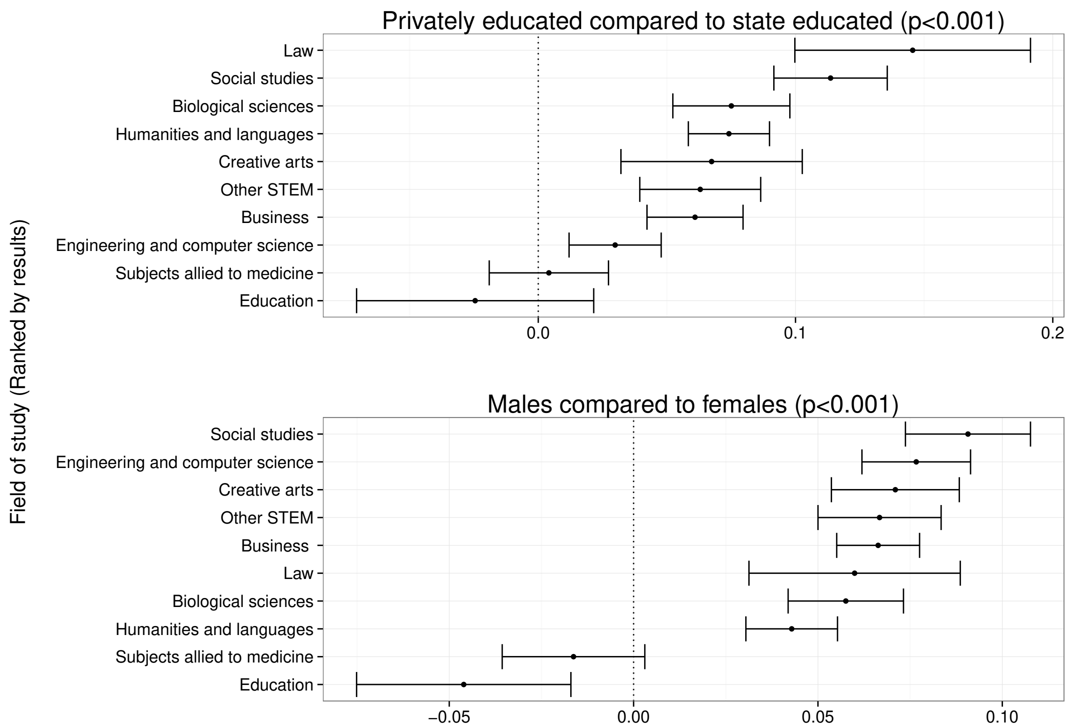

Figure 6.9: Results for models of earnings by fields of study (6 months) (2006/07): Private education and Sex

Evidence of varying stratification by fields of study?

The sub-group analysis shows that there are considerable differences in the relationship between sex, type of HEI, degree classification, private schooling and earnings by fields of study at both 6 and 42 months. However, as with skills utilisation, there is no variation in the relationship between socioeconomic background and earnings by field of study. Figures 6.9 to 6.12 displays some of these results by field of study.

Looking at sex, we can see that there is a consistent pattern in the results at 6 months and 42 months. The difference in earnings between men and women is comparatively high for Engineering and computer sciences, and Other STEM graduates for both periods whilst for graduates with degrees in Education, and Subjects allied to medicine the earnings difference is almost non-existent. In the case of Education, at six months men seem to earn less than women (4.7%). Education and Subject allied to medicine also have virtually non-existent earnings differences between graduates who were privately educated and those who weren't. In contrast, Law graduates who were privately educated earned around 15.7 percent (19.8%) more than those who weren't 6 months (42 months) after graduation. This is a considerable difference. The difference between state and privately educated individuals appears to be lower for people who studied Engineering and computer sciences compared to those who studied the Humanities and languages 6 month and 42 months after graduation. The earnings difference between those who were privately educated and those who weren't varies for Creative arts graduates: the difference seems to be smaller (6.9%) at 6 months but increases dramatically by 42 months (22.4%). However, in this case, large standard errors indicate that we should be wary of making inferences from these results.

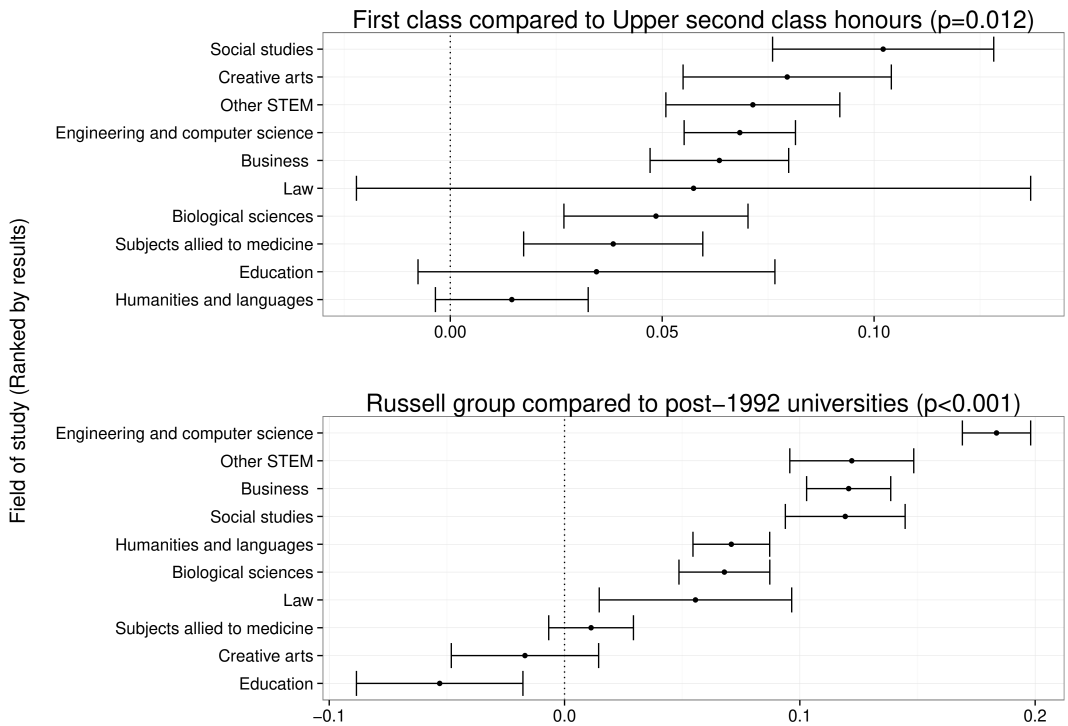

Figure 6.10: Results for models of earnings by fields of study (6 months) (2006/07): Degree classification and university type (2006/07)

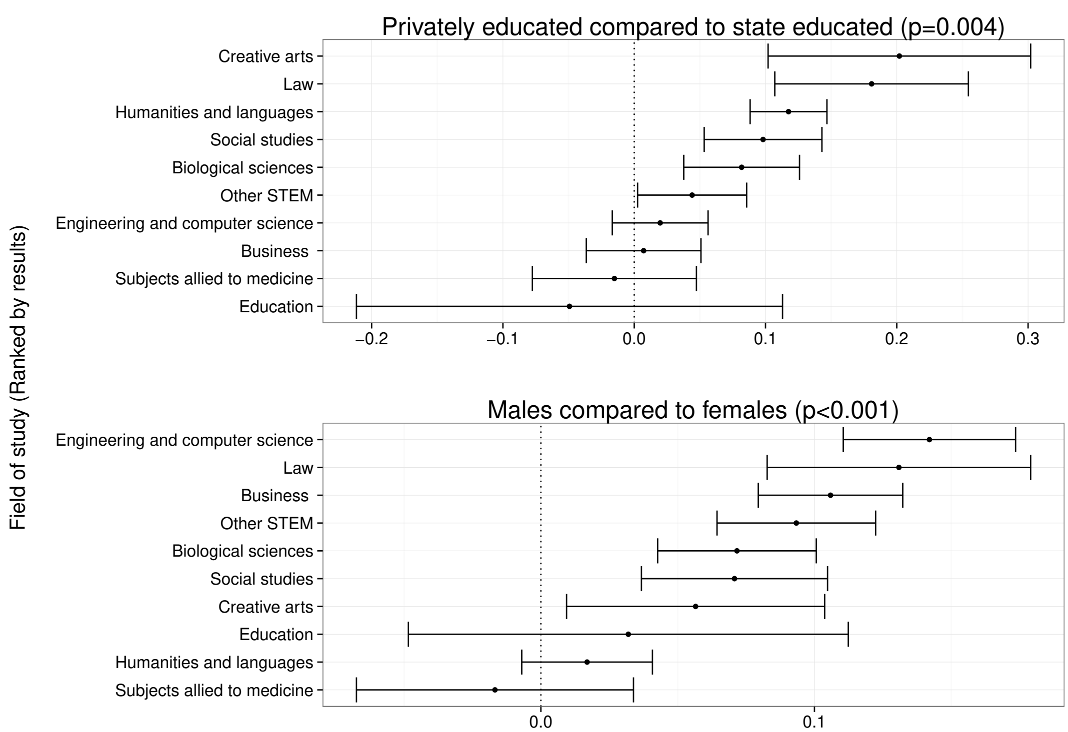

Figure 6.11: Results for models of earnings by fields of study (42 months) (2006/07): Private education and Sex

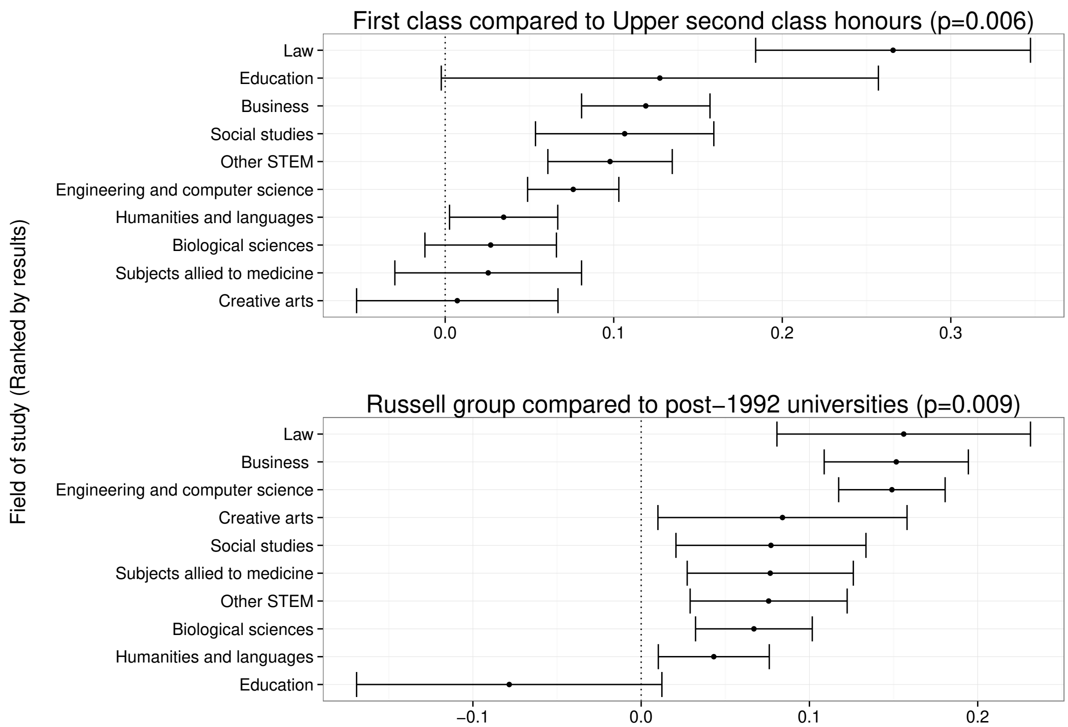

Figure 6.12: Results for models of earnings by fields of study (42 months) (2006/07): Degree classification and university type (2006/07)

The earnings gap between individuals who attended different types of HEI are lowest for those who studied Subjects allied to medicine and Education, and greatest for those studying Engineering and Other STEM subjects. This order of results seems to be fairly consistent at both 6 months and 42 months after graduation—although there is one caveat: the earnings gap also becomes particularly large for Law and Business graduates at 42 months. The difference in earnings between individuals who have a first class or an upper second honours compared to those with lower degree classifications is lowest amongst Humanities and languages graduates 6 months and 42 months after graduation. In contrast these differences can be pretty large for some fields of study, including Engineer and computer science.

Using the Wilcoxon-Mann-Whitney test, I find that the differences in earnings for graduates from Russell group and Pre-1992 universities, compared those from Post-1992 universities, are higher for individuals who studied hard subjects (p=0.12 and 0.07). However these patterns only occur for the analysis using destinations data at 6 months. No other significant patterns of differences were found between hard/soft or pure/applied subjects.

6.4 Discussion

Overall the results provides little evidence that there is a substantial link between socioeconomic background and early labour market outcomes for graduates. This includes any indirect relationships that socioeconomic background may have on outcomes through educational achievements, such as degree classification, or through education choices, such field of study or attendance at prestigious HEIs.

There is also seems to be no evidence that the relationship between socioeconomics background and labour market outcomes differs by fields of study. This is contrary to the results of Hansen (2001) and Hällsten (2013) but in line with the findings of Jackson et al (2008).

However, another potential indicator of comparative advantage can be private education prior to HE. I find overall that private education has a moderate relationship with skills use and earnings overall but there are much stronger relationships between private education and outcomes in some fields of study compared to others. The pattern of variation, for skills use at 6 months, seems to resemble that put forward by several researchers where cultural capital has a minimal impact in technical fields and a greater impact in more 'cultural' fields of study (van de Werfhorst 2002, Hansen 2001). However, this pattern does not seem to hold for earnings. Whilst the gap between graduates who had state and private education seems to be lower in Engineering and computer Science and Other STEM subjects compared to other, the differences do not seem to be particularly substantial. I also observe that modest earnings differences between state and privately educated graduate exist for graduates in the Biological Sciences—these differences are comparable to those found in individuals who studied the Creative arts, or Humanities and languages.

I find that much of the earnings gap between male and female graduates can be traced to factors related to educational achievements or choices at HE level. This is likely due to choice of field of subject (Chevalier 2006). In general the gender earnings gap does not seem to decrease with time (up to 42 months after graduation).

Much like Roska's (2005) study of graduates in the US, I find that differences in labour market outcomes by sex seem to be smaller in fields of study that have higher proportions of women. For example, only 15.1 percent and 41.9 percent of Engineering and computer science, and Other STEM graduates were women. These were the two fields of study where the gender earnings gap was particularly high. In contrast, 86.7 percent and 80.6 percent of graduates who had obtained undergraduate degrees in Education and Subjects allied to medicine were women. These were the two fields of study where the earnings gap between men and women were almost non-existent. This seems to run contrary to expectations that there ought to be less stratification between graduate by sex in more applied or hard fields of study. However, Education and Subject allied to medicine are fields of study which are also strongly associated with careers in the public sector. As a result, there were reasons to expect that the gender earnings gap would be small or non-existent in these fields before the analysis began.

The evidence does seem to support the theory that the relationship between higher education institution (HEI) and labour market outcomes does varies by fields of study (Strathdee 2009). In particular it seems that the relationship between type of HEI and labour market outcomes is particularly strong amongst STEM graduates compared to Humanities and Languages. There seems to be a mixed picture for the Creative arts. The interpretation of these results is not straightforward; some of these differences could be due to variations in the type of course offered across institutions. For instance, Russell group and Pre-1992 HEIs may be more likely to offer courses accredited by professional bodies than Post-1992 HEIs. The degree to which these accreditations may affects labour market outcomes may differ across fields of study. As such, these differences may reflect the impact of accreditation rather than the prestige of particular groups of HEIs in the labour market (Strathdee 2009). Likewise they may also reflect greater variations in course quality between institutions in some fields of study. In addition, I do not observe any substantial differences between for individuals with degrees in Education and Subjects allied to medicine.

Finally turning to degree classification, I observe strong positive relationships between possessing a first class honours degree and labour market outcomes amongst STEM graduates. In contrast, the relationship was weak for graduates who studied Humanities and languages. Furthermore, there are also strong negative relationships for achieving a lower second honours degree (or lower grade/ non-honours degree), compared to an upper second class honours, for STEM. One again, this relationship was weaker for graduates who studied the Creative arts, and Humanities and languages.

Overall I expected that differences in labour market outcomes would between graduates based on sex and socioeconomic background would be relatively smaller in fields of study where the subject matter is more technical. This expectation did not hold true for sex, where the difference in earnings between male and female graduates is particularly large for Engineering and computer science, and Other STEM subject 6 and 42 months after graduation. Differences between state and privately educated graduates are relatively low, for earnings and skills utilisation, for amongst STEM, Education and Subject allied to Medicine graduates (where results by field of study are available). However, for individuals who studied Biological Sciences the strength of the relationship between private education and labour market outcomes is comparable to that found for the Creative arts and business graduates. As mentioned before this results is interesting; Biological Sciences is a hard field of study but there seems to be indications that the labour market for these graduates is loose. However, it is only a single case and caution should be advised regarding this result.

The hypothesis that degree classification would have a greater impact in the hard or technical fields is true to some extent. Whilst the results comparing hard/soft and technical/applied subjects were not statistically significant, the overall patterns of results seem to indicate there is some tentative support for this hypothesis. I observe relatively strong relationships between degree classification and labour market outcomes in STEM fields and weak effects for the Humanities and languages. For the Creative arts, obtaining a first class honours seems to have relatively strong positive relationship with earnings and skills utilisation. However, these seem to be less of a penalty associated with obtaining another type of honours (or a non-honours degree) in the Creative arts, and Humanities and languages compared to the STEM fields.

Finally I expected differences in labour market outcomes based on sex and socioeconomic background to be lower in fields of study closely associated with employment in the public sector, such as Education and Subjects allied to Medicine. The analysis lends support to this hypothesis. I also observe relatively weaker relationships between private schooling, HEI status and degree classification, and labour market outcomes in these fields compared to others. This lends some credence to the idea that the formal hiring procedures and the bureaucratic nature of public sector institutions may have an impact on reducing inequities based on ascribed characteristics (van de Werfhorst and Kraaykamp 2001, Hällsten 2013). Nonetheless, education related factors like degree classification also have weak relationships with outcomes in these fields. One explanation is that there is simply less variations in outcomes for individuals who studied these subjects in general.

6.5 Conclusion

In this chapter I sought to see if any inequalities in earnings and skills use exist amongst graduates and whether these inequalities vary by field of study. I find that variations in stratification by sex, state/private education, HEI status, and degree classification do exist by field of study. However, these patterns of variation do not conform to prior expectations.

So far I have been limited in my abilities to test the mechanisms that explain these patterns of variation. This is because potential results may be explained by several different theories. For instance, applied subjects, such as Engineering and computer science, are also—based on the proportion of graduates in graduate jobs—fields of study where the labour market for graduate labour is tight. If the results showed that earnings differences by socioeconomic background were lower in these fields of study, it would be difficult to attribute the results to the applied nature of the subjects or labour market conditions. In this chapter I suggested comparing results for the Biological sciences, which is a non-applied hard subject with higher rates than average of graduate underemployment, to the results for other non-applied STEM fields.

Another way to do get around this problem is to make use of a natural experiments, and to find a situations where competition in the graduate labour increases but other factors remain roughly the same. This research design is used in chapter 7 where I will use data from two graduate cohorts before and after the 2008 recession to test the theoretical relationship between stratification and competition in the labour market.

Chapter 7

Competition and stratification in the labour market

In the previous chapter, I found that there exists variations in stratification by sex, degree classification, private education, and type of HEI across different fields of study. There are many possible explanations for these variations: the skills used in different occupations, hiring policies across different industries, the level of competition between graduates in different fields of study, and so forth.

I mentioned in the last chapter that it was difficult to test these competing explanations using cross-sectional data. In this chapter I will take advantage of increased competition in the graduate labour market caused by the 2008 recession to answer the question: does greater competition necessarily lead to greater stratification in the labour market? In turn this will allow me to test whether variations in stratification by fields of study is linked to competition for graduates in different subject areas.

7.1 Competition and stratification across fields of study

Researchers have used the characteristics of certain industries and occupations in the labour market to explain variations in stratification by field of study (Roska 2005, Hällsten 2013). For instance, the importance of personal or soft skills in occupations related to sales and services may advantage individuals from certain socioeconomic backgrounds over others (Jackson, Goldthorpe and Mills 2007). This has lead researchers to expect that stratification by socioeconomic background will be greater in soft and non-applied fields, compared to hard and applied subjects (Hansen 2001, Jackson et al 2008). As I mention in chapter 3, there is very limited evidence for this explanation in the empirical literature.

Another explanation is that these variations could be caused by competition in the labour market across different fields of study. As the labour market becomes loose (i.e. the supply of graduates is relatively high compared to the demand for their skills), employers may start selecting candidates basis of characteristics other than their degrees. For instance, employers may resort to using course grade or the prestige of an individuals' HEI as a screening device for new employees (i.e. a stronger C-D relationship in figure 3.1). An upper second class honours degree is commonly used by graduate recruitment scheme to pre-screen potential applicant (Brown and Hesketh 2004). Furthermore employers may start to discriminate between potential employees based on ascribed characteristics, such as gender, instead (resulting in a stronger A-D relationship).

This is not inconsistent with the idea that qualifications are signals for other desirable characteristics that employers may look for (Arrow 1973). Individuals who are more patient, quicker to adapt, or have greater general cognitive ability may be more likely to get degrees. Individuals with these characteristics may also be more productive in the workplace, making it potentially advantageous for employers to use a degree as a signal for productivity. However, as more individuals acquire HE qualifications, the signalling role of a degree would become weaker leading employers to seek other signals for productivity (Jackson, Goldthorpe and Mills 2005).

As the ratio of graduates to available graduate jobs increases, individuals have to make more effort to stand out from their competitors (Brown 2013). The subset of graduates who are able to obtain graduate jobs is likely to become increasingly less representative of the general graduate population. For instance, greater competition in the graduate labour market can be caused by a decline in the number of graduate jobs in the labour market. When employers are forced to make redundancies they may choose to lay off the least productive members of their workforce first. If degree classification was associated with productivity, this will mean that graduates with lower degree classifications are made redundant before graduates with higher degree classifications. This in turn would increase any existing differences in labour market outcomes between individuals with different degree classifications.

The state of competition for graduates in different field of study may vary for many reasons. There has been an increase in the number of individuals leaving higher education with undergraduate and postgraduate degrees in the UK since the 1990s. However this increase has not been uniform across all subject areas. Table 3.2 shows the increase in the number of HE leavers with an undergraduate degrees between the academic years 2002/03 and 2012/13. Figure 7.1 displays the growth in leavers over that period for selected subject areas.

It can be seen that whilst student numbers in subject areas such as Education and the Biological sciences have seen relatively high growth throughout that period (93.9% and 79.5% respectively), other subjects have experienced much weaker growth. For instance, the number of HE leavers with undergraduate degrees in the Computer sciences has actually fell by 11.8 percent between the 2002 and 2012, although the subject area did experience some growth in numbers in the late 1990s.

Since new leavers from HE may be an important supply line of new workers for many occupations, the unequal growth in graduate numbers across subject areas would in theory have some effect on the competition for work. All else being equal, we may expect that the competition for graduates jobs to be stronger in subject areas where there has been more growth in the numbers of leavers with undergraduate degrees.

In summary, the theoretical relationship between competition, stratification, and fields of study can be stated in three points:

1) More competition between graduates in the labour market will results in greater stratification.
2) The competition between graduates in the labour market graduates varies by their field of study. The demand for graduates in some fields, relative to supply, may be particularly high compared to others.
3) Given points 1 and 2, this causes the relationship between different factors—sex, socioeconomic background, and so forth—and labour market outcomes to vary across fields of study.

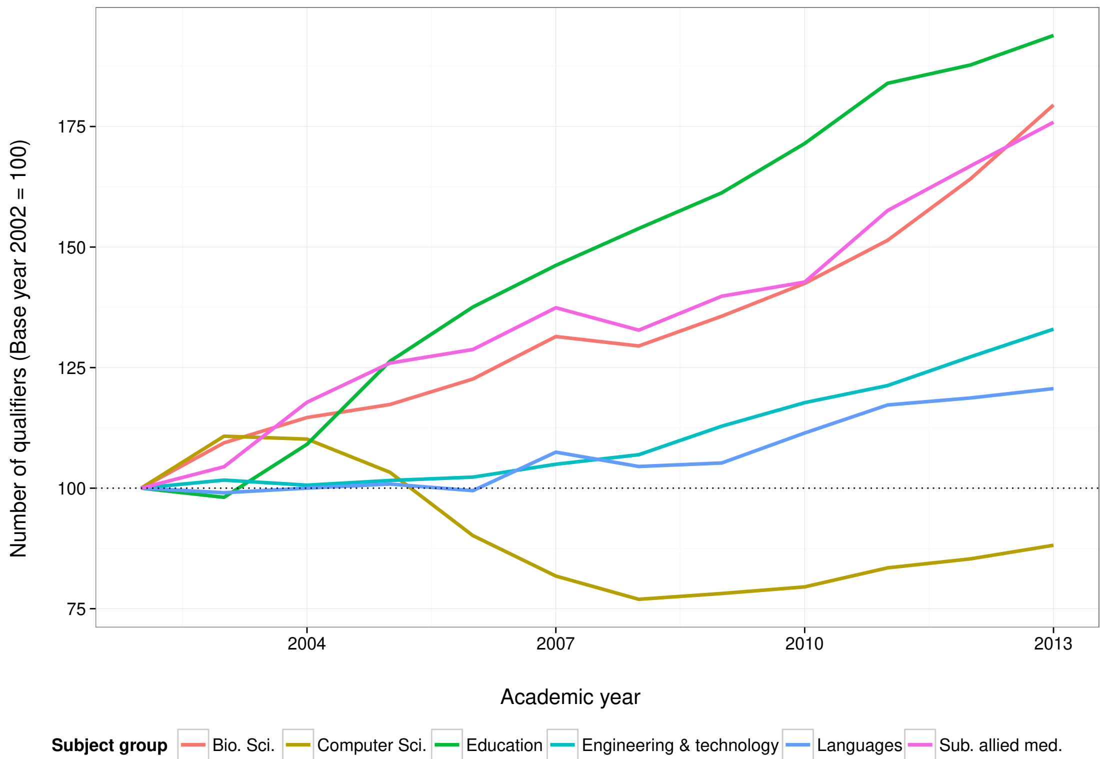

Figure 7.1: Growth in number of individuals qualifyng with undegraduate degrees across selected fields of study by academic year (2002-2013) (Source: HESA)

In order to examine whether this is the case, I will test the hypothesis that greater competition leads to greater stratification in the labour market. This point is essential to the argument outlined aboved. To do this I will use information about the labour market destinations of individuals from two different graduate cohorts. One cohort graduated prior to the 2008 financial crisis and recession, and the other cohort shortly after the event.

7.2 Using the 2008 recession as a natural experiment

The recession can be used as a natural experiment to see whether increased competition in the labour market leads to greater stratification amongst graduates. The demand for labour during the recession was reduced as household consumption fell and businesses suddenly found it increasingly difficult to obtaining loans during a credit crunch (Jenkins 2010, Gittins and Luke 2012). At the same time, the number of new graduates leaving HE shortly before and after the recession is unaffected by the event itself. This is because the average time taken to complete a full-time undergraduate degree is between three to four years. In short, since the number individuals leaving HE with undergraduates degrees before and after the recession will be roughly the same, any corresponding fall in demand for labour as a result of the recession will lead to greater competition between new graduates in the labour market.

Data from the labour force survey shows that in the first quarter of 2008 graduate unemployment amongst recent graduates (>2 year) was at 10.1 percent. However by the first quarter of 2010 it had risen to 20.7 percent. This was peak of graduate unemployment following the recession. As mentioned in chapter 4, the DLHE survey captures the activities of graduates 6 months after they leave HE. For

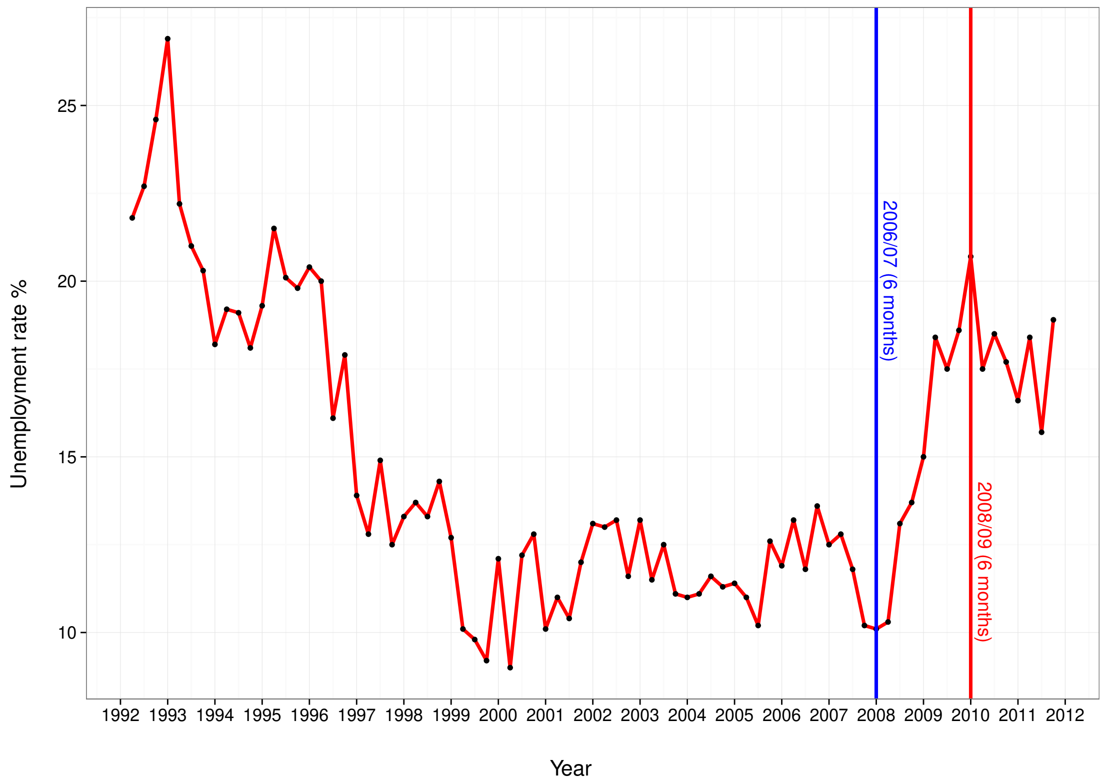

Figure 7.2: Unemployment rate for recent graduates (<2 years) (Source: ONS 2012a, 2013)

the majority of leavers the DLHE captures their activities in January of the following year[1]. For the 2006/07 graduate cohort, the DLHE captures their activities on 14th January 2008 and for the 2008/09 cohort it captures their activities on 11th January 2010. By coincidence, these two dates correspond to periods, before and after the recession, when the rates of graduate unemployment were at their lowest and highest (figure 7.2). In chapter 5 I mentioned that many graduates started looking for work one year before they finished their study, and most graduate schemes start recruitment one year before their start dates. Even if leavers in the 2008/9 cohort had obtained their jobs one whole year prior to graduating, they still would have had to find work in 2009 when levels of graduate employment were still higher than before the recession.

Information from the DLHE surveys also support the idea that the level of competition in the labour market was greater for leavers from the 2008/09 cohort. Tables 7.1 shows the proportion of employed graduates in full-time graduate jobs, as defined by the SOC(HE)2010. Across most subject there was a clear drop in the proportion of individuals in full-time graduate jobs 6 months after leaving HE across the two cohorts. For instance, the proportion of Humanities and languages graduates in graduate jobs dropped by 10.1 percent. The proportion of individuals in full-time graduate roles actually remain fairly stable for graduates from the two cohorts 42 months after leaving HE. These similarities may be due in part to the slow rate of recovery from the recession in the UK which results in similar labour market conditions across these two reporting periods (i.e. 29th November 2010 and 26th November 2012 respectively). In addition, the impact of the economic recession was particularly severe for new graduates whilst the increase in unemployment was far less for more experienced graduates (ONS 2012). As a result, it is unlikely stratification in the labour market will differ much for graduates

[1]The majority of HE leavers graduate between January and July.

Table 7.1: Proportion of employed graduates in full time graduates jobs

	6 months after leaving HE			42 months after leaving HE		
Field of study	2006/07	2008/09	Difference	2006/07	2008/09	Difference
Law	26.53%	19.37%	-7.15%	86.82%	88.84%	2.02%
Biological sciences	28.62%	20.82%	-7.81%	83.93%	82.51%	-1.41%
Humanities and languages	35.74%	25.63%	-10.11%	80.69%	79.50%	-1.19%
Creative arts	37.20%	26.96%	-10.24%	77.54%	76.21%	-1.33%
Social studies	41.95%	35.51%	-6.44%	83.31%	83.51%	0.20%
Other subjects	49.32%	38.57%	-10.75%	90.30%	82.95%	-7.35%
Other STEM	49.81%	39.88%	-9.93%	88.21%	88.16%	-0.05%
Business	52.28%	44.06%	-8.22%	90.12%	87.92%	-2.20%
Education	63.84%	58.36%	-5.48%	84.78%	84.16%	-0.62%
Engineering and computer science	65.19%	62.23%	-2.97%	90.57%	88.73%	-1.84%
Subjects allied to medicine	73.92%	76.68%	2.75%	89.87%	90.14%	0.27%
Medical and veterinary sciences	98.84%	98.71%	-0.13%	90.67%	90.81%	0.14%

Note: Under 21 at the beginning of their studies; Leavers with undergraduate degrees

in these two cohorts at 42 months.

Since these two cohorts graduated so close in time, we can reasonably assume that other relevant labour market factors will remain the same across the two periods. For instance, the skills demanded to become an engineer or a manager would not have changed within two years. The quality of degrees offered by different universities and the subject contents of their degree programmes will also not have changed substantially in two years. Furthermore, we have no strong reasons to believe that the characteristics of individuals between the two cohorts would differ—although there is *one* potential caveat.

Tuition fees were introduced across the UK in 1998 and the amount remained the same until the cap on fees was raised starting in the academic year 2006/07. Whist tuition fees remained the same for individuals across both graduate cohorts, it is plausible that the 2008/09 cohort has a slightly different composition to the 2006/07 cohort due to the then expected increases in tuition fees. Many member of the 2008/09 cohort would have entered HE in the academic year 2005/06; the year prior to the introduction of tuition fees for students domiciled in England and Northern Ireland. Some of these individuals may have otherwise deferred entry to HE that year had the fees system not changed. These individuals who would have deferred may be different from non-deferring individuals in a number of ways. For instance, deferrers may come from more advantaged backgrounds or may be more likely to study non-applied subjects. Many of these differences may be observed and therefore already accounted for in subsequent analyses. The addition of deferrers also increases the number of students entering in a particular academic year. Participation in HE between the academic years 2005/06 and 2006/07 rose from 32.1 percent to 34 percent (see table D.1). This likely to have a small effect on the numbers of graduates leaving HE in 2008/09. If this increase in participation had any effects at all, it will only have further increased the level of competition experienced by the 2008/09 cohort.

7.3 Analysis

The outcomes of interest in this chapter are skills use and earnings. As in chapter 6, I use logistic regression to model the probability that an individual is in a graduate job and multiple linear regression to model earnings. In both cases, the outcomes are regressed on a number of predictors: age, ethnicity, socioeconomic background, disability status, sex, domicile prior to HE, UCAS tariff, private education, degree classification, and an indicator of whether an individual has postgraduate qualifications (42 month results only). Estimates are obtained for all graduates (using dummy variables for field of study) and for each field of study individually. The results of the analysis using the 2006/07 and 2008/09 cohort are compared to see if the relationship between predictors and labour market outcomes differ across the two cohorts.

One issue is that I am still examining labour market outcomes for full-time employed graduates working in the UK. As the labour market changes, the chances of observing an individual working full-time will also change. Furthermore, during a recession, more graduates may choose to go into further study instead of entering the labour market. Consequently, regression estimates may differ across the two graduate cohorts due to sample selection bias. The whole analysis is repeated using control functions to account for sample selection bias in order to test the sensitivity of the results. The results of this additional analysis is reported in appendix A.

7.4 Results

7.4.1 Skills use

I compare partial correlation coefficients between certain predictors and skills use across the two cohorts. For the analysis of destinations at six months after leaving HE, I find that the results are remarkably similar across the two cohorts (table D.12). Selected results are presented in table 7.2. There are no statistically significant differences in the partial correlation coefficients for sex, socioeconomic background, HEI status and degree classification across the two graduate cohorts. This is true for outcomes at both 6 and 42 months after graduation.

Partial correlations by field of study for the 2006/07 and 2008/09 cohorts are reported in tables D.6 and D.13 respectively. These results pertain to graduate destinations at 6 months. The 42 month results are displayed in tables D.7 and D.14. The difference in partial correlation coefficients for selected predictors are reported in table D.15. Across fields of study I do not observe any substantial differences in the results of the 2006/07 and 2008/09 cohorts—with a few minor exceptions. The partial correlations between skills use and socioeconomic background increased for Creative arts graduates (6 months). The partial correlation between skills use and private education increased for Engineering and computer science graduates (6 months).

7.4.2 Earnings

Comparing results across the two cohort for earning for all graduates (tables 7.4), I find similar results for earnings as I did for skills use with minor exceptions. The earnings differences associated with socioeconomic background, sex, private education, degree classification, and type of HEI do not change across the two cohorts. This is true for outcomes 6 months after graduation. Furthermore these results are not affected by sample selection bias (appendix A). The results at 42 months show that the earnings difference associated with socioeconomic background increased between the two cohorts. The earnings difference associated with private education and attending a pre-1992 university decreased between the two periods of time. As I mentioned previously it is unclear what the 42 months results mean in this

Table 7.2: Selected results for partial correlations with skill utilisation using graduates from all fields of study

Predictor	6 months		42 months	
	2006/07	2008/09	2006/07	2008/09
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.018 (0.008)*	0.021 (0.009)*	0.008 (0.013)	0.020 (0.011)
–Managerial or professional	0.028 (0.008)*	0.030 (0.009)*	0.020 (0.013)	0.038 (0.011)*
Male	0.055 (0.008)*	0.058 (0.008)*	0.023 (0.014)	0.038 (0.011)*
Privately educated	0.031 (0.008)*	0.052 (0.009)*	0.038 (0.015)*	0.034 (0.012)*
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.090 (0.009)*	0.118 (0.009)*	0.077 (0.015)*	0.080 (0.013)*
–Other degree class	-0.102 (0.008)*	-0.088 (0.009)*	-0.092 (0.013)*	-0.089 (0.011)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.082 (0.008)*	0.063 (0.009)*	0.023 (0.013)	0.018 (0.011)
–Russell group university	0.086 (0.008)*	0.091 (0.009)*	0.067 (0.014)*	0.063 (0.012)*
N	23889	20564	8104	11922

*$p<0.05$

Table 7.3: Selected results for models of (log) earning using graduates from all fields of study

Predictor	6 months		42 months	
	2006/07	2008/09	2006/07	2008/09
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.016 (0.006)*	0.019 (0.006)*	0.003 (0.012)	0.034 (0.010)*
–Managerial or professional	0.021 (0.005)*	0.022 (0.006)*	0.022 (0.011)*	0.050 (0.010)*
Male	0.062 (0.004)*	0.055 (0.004)*	0.078 (0.008)*	0.072 (0.007)*
Privately educated	0.065 (0.005)*	0.055 (0.006)*	0.075 (0.011)*	0.057 (0.010)*
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.066 (0.005)*	0.077 (0.005)*	0.077 (0.010)*	0.079 (0.009)*
–Other degree class	-0.055 (0.004)*	-0.051 (0.005)*	-0.088 (0.009)*	-0.094 (0.008)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.071 (0.005)*	0.063 (0.005)*	0.070 (0.010)*	0.029 (0.009)*
–Russell group university	0.094 (0.005)*	0.090 (0.005)*	0.101 (0.010)*	0.106 (0.009)*
N	23889	20564	8104	11922

*$p<0.05$

Table 7.4: Results for models of (log) earning using graduates from all fields of study

Predictor	6 months		42 months	
	2006/07	2008/09	2006/07	2008/09
Intercept	9.540 (0.012)*	9.498 (0.013)*	9.863 (0.027)*	9.854 (0.023)*
Age (Base=18)	0.036 (0.002)*	0.042 (0.002)*	0.025 (0.005)*	0.030 (0.004)*
Non-white ethnicity	0.018 (0.006)*	0.006 (0.007)	-0.012 (0.012)	0.003 (0.011)
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.016 (0.006)*	0.019 (0.006)*	0.003 (0.012)	0.034 (0.010)*
–Managerial or professional	0.021 (0.005)*	0.022 (0.006)*	0.022 (0.011)*	0.050 (0.010)*
Has a known disability	0.008 (0.007)	-0.009 (0.007)	-0.067 (0.013)*	-0.019 (0.011)
Male	0.062 (0.004)*	0.055 (0.004)*	0.078 (0.008)*	0.072 (0.007)*
Domicile prior to HE				
(Ref: London)				
–North England	-0.154 (0.007)*	-0.125 (0.007)*	-0.125 (0.015)*	-0.145 (0.013)*
–Northern Ireland	-0.238 (0.012)*	-0.226 (0.012)*	-0.250 (0.018)*	-0.257 (0.017)*
–Scotland	-0.141 (0.008)*	-0.104 (0.010)*	-0.093 (0.017)*	-0.117 (0.016)*
–SE and East England	-0.057 (0.006)*	-0.048 (0.007)*	-0.038 (0.014)*	-0.039 (0.012)*
–SW and Mid England	-0.128 (0.006)*	-0.096 (0.007)*	-0.097 (0.014)*	-0.098 (0.012)*
–Wales	-0.150 (0.010)*	-0.108 (0.011)*	-0.150 (0.019)*	-0.140 (0.017)*
UCAS tariff quartile				
(Ref: 1st Quartile)				
–2nd Quartile	0.017 (0.005)*	0.029 (0.005)*	0.027 (0.009)*	0.028 (0.008)*
–3rd Quartile	0.034 (0.006)*	0.046 (0.006)*	0.071 (0.012)*	0.056 (0.010)*
–4th Quartile	0.038 (0.006)*	0.030 (0.006)*	0.057 (0.012)*	0.021 (0.011)*
Privately educated	0.065 (0.005)*	0.055 (0.006)*	0.075 (0.011)*	0.057 (0.010)*
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.066 (0.005)*	0.077 (0.005)*	0.077 (0.010)*	0.079 (0.009)*
–Other degree class	-0.055 (0.004)*	-0.051 (0.005)*	-0.088 (0.009)*	-0.094 (0.008)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.071 (0.005)*	0.063 (0.005)*	0.070 (0.010)*	0.029 (0.009)*
–Russell group university	0.094 (0.005)*	0.090 (0.005)*	0.101 (0.010)*	0.106 (0.009)*
Field of study [Ref: Biological sciences]				
–Business	0.162 (0.007)*	0.138 (0.007)*	0.129 (0.015)*	0.161 (0.014)*
–Creative arts	-0.023 (0.008)*	-0.038 (0.009)*	-0.093 (0.017)*	-0.070 (0.016)*
–Education	0.225 (0.010)*	0.282 (0.010)*	0.133 (0.026)*	0.151 (0.021)*
–Engineering and computer science	0.228 (0.007)*	0.222 (0.008)*	0.161 (0.015)*	0.176 (0.014)*
–Humanities and languages	0.018 (0.007)*	-0.013 (0.007)	-0.036 (0.014)*	-0.019 (0.012)
–Law	0.078 (0.010)*	0.055 (0.012)*	0.080 (0.018)*	0.090 (0.017)*
–Other STEM	0.144 (0.008)*	0.121 (0.009)*	0.097 (0.015)*	0.105 (0.013)*
–Social studies	0.140 (0.007)*	0.147 (0.008)*	0.086 (0.016)*	0.098 (0.015)*
–Subjects allied to medicine	0.147 (0.008)*	0.222 (0.008)*	0.207 (0.018)*	0.236 (0.016)*
Has postgraduate qualifications			0.011 (0.009)	0.001 (0.008)
Residual SD	0.261	0.266	0.318	0.345
R-square	0.24	0.23	0.20	0.17
N	23889	20564	8104	11922

*p<0.05

context given that the labour market conditions for leavers in the 2006/07 and 2008/09 cohorts are so similar at this point in time.

Turning to the results of the analysis by fields of study, the results for earnings 6 months after graduation are reported in tables D.10 and D.16. Results for outcomes at 42 months are reported in tables D.11 and D.17. I find that the results across the two years stayed the roughly same across all fields of study (table D.18).

7.5 Discussion and conclusion

In general, I do not observe any significant changes in the relationship between socioeconomic background, sex and educational characteristics, and labour market outcomes as result of the recession. Whilst there were exceptions these results are generally confined to outcomes at 42 months or for certain fields of study. These exceptions are few, and do not present any sort of consistent pattern.

The results are counter-intuitive, and run against my expectations about the relationship between competition and inequalities (Jackson, Goldthorpe, and Mills 2005; Brown and Hesketh 2004). The recession caused a very significant and observable change in the conditions of the labour market for new graduates. Rising rate of unemployment and skills mismatch amongst new graduates indicate that individuals from the 2008/09 cohorts *did* graduate into a more competitive labour market.

There are a few post-hoc explanations for the lack change in stratification before and after the recession. First some graduates may have chosen to pursue further studies instead of looking for work when the labour market became more competitive. As such, we do not observe their labour market outcomes. In appendix A.3.2, I try to account for the impact of sample selection on the results of the analysis for earnings. Even after accounting for sample selection I do not find any substantial differences in results between the two graduate cohorts. However, it could be likely that I have failed to sufficiently account for sample selection bias.

Secondly, the recession had a strong and sudden effect on the labour market through a change in the demand for labour. Many researchers, when writing about the link between labour market competition and inequalities, usually focus on long-term mismatches between labour supply and demand. One relevant example is the increased participation of individuals going into higher education over time and the concern that are not enough jobs that make use of their skills (Brown 2013). Due to the sudden nature of the recession, any adjustments that employers make to their hiring strategies may be varied and inconsistent in the short term. In the long term, more consistent screening strategies may emerge—resulting in clearer and stronger patterns of stratification as time goes on. In addition, I only present results pertaining to early graduate outcomes up to 42 months after leaving HE and therefore may not capture the impact of increased competition on long term outcomes.

The results of the analysis done in this chapter does not support the theory that greater competition necessarily leads to greater stratification between graduates in the labour market. As a consequence, any variation in stratification by field of study is unlikely to be explained by competition in the labour market. In the next chapter I explore other explanations based on employer characteristics and the type of skill required across different occupations (Hällsten 2013, Jackson, Goldthorpe, and Mills 2005, Hansen 2001).

Chapter 8

Employer bureaucracy and the demand for skills across occupations

The previous chapter looked at whether patterns of stratification across fields of study can be explained by competition in the labour market. Using the 2008/09 recession as a natural experiment, I find little support for the argument—which is also central to positional competition theories—that stratification in the labour market is affected by increased competition (Thurow 1972, Brown and Hesketh 2004, Arrow 1973). Now I examine the level of bureaucracy in a firm and the demand for skills in different occupations as possible explanations for the existence of variations in stratification (Hällsten 2013, Hansen 2001).

8.1 Employer bureaucracy

One of the defining features of a bureaucratic organisation is the existence of rationally determined explicit rules that govern decision-making (Weber 1968). Bureaucratic firms will be more likely to have formal procedures for appointing employees, with the purpose of hiring and promoting the most productive individuals. This property may reduce inequality between workers based on ascribed characteristics, which do not affect productivity, in bureaucratic organisations (Hällsten 2013). The use of these procedures reduces the discretionary power of individuals who are responsible for making appointment. As a consequence, this reduces the effects of any conscious or unconscious biases that bosses or employers may have on recruitment and promotions.

In practise, the type of methods employers use for selecting new hires or evaluating current employees can vary. The validity of these methods is usually assessed in terms of the correlation between the evaluations made by an assessment technique and some outcome of actual job performance (e.g. hourly output of a worker). Meta-analyses show that tests of general mental ability have the greatest validity whilst unstructured interviews have very poor validity (Schmidt and Hunter 1998, Robertson and Smith 2001). In cases, where selection is based on assessment techniques with high validity the appointment of individuals is more likely to be based upon meritocratic principles (i.e. job performance) rather than the personal preferences of bosses or recruitment staff.

However, there are concerns that these assessment methods may favour individuals who have some knowledge about how to succeed in these types of assessment. In particular, this advantage graduates who, through their social networks or family, have greater awareness of the assessment techniques used in different organisation (Brown and Hesketh 2004; Bathmaker, Ingram, and Waller 2013).

In many studies the size of a firm is commonly used as an indicator of the level of bureaucracy in an organisation (Hällsten 2013, Mastekaasa 2004). There is some evidence that smaller firms in the UK are less likely to use formal assessment techniques when hiring new employees (Jenkins and Wolf 2002; Campbell, Lockyer and Scholarios 1997). For instance, Bartram et al (1995) compiled information from different studies and found that only 3.6 percent and 15.3 percent of small business used personality questionnaires, and ability and aptitude tests when hiring young people (p. 354). In comparison, another similar study found that 30 percent and 68.3 percent of large and medium businesses used these assessment methods when hiring young people (Bartram, Lindley and Foster 1992).

Furthermore, smaller firms may be less likely to use formal means of recruitment, such as job advertisements. These firms may rely more heavily on informal means, such as employee referrals, to recruit, favouring groups of people with larger and more diverse social networks (Carroll et al 1999, Lin 1999).

There are several reasons why smaller organisations may be less likely to have to formal and structured approaches to appointing employees. By their nature larger firms are more likely to hire new employees on a regular basis. To minimise repeated transaction costs, they may install more formal recruitment procedures and have dedicated Human Resources staff. Furthermore, larger organisations may be more visible and open to scrutiny from regulators and the public (Barber et al 1999). This will also be the case for public sector employers. Under the Equalities Act 2010, employers are obliged to not discriminate on the basis of sex, ethnicity and so forth. However public sector employers may experience greater pressures to eliminate discriminatory practises given the nature of their relationship with the government.

Turning to fields of study, different subjects are related to work in different occupations and industries. Some industries, such as education, are dominated by large employers and employers in the public sector. For graduates in fields related to these industries, there is less potential for discrimination due to the high level of bureaucracy amongst employers in these industries. As I mentioned before, bureaucracy will reduce inequalities based on ascribed characteristics so long as these characteristics are not associated with productivity. For instance, if workers from advantaged socioeconomic backgrounds were not somehow more productive than other workers. However this assumption may not be true.

8.2 The skills demanded by different occupations

Different occupations make use of different sets of skills. In jobs that require a large degree of 'personal' skills, such as communication or leadership, there might be a stronger association between socioeconomic background and career success (Jackson, Goldthorpe and Mills 2005; Jackson 2007). Upbringing and life experiences may give individuals from advantaged backgrounds the chance to acquire valuable personal skills. This would be give people from advantaged backgrounds a competitive edge in certain occupations. We may further extend the argument to privately educated individuals; privately educated students may have more acquaintance with elite cultural settings or access to more power social networks which in turn gives them an advantage in certain occupations.

Since different fields of study are associated with different occupations, the advantages associated with socioeconomic background or private education will vary by field of study. In contrast we would not expect socioeconomic background or private education to be associated with labour market outcomes——after accounting for educational attainment——in occupations which make greater use of technical expertise (Hansen 1996; Hansen and Mastekaasa 2006). Furthermore since factors like socioeconomic background may be associated with higher productivity in some jobs, workers from advantaged backgrounds may earn more than similar workers in jobs that make use of personal skills.

Given the theoretical relationship between stratification, and employer bureaucracy and skill demands, I will answer the following research questions:

1) Is there an association between ascribed characteristics, educational attainment, and the skills used in an occupation? Do different skills, such as Communication and Expertise, have varying relationships with earnings?

2) To what extent are variation in stratification by fields of study explained by bureaucracy and the skills used in an occupation?

8.3 Analysis

In this chapter, I use information from both the DLHE and Longitudinal DLHE survey for 2006/07 and 2008/09. I will only comment on results for HE leavers from the 2006/07 cohort to save space. I use the SOC(HE)2010 measure of skills as an indicator of the skills used in an occupation (see chapter 4 and appendix A). Three types of skills are recorded by the SOC(HE)2010: Expertise, Orchestration, and Communication skills. The skills used in an occupation are ranked on a scale from 1 to 9 (lowest to highest level of skills use). Orchestration and Communication skills can be categorised as personal skills, and can be acquired through experiences outside of formal education. Expertise is much more likely to be acquired through formal education itself (Elias and Purcell 2010).

8.3.1 The relationship between different characteristics and the type of skills used in a job

In order to evaluate whether there is an association between ascribed characteristics or educational achievements and the skills used in a job, I use ordinal logistic regression models and the KHB method introduced in chapter 4 to extract partial correlation coefficients (Breen, Holm and Karlson 2013). Proportional odds are assumed in the ordinal logit models (McCullagh 1980). Separate models were estimated using the level of Expertise, Orchestration, and Communication skills required in an occupation as the outcome [1]. Predictors included age, sex, ethnicity, disability status, private education, type of university classification, domicile, UCAS tariff, field of study, and highest qualification obtained (for the 42 month results). The association between predictors and each of the three type of skills can be compared using their partial correlation coefficients. I use multiple linear regression to estimate

[1] The skills scores are rounded to the nearest whole number.

the relationship between skills and earnings. The model includes all the predictors mentioned earlier (e.g. sex, degree classification etc.) as well as employer location, employer size and the SOC(HE)2010 skills. This essentially the *Employer size and skills* model that I will mentioned in the next section.

8.3.2 Explaining variations in stratification by field of study

To answer the second research question, I will compare the results of five different regression models of earnings. I will only focus on earnings for this analysis. Robust standard errors are used to account for heteroskedasticity by fields of study (White 1980). If employer bureaucracy and skills explained the existence of variations in stratification by fields of study, then these variations ought to reduce or disappear entirely once we account for bureaucracy and the skills use in an occupation.

Modelling strategy

Model one uses information includes all graduates and includes the same predictors used in the analysis of earnings in chapters 6 and 7: age, sex, ethnicity, socioeconomic background, disability indicator, domicile, UCAS tariff, indicator of private education, degree classification, university type, field of study, and whether an individual has received any additional qualifications (42 month results only). In addition, in the model I fit interactions between fields of study and the following predictors: ethnicity, sex, UCAS tariff, an indicator of private education, degree classification, and type of HEI. This is because the relationship between these predictors and earnings varies across fields of study (as shown in chapter 6). I will refer to this model as the *No Employers Predictors* model.

Model two includes all the same information as model one plus the three SOC(HE)2010 skills, employer size, and employer location as predictors. I will refer to this model as the *Employer Size and Skills* model. Another indicator that is used by researchers for bureaucracy is whether an employer is in the private or public sector. Unfortunately this information is absent from the DLHE survey. The model also includes between interactions the skills used in a job, and sex, private education, degree classification, and type of HEI. This is to account for any extra rewards that workers may receive for being in a job that matches their particular set of skills or strengths (van de Werfhorst 2002b). Model three uses the same predictors as model two but omits SOC(HE)2010 skills (and its interactions) as predictors (*Without Skills*). In contrast, model four uses the same predictors as model two but omits employer size (*Without Employer Size*). Model five has the same predictors as model two but replaces the SOC(HE)2010 skills with dummy variables (or fixed effects) for occupation using 4 digit SOC(HE)2010 codes.

In summary the predictors contained in each of the five models are:

1) Model one: All pre-employment information plus interaction terms between fields of study and certain predictors (***No Employer Predictors***).

2) Model two: All pre-employment information plus interaction terms between fields of study and certain predictors plus employer size, location and skills required for a job (along with interactions terms) (***Employer Size and Skills***).

3) Model three: All pre-employment information plus interaction terms between fields of study and certain predictors plus employer size and location (***Without Skills***)

4) Model four: All pre-employment information plus interaction terms between fields of study and certain predictors plus skills required for a job and location (***Without Employer Size***)

5) Model five: All pre-employment information plus interaction terms between fields of study and certain predictors plus fixed effects for occupation, employer size and location (***Occupation and Employer Size***)

Estimating variations in stratification by field of study

For each model I calculate the variance in the parameters associated with sex, private education, type of university and degree classification across different fields of study.

For clarity, let $\tilde{\beta}_{\text{jks}}$ be the earnings difference associated with predictor k in field of study s as estimated by model j. The subscript $k = 1,\ 2 \ldots K$ can stand for sex, private education and so forth, $s = 1, 2 \ldots S$ indicates a field of study, and j corresponds to one of the five model mentioned above. For example, $\beta_{1,1,2}$ could stand for the estimated difference in earnings between men and women (i.e. $j = 1$ stands for sex) in the Biological sciences ($s = 1$) as estimated in model 2 (or the *Employer Size and Skills* model, $j = 2$). $\tilde{\beta}_{\text{jks}}$ is merely estimate of the real unknown earnings difference β_{jks} associated with predictor k in field of study s. Using the previous example, β_{jks} could stand for the difference in earnings between similarly educated men and women with degrees in the Biological sciences in the actual graduate population.

I wish to capture how β_{jks} varies by field of study and one measure of that is the variance of β_{jks} which I will refer to as σ^2_{jk}. This variance can be estimated by:

$$\frac{\left[\sum_{s=1}^{S}\left(\tilde{\beta}_{\text{jks}} - \beta_{\text{jk}}\right)^2 - \sum_{s=1}^{S} Var(\tilde{\beta}_{\text{jks}})\right]}{S}$$

Where β_{jk} is the mean of $\tilde{\beta}_{\text{jks}}$ taken all fields of study, and $Var(\tilde{\beta}_{\text{jks}})$ is the square of the standard error for $\tilde{\beta}_{\text{jks}}$. S is the number of fields of study that we have. In short, σ^2_{jk} is simply the variance in $\tilde{\beta}_{\text{jks}}$ across different fields minus the mean of the square of the standard error for $\tilde{\beta}_{\text{jks}}$ across all fields of study[2]. Larger values for the estimate of σ^2_{jk} indicates greater variations in the relationship between predictor k and earnings across fields of study.

Comparing the size of variations in stratification after accounting for different factors

To evaluate whether variations in stratifications by field of study can be explained by bureaucracy or skill, I compare the estimates of σ^2_{jk} across the different five models mentioned previously. For the sake of example let $k = K$ denote sex and σ^2_{jK} denote variations in the earnings difference between men and women across fields of study. Estimates of σ^2_{1K} corresponds to the variance in model one (or the *No Employers Predictors* model) and represents variations in the gender earnings gap for graduate across different fields of study after accounting for various pre-employment predictors. If bureaucracy or skills used in a job was responsible for these variations in the gender earnings gap then we would expect these variations to reduce once we account for employer size and skills, as well as employer location, in model two (i.e. $\sigma^2_{2K} < \sigma^2_{1K}$).

[2]Any uncertainty in the regression estimates for β_{jks} are not of interest and since this is a known quantity it can be eliminated when we attempt to estimate σ^2_{jk}.

I simply extend this approach to see whether any reductions in variation can be attributed to skills or bureaucracy alone. If bureaucracy is an explanation for variations in the gender earnings gap then σ^2_{jK} ought to be higher in the model that does not account for employer size. Therefore we can compare estimates of σ^2_{jK} between model two (*Employer Size and Skills*) and model four (*Without Employer Size*), which only account for skills. If skills explained some of the variation then we would expect $\sigma^2_{2K} > \sigma^2_{4k}$. Similarly if skills required in an occupation explained some of the variations in stratification then $\sigma^2_{2K} > \sigma^2_{3K}$.

Finally we can compare values of σ^2_{jK} in models two (*Employer Size and Skills*) and five (*Occupation and Employer Size*) to see how much of the variance can be attributed to factors related to occupation, employer size and employer location. Factors related to occupation includes the skills required for an occupation as well as other unknown factors. The results of the analysis are contained in tables D.21 and D.22 for the 2006/07 cohort. Similarly results using outcomes at 6 months and 42 months are displayed in tables D.23 and D.24. Since the variance parameter σ^2_{jk} has no meaningful scale, I will use the standard deviation σ_{jk} in figures and tables.

8.4 Results

8.4.1 The relationship between different characteristics and the type of skills used in a job

The full results of the analysis looking at the relationship between predictors and each SOC(HE)2010 skill are reported in table D.19. Selected results for are presented in table 8.1. There is a strong degree of variation in the association between certain characteristics and the type of skills used in an occupation.

There is a modest positive correlation between being male, and both the level of Expertise and Orchestration skills used in a job (0.08 and 0.07) but not in the level of Communication skills used. Degree classification has a modest correlation with levels of Expertise but has a weak correlations with Orchestration and Communication. Attending a Pre-1992 or Russell group university has a modest positive correlation with both Expertise and Orchestration but not Communication skills. Finally private schooling is positively correlated with higher Orchestration skills (0.05) and weakly correlated with Communication skills (0.03). There seems to be no correlation between private schooling and Expertise skills after accounting for other factors such as field of study. This seems to be in line with expectations that private school is associated with certain characteristics or a higher degree of personal capital that employers may hold in high regard for certain graduate roles (Brown and Hesketh 2004). Contrary to expectations, socioeconomic background seems to have little to no correlation with skills use in a job (Jackson, Goldthorpe and Mills 2005, Jackson 2007). Similar results also appear for graduate destinations at 42 months, and for the 08/09 cohort.

So far the results seem to be consistent with the expectation that educational achievements are positively correlated with the level of specialist expertise or technical knowledge used in a job. I find no support for the hypothesis that socioeconomic background is correlated with the level of 'soft' skills used in a job. Private schooling is associated with higher levels of Orchestration and Communication skills used in a job but the association is rather weak.

Table 8.1: Partial correlations between selected predictors and SOC(HE) skills (2006/07)

Predictors	6 months			42 months		
	Expertise	Orcherstration	Communication	Expertise	Orcherstration	Communication
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.004 (0.006)	0.012 (0.006)	0.005 (0.006)	-0.007 (0.011)	0.009 (0.011)	0.01 (0.011)
–Managerial or professional	0.015 (0.006)*	0.018 (0.006)*	0.023 (0.006)*	0.002 (0.011)	0.021 (0.011)	0.018 (0.011)
Male	0.075 (0.006)*	0.067 (0.007)*	-0.019 (0.006)*	0.052 (0.011)*	0.049 (0.011)*	-0.042 (0.011)*
Privately educated	0.008 (0.006)	0.048 (0.006)*	0.029 (0.006)*	0.003 (0.011)	0.044 (0.011)*	0.018 (0.011)
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.084 (0.006)*	0.031 (0.006)*	0.012 (0.006)*	0.066 (0.011)*	0.025 (0.011)*	0.002 (0.011)
–Other degree class	-0.086 (0.006)*	-0.044 (0.006)*	-0.05 (0.006)*	-0.078 (0.011)*	-0.057 (0.011)*	-0.062 (0.011)*
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.096 (0.006)*	0.05 (0.006)*	0.008 (0.006)	0.043 (0.011)*	0.019 (0.011)	-0.004 (0.011)
–Russell group university	0.096 (0.006)*	0.068 (0.006)*	-0.006 (0.006)	0.066 (0.011)*	0.06 (0.011)*	-0.004 (0.011)
Field of study [Ref: Biological sciences]						
–Business	0.036 (0.006)*	0.097 (0.007)*	0.009 (0.006)	-0.087 (0.011)*	0.029 (0.011)*	-0.029 (0.011)*
–Creative arts	0.017 (0.007)*	-0.074 (0.007)*	0.023 (0.007)*	-0.003 (0.011)	-0.079 (0.011)*	0.061 (0.011)*
–Education	0.089 (0.006)*	0.042 (0.006)*	0.268 (0.006)*	0.018 (0.01)	-0.002 (0.01)	0.151 (0.011)*
–Engineering and computer science	0.274 (0.007)*	-0.004 (0.006)	-0.036 (0.006)*	0.146 (0.011)*	-0.038 (0.011)*	-0.072 (0.011)*
–Humanities and languages	-0.023 (0.006)*	0.007 (0.007)	0.042 (0.007)*	-0.063 (0.011)*	-0.001 (0.011)	0.052 (0.011)*
–Law	0.002 (0.006)	0.023 (0.006)*	0.004 (0.006)	0.111 (0.012)*	0.075 (0.01)*	0.046 (0.011)*
–Other STEM	0.094 (0.006)*	0.059 (0.006)*	-0.041 (0.006)*	0.034 (0.011)*	0.009 (0.011)	-0.065 (0.011)*
–Social studies	0.024 (0.006)*	0.093 (0.007)*	0.026 (0.006)*	-0.048 (0.011)*	0.064 (0.011)*	-0.008 (0.011)
–Subjects allied to medicine	0.245 (0.006)*	-0.048 (0.006)*	0.008 (0.006)	0.151 (0.011)*	-0.084 (0.011)*	-0.033 (0.01)*
Has postgraduate qualifications				-0.12 (0.011)*	0.024 (0.011)*	-0.225 (0.011)*
R-square	0.07	0.03	0.03	0.05	0.02	0.04
N	23889	23889	23889	8104	8104	8104

*p<0.05

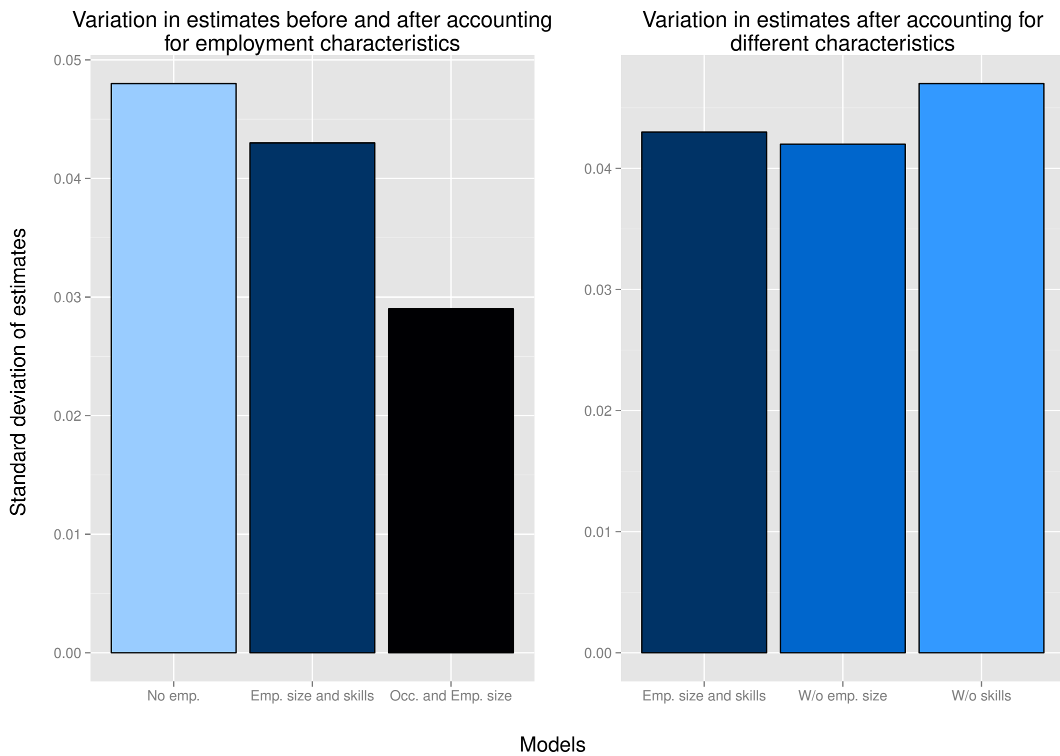

Figure 8.1: Plots of variations in earnings for Sex by fields of study 6 months after graduation

8.4.2 Explaining variations in stratification by field of study

Sex

Figure 8.1 plots variations in the gender earnings gap across different fields of study. The first plot shows that this variation does reduce once we account for skills and employer size. However, the decrease is far more substantial if we include occupations directly as fixed effects; roughly three quarters of the variance in model one (*No Employer Predictors*) could be explained by occupation and employer size. This suggests that perhaps factors related to people's occupation other than skills could be driving variations in the gender earnings gap across different fields of study.

Turning to the second plot, we can see that omitting employer size from model two (*Employer Size and Skills*) does not seem to affect the variance whilst omitting skills increases the variance. It would seem that employer size does not explain much of the variation in the gender earnings gap by fields of study.

Private education

Plot one in figure 8.2 shows that variations in the earnings gap between state and privately educated individuals does not seem to decrease after we account for employer size or skills. It does decrease by a modest amount after we account for occupations directly. The second plot shows that variations seem to increase between model two and model four (i.e. by omitting skills); it is hard to give substantive reason why this may be the case. However this may simply be caused by any random error in our estimates of the variance statistic σ^2_{jk}.

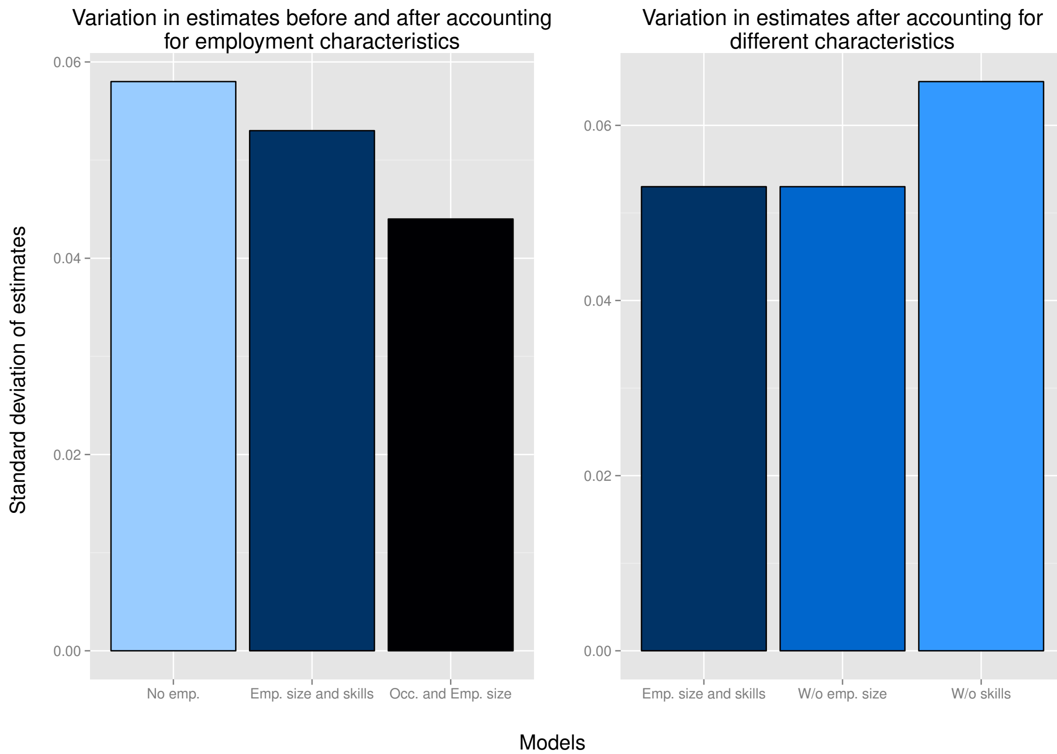

Figure 8.2: Plots of variations in earnings for Private education by fields of study 6 months after graduation

Degree classification

Figure 8.3 displays the variations in earnings between first and upper second class degree holders across different fields of study. Results for the difference in earnings between upper second class degree holders and individuals with other degree classification are not shown but are broadly similar. Plot one shows that none of the variation by fields of study can be explained by employer size, skills and employer location. However turning to plot two, it seems that the variance does not changes if we decide to omit employer size or skills from model 2 (*Employer Size and Skills*). This implies that much of the reduction in variance found in plot one can be attributed to employer location alone.

Type of university

Figure 8.4 shows the variations in the earnings gap between graduates from Russell group universities and those who attended Post-1992 universities. The results for those who attended pre-1992 universities are broadly the same. Plot one shows that a large proportion of the variation in the earnings gap can be explained by employer size, skills and employer location. The marginal decrease in variation caused by replacing skills used with fixed effects for occupation is low.

Plot two in the same figure shows that most of the reduction in variation can be explained by the skills used in an occupation; employer size seems to contribute almost nothing to the reduction. The results for the analysis using the Longitudinal DLHE data and the 08/09 cohort are broadly the same.

Finally I examine the relationship between different skills used in a job and earnings. The

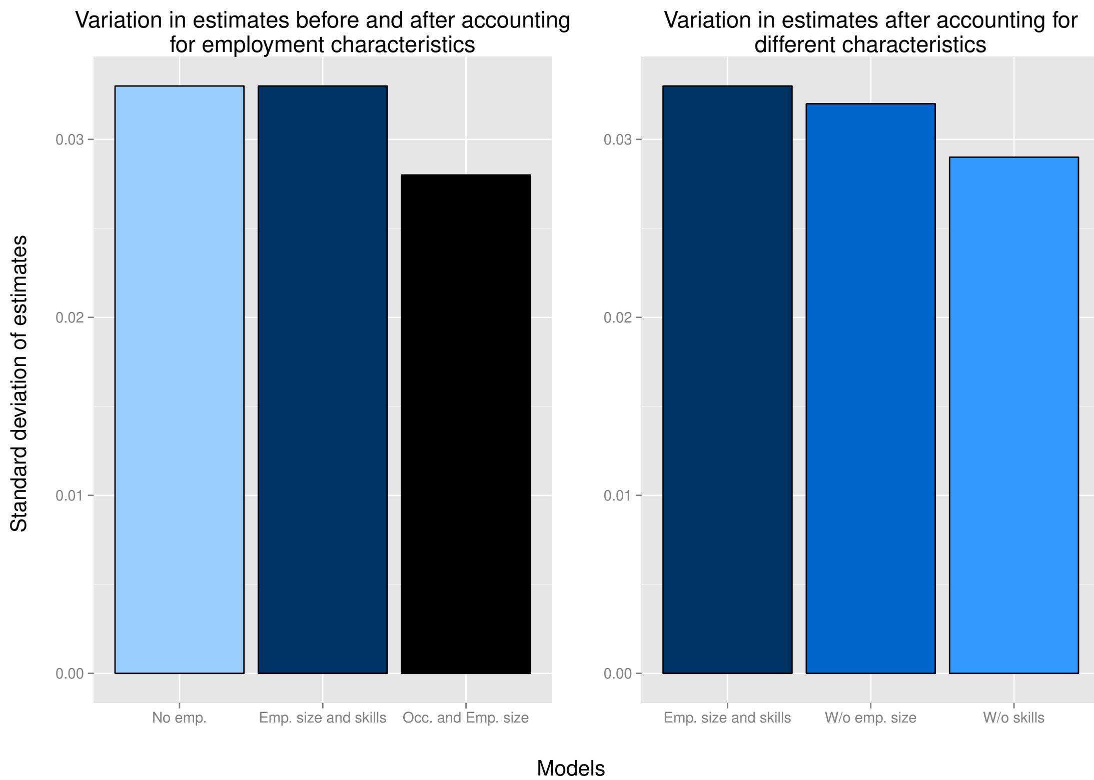

Figure 8.3: Plots of variations in earnings for first class degree holders by fields of study 6 months after graduation

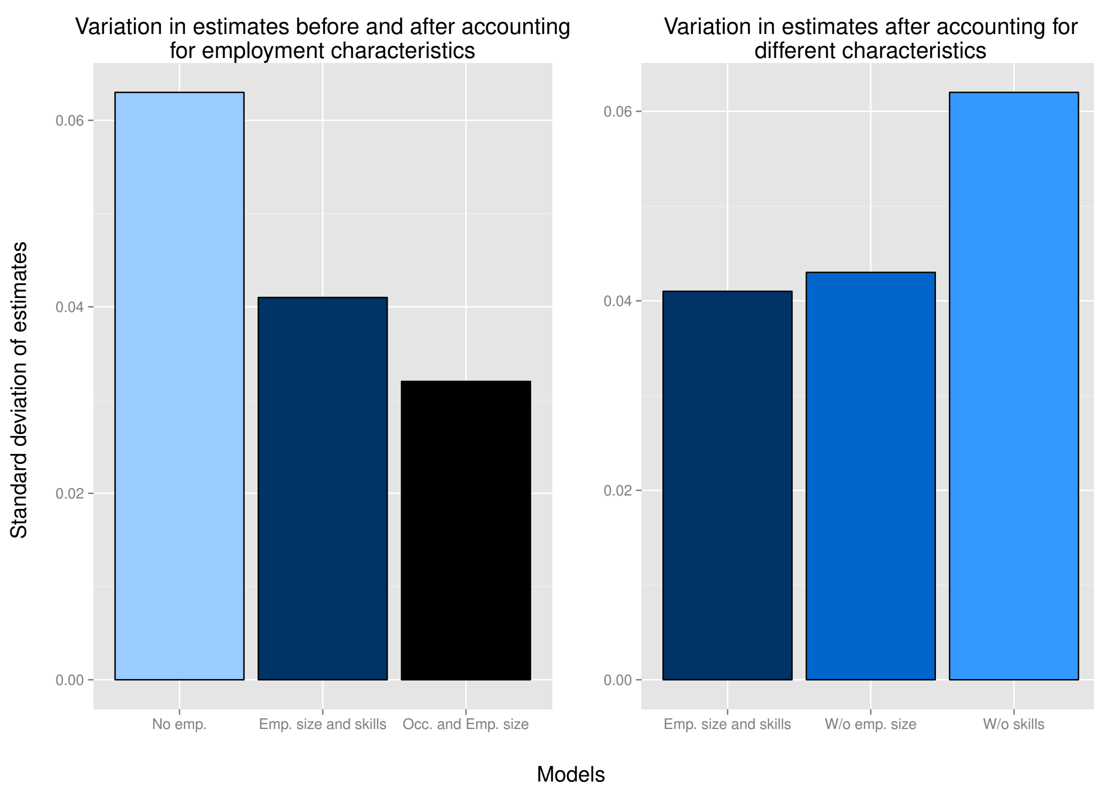

Figure 8.4: Plots of variations in earnings for university type by fields of study 6 months after graduation

relationship between skills and earnings are contained in the results of model two (*Employer Size and Skills*) but without interactions with skills, and sex, HEI, degree classification, and private education; both Expertise and Orchestration skills are associated with higher earnings whilst Communication skills do not have a statistically significant relationship with earnings. An increase in one point of Expertise is associated with a 4 percent increase in earnings. Similarly a one point increase in Orchestration is associated with a 2 percent increase in earnings (table 8.2). I also used a random effects model to estimate the relationship between skills and earnings (with occupations as the random effect). The results are extremely similar. Strictly speaking the relationship between the SOC(HE)2010 measure of skills and (log) earnings might not be linear. However attempts to fit the relationship using both polynomials and splines shows that assumptions of linearity is approximately correct. Comparing fixed effect models with and without interactions between skills and other characteristics, I find that the interaction terms do improve model fit and this improvement is statistically significant. Since there are many interaction terms I will only comment on the most substantial effect sizes. Compared to female graduates' earnings, a one point increase in Expertise scores is associated with less of a benefit to male graduates (-0.3%) but male graduates seem to benefit more from increase in Orchestration (0.5%) and Communication skills (0.4%). Furthermore earnings increases associated with a one point increase in Orchestration are higher (2.4%) for those who graduates from Russell group universities compared to Post-1992 universities. Similar results exist with respects to the relationship between Pre-992 and Post-1992 universities. However earnings increases associated with higher Expertise and Communication scores are lower for Russell group universities.

Table 8.2: The relationship between SOCHE2010 skills and (log) earnings (model 2, 2006/07)

Predictors	6 months	42 months
Expertise	0.039 (0.001)*	0.028 (0.002)*
Orchestration	0.018 (0.001)*	0.023 (0.002)*
Communication	0 .000 (0.001)	0.006 (0.002)
N	23889	8104

*p<0.05

8.5 Discussion

There seems little to no relationship between one's socioeconomic background and the type of skills used in a job. It was expected that relationship between the level of personal or soft skills used in a job and socioeconomic background would be stronger than the relationship between socioeconomic background and Expertise. Individuals from managerial and professional backgrounds were more likely to be in jobs with higher levels of skill usage in general but the relationship is very weak. This runs counter to the claims of Jackson, Goldthorpe and Mills (2005). However there is a relationship between Communication and Orchestration skills and private education. In general higher levels of skills usage does not actually translate into higher expected earnings, analysis shows that only higher levels of Expertise and Orchestration are associated with higher earnings. Communication skill has either no or a weak negative relationship with earnings. This means that differences in Communication skills cannot explain any differences in earnings between groups of graduates. These results are similar to the findings of Elias and Purcell (2013) who looked at the relationship between the SOC(HE)2010 skills and earnings using the UK Labour Force Survey (Appendix table 3, p. 33).

In most cases little of the variation in stratification between recent graduates across different fields of study could be explained by employer size. This casts doubts on whether the existence of formal rules and practises for hiring and promotions in an organisation is actually an explanation for variations in stratification. This result is somewhat surprising given the findings of studies done in other countries (Hällsten 2013, Mastekaasa 2004).There may be several reasons for this unexpected result. Firm size may not actually be strongly associated with formal rules and practises. Usually researchers have included indicators of private or public sector employer as an additional indicators for bureaucracy as well.

A large amount of the variation in the earnings gap between graduates from Russell group (and Pre-1992) universities and those from Post-1992 universities can be explained by the level of skills used in an occupation. In contrast, little of the variation in the earnings gap between those with different degree classification could be explained by either the skills used or employer size. In general, for many predictors, occupational skills explained a modest amount of the variation but the analysis also showed that much of the variation could be explained by other factors related to occupations. This is especially true in the case of sex where the majority of the variation in the gender earnings gap can be explained by factors related to occupations other than skills.

The findings show that much of the variation in the gender earnings gap is because similarly educated male and female graduates end up in different jobs after graduation. However the processes by which men and women end up in different jobs are still unknown. For instance, it is not possible to say whether this is as a result of employer discrimination or gendered differences in career ambitions. There may be further complicated interactions between the two: women may anticipate discrimination and adjust their career ambitions accordingly for example.

8.6 Conclusion

This chapter is the last of the four finding chapters in this thesis. I find little support that there is a substantial relationship between socioeconomic background and the type of skills used in a job, contrary to the claims of other researcher (Jackson 2007). Furthermore only occupations with higher levels of specialist Expertise and Orchestration skills use are associated with higher worker earnings. I also find that employer bureaucracy can explain very little of variations in the earnings gap between men and women, graduates with first class honours and those without, and so forth across fields of study. There is some support variations in stratification by sex and university type does reduce once we account for the skills used in an occupation. The final chapter concludes by summarising the findings of this thesis and the implications of these results.

Chapter 9

Discussion and concluding remarks

9.1 Introduction

This thesis started with a few simple questions: are there any differences in labour market outcomes between otherwise similar graduates by sex, socioeconomic background, and educational attainment? Are these differences larger or smaller in some fields of study compared to others? If so, why?

Using interviews with graduates and survey data, I have tried to understand how graduates from different fields of study found work (chapter 5); whether there are any variations in labour market stratification across fields of study (chapter 6); whether competition in the labour market could explain these variations (chapter 7); and whether these variations could be explained by either employer bureaucracy or the skills used in different occupations (chapter 8). A summary of the key findings addressed in each chapter is givein in table 9.1.

I have attempted to advance what is already known about the topic in several way. I have extended the scope of the literature by looking beyond variations in stratification by socioeconomic background and sex to also include stratification by university type, degree classification, and private education prior to HE. I have put forward a new interpretation for why levels of stratification may vary across fields of study and have tested my hypotheses. I have also put existing ideas and explanations to the test (Hansen 1996, 2001; Jackson et al 2008; Roska 2005; Hällsten 2013). In the course of addressing the main research questions, I have found interesting results that are relevant to other debates about the nature of competition and inequality in the labour market for graduates (Brown and Hesketh 2004) and the link between socioeconomic background and labour market outcomes (Jackson, Goldthorpe and Mills 2005; Jackson 2007).

9.2 Main findings

9.2.1 There are substantial variation in levels of stratification by sex, type of schooling, university type and educational attaiment across different fields of study

The difference in labour market outcomes between male and female graduates varies greatly depending on field of study, after accounting for other factors such as differences in education (i.e. A-D varies across fields of study; see figure 3.1). Previous studies have found some evidence that the difference between men and women would be smaller in technical (or applied) studies and the sciences but I find that this not the case (Purcell and Elias 2004; Roska 2005). The gender gap in outcomes was shown to be relatively high in many STEM subjects.

The disproportionate amount of privately educated individuals in elite occupations have raised issues about social justice/ inequalities in opportunities in the UK (Milburn 2014). The results of this study finds that privately educated graduates tend to do better than their state educated counterparts in many fields of study. After accounting for educational attainment and other factors, privately educated graduates who studied law earned 15.7 percent more than their state educated counterparts 6 months after leaving university (table D.10). This finding resonates with statistics that show that 71 percent of senior judges in the UK were privately educated (Milburn 2014). The advantage that privately educated individuals hold in some fields has not been easy to explain. Privately educated individuals are more likely to be in jobs that require higher levels of Orchestration skill but not Expertise and other Communication skills. However, level of skills used in a job does not explain much of the variation in differences between private and state educated individuals by fields of study. Another explanation is that private education may be associated with greater social confidence or access to more powerful social networks. These things may not have been accounted for in my analysis due to lack of information. Furthermore, from interviews with graduates, I find that social contacts and networking can be an invaluable way of receiving information about jobs. This could help privately educated individuals secure work in occupations with better rewards. However, when I look at graduates in similar occupations, I still find that privately educated graduates earned 10.7 percent more than their state educated counterparts (table D.19).

Many researchers have put forward evidence that suggests going to a prestigious universities or getting a higher degree classification has a positive effect on one's labour market outcomes (Chevalier and Conlon 2003; Ramsey 2008; Wilton 2011; Smetherham 2008; Walker and Zhu 2011; Blasko 2002). The perception that degree classification is very important to employers has also been echoed by graduates themselves (Tomlinson 2008, Brown and Hesketh 2004). However my study shows that the relationship between university type, degree classification, and labour market outcomes can vary depending on fields of study (also see Feng and Graetz 2015). Differences in earnings and skills use between graduates by degree classification are much smaller for those who studied the humanities, education, and subjects allied to medicine. In addition differences in labour market outcomes between graduates by the type of university they attended are far larger for those who studied the sciences.

There was no variation in stratification by socioeconomic background across different fields of study—in fact socioeconomic background was, relatively speaking, only weakly associated with labour market outcomes. The latter finding is also supported by other studies which have looked at graduate destinations in the UK (Ramsey 2008; Naylor, Smith and McKnight 2002; Macmillan, Taylor and

Vignoles 2013). One reason for these findings may be that individuals from disadvantaged backgrounds who have degrees have already overcome many earlier obstacles in the education system (Lucas 2001). These people may be particularly able or ambitious, and as such this reduces any potential differences in outcomes between individuals from different socioeconomic backgrounds.

Regarding graduates perceptions of employability and labour market conditions, in my small interview sample I found that graduates across different fields of study did not hold very different opinions about what makes them attractive to employers. However these graduates did have different perceptions of the competition for jobs depending on what subjects they studied at university. In particular, those who had studied subjects allied to medicine found the graduate labour market to be less competitive than they had feared. Furthermore graduates who studied different fields of study placed different emphases on the ways they looked for work. Those who studied the creative arts and design emphasised the importance of personal and professional contacts as methods for obtaining work.

9.2.2 There is little evidence to support that variations in stratification are the result of employer bureaucracy or the applied nature of certain subjects. There is weak evidence to suggest that the relationship between education and labour market outcomes is greater in hard fields of study.

Several researchers have put forward the idea that differences in labour market outcomes between graduates from advantaged and disadvantaged socioeconomic backgrounds, or different sexes will be larger in soft field of studies. These researchers have also presented evidence to support their claims (Hansen 2001; Roska 2005; Hällsten 2013). I find little evidence that to support their findings based on my analysis of graduates destinations in the UK (also see Jackson et al 2008). As I mentioned in chapter 3, few studies looking at stratification by socioeconomic background have actually found evidence of any substantial variation across different fields of study—save Hansen (2001) and Hällsten's (2013) studies. One reason for these results is that Hansen's studies rely on a questionable measure of income that included employed and self-employed income which no other study to date uses (Jackson et al 2008). Furthermore Hällsten and Hansen did not attempt to adjust for multiple comparisons in their analyses.

Contrary to expectations the gap in outcomes between men and women is greatest in maths, engineering, physical sciences, and computer sciences. For instance, the men who studied engineering and computer sciences earned around 8.0 percent more than women with similar educational attainments and background 6 months after they receiving their degrees. This difference only grows over time: the earnings gap between men and women who studied these subjects is 15.3 percent three and a half year after graduation.

Roska (2005) and Hällsten (2013) also proposed that greater levels of employer bureaucracy, in the form of formal rules for hiring and assessment, could explain variations in stratification across field of study. Both authors were referring to variations in stratification by ascribed characteristics, such as sex and socioeconomic background, rather than by educational achievements. Since stratification by socioeconomic background does not vary by field of study I can only focus on stratification by sex. I find mixed support for their hypotheses. One indicator of employer bureaucracy is firm size. In chapter 9 I find that employer size does not explain variations in the gender earnings gap across fields of study.

However it was expected that public sector employers would have more bureaucratic practises in place than those in the private sector. In chapter 6 I find that gender earnings gap is almost non-existent for graduates who studied Subjects allied to medicine and Education; both fields of study which are related to employment in the public sector. One possible explanation is that whilst larger firms are more likely to use formal and bureaucratic processes to hire employees (Barber er al 1999; Bartram et al. 1995; Jenkins and Wolf 2002; Campbell, Lockyer and Scholarios 1997) the actual strength of association between bureaucracy and employer size may be quite weak. Another explanation is that public sector employee are not so stratified by sex or socioeconomic background for other reasons unconnected to bureaucracy.

Stratification by degree classification and type of university attended varied by fields of study. In general, individuals who went to more prestigious universities or got better degree classifications seem to do relatively better in the labour market if they studied a hard (or mono-paradigmatic, Biglan 1973) field of study—such as the natural sciences or engineering. In other fields of study these two factors had a weaker relationship with labour market outcomes as measured by earnings and skills use. This pattern was not statistically significant, as noted in chapter 6, however this could be due to a lack of statistical power.

9.2.3 Stratification by sex and type of schooling is lowest for graduates who studied subject related to employment in the public sector

Differences in earnings for those men and women, and state and privately educated individuals were lowest for those who studied Education and Subjects allied to medicine. Whilst organisations in the public sector are larger, in chapter 8 I did not find that firm size accounted for any of the variations in stratification across fields of study. In the same chapter I stated that the gender wage gap reduces substantially once we compared men and women working in the similar occuations. One reason for these two subjects is that wage differential between workers in the public sector, in general, are smaller than those in the private sector. Since the 1970s the earnings of the highest paid workers in the private sector, relative to the average, has been growing. In contrast the relative earnings of the highest paid in the public sector has remained the same (Cribb, Emmerson and Luke 2014). In 2013-13, the ratio of earnings of the top 90th percentile earning to the median was 3.2 in the public sector and 4.1 in the private sector (p. 16, *ibid*). This wage compression in the public sector could explain why stratification amongst graduates are so low in these two subject areas. Another reason may be that variations in earnings between workers in similar jobs could be caused by variations in how different firms compensate their workers. Likewise some workers may choose to work for firms that offer lower salaries but a range of other non-pecuniary benefits. In both cases a greater diversity of employers may be creating greater variations in pay. Since the NHS is an organisation that dominates the healthcare sector, it impose greater uniformity in how individuals, working in similar jobs, are paid. However there was little that could explain the variation in the earnings gap between state and privately educated graduates by fields of study.

9.2.4 There is little support for the theory that increased competition will lead to greater stratification between graduates in the labour market

There have been concerns that greater competition between graduates, either as a result of expansion of HE or technological changes, would lead to greater stratification between graduate by socioeconomic background and other factors (Brown 2010, 2013; Brown et al 2010; Gerber and Cheung 2008). This has led many debates about whether there has been an 'oversupply' of graduates and whether the financial returns to a degree have also decreased over time (Walker and Zhu 2011). There is little research looking at whether competition in the labour market actually causes greater stratification between workers—graduates or not (as assumed in Brown and Hesketh 2004, Blaug 1976). One example is the work of Guadalupe (2007) who made use of natural experiments to conclude that increased competition did increase wage inequality between workers. In a similar vein I made use of the recession as natural experiment to examine the effects of a sudden fall in demand for graduate workers—but not in the supply of new graduates—on labour market stratification. I find that there was no evidence to suggest that levels of stratification amongst graduates by sex, socioeconomic backgrounds and other characteristics changes before and after the recession. These results apply to both differences in earnings and the association between different characteristics and skill utilisation.

These results do not support concerns that increasing competition between graduates will lead to greater stratification although present levels of stratification may be maintained nonetheless. The unexpected results should encourage more research to be done into the relationship between competition and stratification. It is entirely possible that these results are entirely confined to the graduate labour market, people in their early careers, or some other feature unique to the population of interest in this study. The unexpected results should encourage further replication and research into this topic; the relationship between competition and stratification is often discussed (Brown and Hesketh 2004, Blaug 1976, Thurow 1975) but under-researched.

9.2.5 There is not a strong relationship between socioeconomic background and the type of skills used in a job

The study results has relevance for recent sociological debates about stratification in labour market in general. Despite improvements in social mobility over the past few decades, there still exists a persistent link between people's socioeconomic origins and later occupational destinations (Jackson, Goldthorpe and Mills 2005). Jackson et al offers evidence and support for the idea that these links are maintained through time because individuals from more advantaged backgrounds are more likely to enter occupations which require more personal skills. These individuals can draw on their stock of cultural and social capital to improve their productivity in certain job, such as sales and management. As a result, this creates stratification by socioeconomic background between workers in many industries and occupations. The analysis in chapter 8 shows that individuals from more advantaged backgrounds are generally more likely to work in jobs that require higher degrees of Expertise as well as personal skills such as Orchestration and Communication. Furthermore the association between socioeconomic backgrounds and skill used on a job is statistically significant but substantively weak. The partial correlations between skills use and socioeconomic background are extremely low (<0.02) especially when compared to the relationship between factors like degree classification and skill use.

Some caveats must be made. Goldthorpe and Jackson (2008) also argue that individuals from advantaged socioeconomic backgrounds who have not succeeded in the education system can fall back on other means to get ahead in the labour market. This would mean that the relationship between socioeconomic background and outcomes for graduates may not be applicable to all workers.

Chapter 8 also suggests a refinement and extension of the Jackson et al. hypothesis with respect to earning. Whilst Jackson et al. focus on occupational destinations; my results suggest that the earnings gap between individuals from different socioeconomic backgrounds cannot be attributed to personal (or soft) skills in general. This is because only certain personal skills, in particular those associated with leadership and organisation, seem to be financially rewarded in the labour market. Analysis of earnings in chapter 8 show that occupations that require greater presentation or general communication skills, as measured by the SOC(HE)2010, do not seem to be associated with earnings. These results were also found by Elias and Purcell (2013).

9.2.6 Methodological contributions

I have also sought to make advances to methodology that can help other researchers studying the same topic area. I have discussed how skills use as recorded by the SOC(HE)2010 could be a measure of the skills used in a job. The SOC(HE)2010 measure of skills used is derived from detailed information about job descriptions (chapter 4). This makes the scale a better indication of skills used in an occupation than some other measures of skill. For instance, Jackson (2007) used information from job advertisements to gather information about the skills required for certain occupations. Information in job adverts may be misleading. For instance, in a loose labour market, employers may make additional skills demands beyond that required for a job in order to filter job candidates. However the SOC(HE)2010 skills scale can only be used whenever researchers have access to information about occupations as measured by the SOC2010. Many earlier datasets may only include information about occupations as coded by the SOC2000. In the course of this study I have demonstrated how to adjust the SOC2000 to make use of the SOC(HE)2010 (appendix A). This is particularly useful in situations where researchers have information about an individual's occupation but not any self-reported information or observational data on what kind of skills they use in their jobs (unlike in the Skills and Employment Survey for example, Felstead, Gailie and Green 2012).

Most previous studies have failed to take into multiple comparisons across numerous fields of study into account in their analysis (Hansen 1996, 2001; Hällsten 2013; Roska 2005). Researchers have also often failed to take heed of warnings not to compare the results of different logistic or probit regression models when trying to make inferences (Allison 1999, see Roska 2005 and Hansen 1996). In this thesis I have proposed a straightforward way of testing for variations in effect sizes across fields of study by using the chi-square statistic (appendix A.2.2). I have also demonstrated how problems of comparison between non-linear probability models could be resolved using a method introduced by Breen, Holm and Karlson (2013). I have also proposed and demonstrated original strategies for dealing with sample selection bias in analyses of earnings using the DLHE survey and Longitudinal DLHE (appendix A, see Chevalier 2012 for an alternative strategy). Given the widespread use of the DLHE and Longitudinal DLHE survey for research into graduates in the UK, these methods may be particularly useful to future researchers.

Table 9.1: Summary table of thesis findings

Section	Research question	Findings
Chapter 5	Do graduates from different fields of study vary in their perceptions of employability?	Overall the interviews do not show any substantial variations in what graduates thought affected their employability.
	Do graduates from different fields of study vary in the ways they find work?	Graduates from the Creative arts were more likely to employ informal means to find work. Furthermore, those who studied Subjects allied to medicine almost exclusively used specialist websites to find work.
Chapter 6	Is the relationship between sex, socioeconomic background, and labour market outcomes mediated by education related factors?	The level of stratification by sex reduces substantially after accounting for education. However, accounting for education only reduces differences in earnings by socioeconomics background.
	Does the indirect relationship between sex, socioeconomic background, and outcomes vary by field of study?	From the previous question, we know that sex and socioeconomic background has an indirect relationship with labour market outcomes through education. However magnitude of this indirect relationship does not vary across fields of study.
	After accounting for education and other characteristics, is there less stratification by sex and socioeconomic background in hard and applied fields of study compared to soft and pure fields of study?	Looking at both earnings and skills use, I find no evidence that levels of stratification by socioeconomic background varies across fields of study. In contrast there are substantial variations in stratification by sex. Furthermore differences in outcomes between those that attended private and state schools also varied across subjects. I do not find any consistent evidence to support that there is less stratification in hard or applied fields of study.

	Is there greater stratification by educational achievements in hard and applied fields of study?	There is evidence that stratification by type of university and degree classification does vary across fields of study. The gap in outcomes between those that went to more prestigious universities and those that didn't was greatest in hard fields of study. Overall, due to small sample sizes, these results were mostly not statistically significant.
	Is there less stratification by sex and socioeconomic background in fields of study related to careers in the public sector?	Differences in outcomes by sex and socioeconomic background were negligible for Education and Subject allied to medicine–two fields related to industries that are primarily in the public sector.
	Is there greater stratification between graduates in fields of study where the labour market is loose?	Overall it was difficult to answer this question using cross-sectional data since many fields with low levels of graduate underemployment were also hard or applied fields of study.
Chapter 7	All else being equal, does greater competition in the graduate labour market results in greater stratification between graduates?	Using the 2008 recession as a natural experiment, I find that the increased level of competition in the graduate labour market did not affect levels of stratification. Furthermore these results are consistent once we account for selection bias due to greater levels of unemployment and graduates going onto further study after the recession.

Chapter 8	Is there an association between ascribed characteristics, educational attainment, and the skills used in an occupation?	Using the SOC(HE)2010 measure of skills I find that, after accounting for other factors, male graduates in general worked in occupations with higher levels of expertise and orchestration. Those with better degree classifications in general worked in occupations requiring higher levels of all skills. Similarly those who attended more prestigious universities worked in occupations requiring higher levels of expertise and orchestration. Private schooling has a weak relationship with the skills used in an occupation.
	Does different skills, such as communication and expertise, have different relationships with earnings?	I find that graduates in occupations using higher levels of expertise or orchestration also earned more. However, after accounting for other factors, there was no substantial relationship between earnings and the level of communication skills used.
	To what extent are variations in stratification by fields of study explained by bureaucracy and the skills used in an occupation?	Overall, almost none of the variation in stratification can be explained by the level of bureaucracy in different firms (as indicated by firm size). The skills used in an occupation accounted for variations by sex, private education and university type. However, in the case of gender, much of the variation in stratification can be explained by other unobserved factors related to graduates' occupations.

9.3 Practical implications for stakeholders

As mentioned in chapter 2, improving educational, as well as labour market, opportunities and outcomes for disadvantaged groups is a goal for many stakeholders in HE. Aside from pursuing greater equality as an end in itself, it is also argued that increasing educational opportunities will boost the economy. The Sutton trust estimates that feasible increases in social mobility could add an additional 4 percent to UK GDP by 2050—although their estimates assume that investments in education will increase the overall productivity of the workforce (Sutton trust 2010, see Brown, Lauder and Ashton 2011 for an opposing view). With regards to HE, it is well known that various factors, such as institution and field of study, are associated with labour market outcomes. In particular, the relationship between earnings and field of study have led to efforts by various organisation to encourage disadvantaged group of individuals to study certain subjects or to pursue careers in certain industries. For instance there are various efforts involving the Sutton Trust, alongside various other organisations, to help low-middle income secondary school students apply to STEM, Law, and Medicine. Furthermore there are many governments and organisation interested in encourage more women into STEM —both in the UK and across the world (CaSE 2014, OSTP 2016).

This current shows that whilst there may be further challenges to disadvantaged groups depending on their educational choices. Male graduates are on average likely to earn more than their similarly educated female counterparts in most fields of study with the exception of Education and Subjects allied to medicine. The gender earnings gap still exists at three and a half years after graduation where it is particularly high amongst graduates studying Law, Business, Engineering and computer science, and other STEM subjects. This is a concerning results because, as discussed in chapter 2, women are already underrepresented in these STEM fields. There have been successive efforts to address the persistent gender imbalance in STEM subjects by initiatives such as the Women into Science and Engineering campaign, which was established in 1984 (Purcell and Elias 2004). The existence of large gaps in earnings and occupational skills use between men and women in the very fields of study where women are already underrepresented is unlikely to help drives to encourage more women study STEM subjects. One interpretation of the results is that the female graduate may face greater difficulties in the labour market, compared to their male counterparts, if they chose to study STEM subjects. This is not to say that individuals are not better off in STEM subjects—overall earnings for STEM graduates are still high compared to other subjects. However it does suggest that effective actions to encourage female participation in STEM cannot just be targeted at education choice alone. Since STEM industries and workplaces tend to be male dominated (CaSE 2014), STEM employers may be less empathetic or accommodating to female employees. The may lead to fewer women science graduates working in STEM jobs (this is known as the 'leaky pipeline' effect; Chevalier 2006, Purcell and Elias 2008).

Furthermore the current study also shows that the differences in outcomes between state and privately educated individuals varies substantially between fields of study. I find that there is a consistent and considerable earnings gap by schooling prior to HE amongst Law graduates at 6 and 42 months after graduation. Schemes, such as the Sutton trust Pathways into Law, offer help by guiding and encouraging state school students to apply to prestigious universities (Sutton trust 2016). This may be a relatively effective method for addressing the gap as the earnings difference between similar individual who studied at Russell group and post-1992 universities is highest amongst Law graduates (42 months after graduation). The relationship between degree classification and earnings is also stronger for Law graduates. However, even after accounting for education, the difference in earnings between private and state educated Law graduates are still relatively high compared to other subjects. This suggests that there are still other factors that have a strong impact on the earnings gap; these factors may include unconscious employer biases or a relative lack of self-confidence state educated graduates.

In general, by looking at differences in labour market outcomes by degree classification and university type, the current study gives some indication to the likely efficacy of certain schemes designed to improve opportunities for disadvantaged groups. As mentioned before, many of these scheme aim to help disadvantaged students with their studies or to go to more prestigious institutions. The potential efficacy of these schemes are likely to vary depending on field of study. For instance, at 42 months after graduation, type of institution seems to have a relatively modest relationship with earnings for graduates in the Humanities and languages (see 6.12). Whilst this may not be causal relationship, it does suggest that encouraging more disadvantaged students into prestigious institutions may have less of an impact on the earnings gap amongst Humanities graduates (compared to other fields of study).

9.4 Limitations and caveats

There are a number of limitations in this thesis that could not be addressed and I will mention a number of ways that future studies may overcome them. One of the biggest limitations is the fact that the DLHE and longitudinal DLHE survey recorded individuals' salaries but not their hours worked. This meant that full time and part time workers were not comparable but also it could to bias the results. Only information about full-time working graduates were used in most of the analyses. This is a limitation that plagues all studies that have used the DLHE survey data in the past (Chevalier and Conlon 2003; Chevalier 2006, Macmillian, Taylor and Vignolesl 2013; Ramsey 2008). As I explained in chapter 4, attempts to resolve the matter by imputing earnings data from another source have major drawbacks (Feng and Graetz 2015, see chapter 4). Fortunately more recent versions of the DLHE survey include a question about the number of hours worked. Future studies that wish to make use of the same data could make use of the information to investigate whether the results of any multi-variable analysis of earnings changes if earnings per hour was used as the outcome, and both full-time and part-time workers were included in the analysis. This would answer an interesting methodological question about the sensitivity of results from older studies using the DLHE and Longitudinal DLHE.

Even if information was available on the hours worked there still remains sample selection issues due to the number of unemployed graduates, individuals who went into further study, and those that did not respond to the DLHE survey or the longitudinal survey. I have attempted to examine the effects of sample selection on my results but the approach used is sensitive to a number of assumptions (see Puhani 2000 and Breen 1996 for reviews). I have also only examined selection bias in analyses of earnings. For non-linear probability models, such as logistic regression models looking at whether an individual is in a graduate job or not (chapter 6 and 7), the extension of the Heckman model is even more sensitive to departures from assumptions and harder to compute (Freedman and Sekhon 2010). Furthermore my strategy involves applying the logic of path analysis or omitted variables to the results. This becomes more complicated when we are using non-linear probability model (see Winship and Mare 1983). Finally it would also take some further work to extend the method of partial correlations to sample selection models (Breen, Holm and Karlson 2013).

Smaller sample sizes for the Longitudinal DLHE has meant that the analysis may lack sufficient statistical power to detect any variations in stratification by fields of study. This will affect any analyses looking at graduate destinations 42 months after leaving HE. The lack of any statistical significance does not mean any variations do not exist and I have tried always tried to quote effect sizes as well as statistical significance.

The majority of the analysis also look at what graduates were doing 6 and 42 months after graduation. This only captures what young graduates are doing in their early careers and may not be indicative of what they do later on in life. The results also only focus on graduates and they do not necessarily generalise to the wider working population without graduate qualifications. However workers with degrees do make up a substantial proportion of the labour market (approximately 38% in 2013, ONS 2013). The results also have strong internal validity since I have been able to replicate them for both the 2006/07 and 2008/09 cohort of graduates; two years where the labour market conditions were very different. This shows that these variations in stratification across fields of study are relatively stable.

Ultimately most of the analysis in this thesis has been concerned with finding out whether differences in outcomes exist between different groups of graduate and whether these differences still persist after we account for other factors. For instance, in chapter 8 I look at whether the gender earnings gap still exists for people with similar backgrounds and similar educational attainments across different fields of study. I examined whether the gender wage gap varies by field of study, and then try to see if this variation still persists after we take people's occupations into account. This is akin to looking at an effect (i.e. variations in the gender wage gap) and the potential causes of that effect (i.e. what factors could explain variations in the gender wage gap) (Holland 1986). This is not the same as establishing whether being a women would cause workers to earn less in the labour market, either through employer discrimination or any other labour market mechanisms. Differences could exist as a result of different career aspirations or preferences between men and women for example (Chevalier 2006). It has not been the intention to extract casual effects of the kind 'does having a first class degree cause people to get better paid jobs?' (Feng and Graetz 2015)—except in chapter 7 where I look at whether competition causes greater stratification.

In order to compare outcomes for similar individuals, I made use of regression models. However, there are many equally valid ways of modelling the same data. For instance, I could have analysed outcomes for men and women seperately by field of study. I could also have made use of more complex techniques such as regression trees in my analyses. These techniques can inductively introduce all sorts of complex interactions into a model which may arguably more closely resemble the actual relationship between factors like sex, socioeconomic background, and labour market outcomes (Strobl, Malley and Tutz 2009). There are always going to be some limitations in any analysis, and the analyses in this study tried to balance complexity and rigour with parsimony and easy of interpretation.

9.5 Concluding remarks

This thesis examines labour market stratification between graduates across different fields of study in the UK. It has tried to address all the substantive questions and theories raised by other studies looking at this topic (Hansen 1996, 2001; Hansen and Mastekaasa 2006; Jackson et al 2008; Strathdee 2009; Smyth and Strathdee 2010; Roska 2005; Hällsten 2013; Feng and Graetz 2015). In addition, it has contributed to our understanding of the relationship between socioeconomic origins and skills used in occupation (Jackson 2007; Jackson, Goldthorpe and Mill 2005), and the relationship between stratification and competition in the graduate labour market (Brown and Hesketh 2004; Brown 2013; Bathmaker, Ingram, and Waller 2013; Lauder et al 2009).

Whilst researcher have been mostly interested in labour market stratification by socioeconomic origins across fields of study, my findings show that there exists much larger variations in stratification by sex, type of HEI, private schooling, and degree classification. I would argue that on the basis of my results and other findings that there exists greater need to focus on these other types of stratification (Jackson et al 2008; Roska 2005; Rumberger and Thomas 1993).

Questions still remain about causality. For instance, what effect does going to a more prestigious university have on earnings? Does this effect vary by field of study? This thesis has only looked at whether there are difference in outcomes between similar individuals—I have taken pains to avoid using causal language. Nonetheless casual effects are of great interest to academics, and to a certain extent to policy maker and students (Moreau and Leathwood 2006; Hillage and Pollard 1998; Browne 2010). I have shown that differences in labour market outcomes by degree classifiation and so forth varies across fields of study; it is natural to then ask whether the *causal* effects if these factors also varies by field of study. As I have mentioned in chapter 4, efforts to answer causal questions have often attempted to do little more than what I have already done—compare outcomes for similar individuals—albeit using a wider range of ever more sophisticated statistical methods (Chevalier 2011; Chevalier and Conlon 2003; Ramsey 2008; O'leary and Sloane 2005; Rumberger and Thomas 1993; Walker and Zhu 2008, 2011; Blasko 2002; see Feng and Graetz 2015 for an exception). These efforts can be criticised for being unconvincing for a number of reasons (Holland 1986; Heckman 2005; Heckman and Vytlacil 2007). It would be interesting to see whether future studies are able to look at the casual effects of HEI or private schooling by field of study *and* whether these studies are able to use other research designs than studies in the past.

Appendix A

Methods and proofs

A.1 Graduate jobs and skills: Converting the SOC(HE)2000 to SOC(HE)2010

As an exercise in harmonising the SOC2000 and SOC2010, the ONS dual coded two quarterly Labour Force Surveys and a 1 percent economically active subsample of the 2001 census (ONS 2012b). For the purpose of adding the SOC(HE)2010 skills scale to the SOC2000 I have used the results of the census dual coding.

For each SOC2000 code, the ONS recorded the proportion of workers that fell into a particular SOC2010 code by gender in the census. This proportion was used to weight the SOC(HE)2010 skills scores assigned to a SOC2000 code. For most cases in the SOC2000 this was straightforward as the majority of individuals in one SOC2000 code came from only one SOC2010 code. To clarify, if all workers classified under one SOC2000 code were also classified under one SOC2010 code then it is simple to convert that SOC2000 code into the SOC(HE)2010. For a SOC2000 code, if half of workers belonged to one SOC2010 code and the other half belonged to another then I simply took the average of the two SOC(HE)2010 skills scores for its SOC2010 codes.

In the ONS exercise percentages were broken down by gender but the gender breakdown of each SOC2000 code was unreported. As a result I had to assume an equal balance of genders amongst workers in each occupation when assigning SOC(HE)2010 skills scores to a SOC2000 code. To check if this assumption had a large impact on the derived skills scores for the SOC2000 I conducted a hypothetical exercise. I computed scores under two scenarios: one where all workers in an occupation were assumed to be male and another where all workers were assumed to be female. The results showed that the differences in derived SOC(HE)2010 skills score for each SOC2000 code between these two extreme scenario are not very substantial. Therefore the bias from assuming equal gender breakdowns for each occupation will not be particularly large in any subsequent analyses.

The conversion was done using details on unit groups using both the SOC2000 and SOC2010. This is the most detailed breakdown of occupations that either the SOC2000 or SOC2010 will allow. When the number of individuals in a SOC2000 group belonging to a particular SOC2010 group was below 5, the proportion of workers in one SOC2000 code that belonged to a particular SOC2010 group would not be displayed in the ONS report. This would be an issue for the robustness of my conversion if any particular SOC2000 was made up of multiple SOC2010 groups which were all very different and of low frequencies. Fortunately, this was not the case and for most SOC2000 codes the proportion of workers that belonged to a particular SOC2010 code was known.

For the SOC(HE)2010, an occupation was deemed as 'graduate' if any of the three SOC(HE) skills scores (i.e. specialist expertise, orchestration and communication) was 6 or above. For the converted SOC2000, any occupation was deemed graduate if the majority of individuals within it were classified as being in 'graduate' occupations as defined by the SOC(HE)2010. The reasons is mainly to avoid situations where the majority of individuals in a SOC2000 category belonged to a SOC(HE)2010 category that is on the cusp of being a graduate job, whilst a small minority were in non-graduate jobs. For instance, if the 95 percent of individuals belonged to a SOC2010 with an expertise score of 6 whilst the other 5 percent belonged to a SOC2010 with a score of <6. The converted SOC(HE)2010 skills score would be below 6 for that SOC2000 category even though the vast majority of respondents would be in to a 'graduate' job according to the SOC(HE)2010.

Again the conversion method would run into issues if there was a large degree of indeterminacy, for example if 50 percent of the SOC2000 group were in non-graduate jobs as classified by the SOC(HE)2010 whilst the rest were to graduate jobs. In cases where some indeterminacy exists, as defined by the proportion of graduate (or non-graduates) being under 80 percent, these cases were reviewed individually. These occupations were generally all very specialised jobs, such as air traffic controllers, and appeared rarely in the DLHE and the Longitudinal DLHE for both the 2006/07 and 2008/09 cohorts. As such, they are extremely unlikely to affect the results of any subsequent analyses. For simplicity, if any of these occupation had converted SOC expertise scores over 5.5 then it was categorised as a graduate job. The method outlined here enables subsequent analyses to make use of the definition of graduate jobs and skills defined by the SOC(HE)2010, even when only information about the SOC2000 is available (Elias and Purcell 2013).

A.2 Explanation of Analytical Methods used

A.2.1 Comparing results from different probit/logit models

In many instances, we are interested in evaluating the relationship between certain predictors and skill use. Unfortunately often we only have indicators of graduate underemployment as a measure of skills use. Whether a graduate is underemployed or not is a binary category and it is often modelled using a probit or logistic regression. As part of this thesis, I am interested in whether factors, such as sex, are associated with skills use to different extents by fields of study. However, it is problematic to compare results from different logistic or probit regression models in the same way that we compare results from linear regression models. The same issues arise when we are using ordered response models and interaction terms in logistic/probit model (as in Roska 2005). I will explain the problem with references to the logic behind such models and explain the proposed solution used in this thesis.

The probit and logistic regression models

It is well known that the probit and logistic regression models can be described in the form of latent variables that we do not directly observe. Let us say that Y^* is one such variable , and the relationship between Y* and two other variables X and Z can be captured by the standard linear regression formula below.

$$Y^* = \gamma Z + \beta Z + e \tag{A.1}$$

γ and β are parameters and e is an error term. Y*is our actual come of interest and may stand for some abstract concept or a variable that is not measured (or inherently unmeasurable). In the case of graduate underemployment, the concept may be skills utilisation. In Roska's (2005) study it was how far up the occupational hierarchy an individual's job was. We do not directly observe Y^* however we do observe Y. Where:

$$Y_i = \begin{cases} 1, & \text{if } Y^* > C \\ 0, & \text{otherwise} \end{cases}$$

This is often the situation in empirical research where we only observe an outcome Y for an individual if Y^* is over some threshold. Y could be an outcome such as being employed in graduate job, surviving an illness or being the top quartile of jobs in an occupational hierarchy. Following the example of underemployment, we may say that an individual is not underemployed and in a 'graduate' job ($Y = 1$) if their level of skills use is over a certain threshold ($Y^* > C$). Since we are often more interested in abstract, and perhaps purely theoretical, constructs such as 'employability', 'resilience' or 'utility' than simply binary outcomes, we are interested in the relationship between Y^* and X (or Z). We may not care about the relationship between the binary outcome Y and X (or Z). In short, we are interested in knowing something about a latent variable that we cannot observe in practise.

Now it follows from a bit of rearranging that:

$$\Pr\left(Y = 1|X, Z\right) = \Pr\left(Y^* > C|X, Z\right) = \Pr\left(e > C - \gamma Z - \beta X\right)$$

If we were, for the sake of argument, to assume that e was normally distributed with mean 0 and standard deviation σ. Then we can show that:

$$\Pr\left(e > C - \gamma Z - \beta X\right) = \ \Phi\left(-\frac{C}{\sigma} + \frac{\gamma}{\sigma}Z + \frac{\beta}{\sigma}X\right) = \Pr\left(Y = 1|X, Z\right)$$

Where Φ is the cumulative distribution function for the standard normal distribution (mean 0 and standard deviation of 1). If we assumed that e was logistically distributed, we can obtain a similar result using the cumulative distribution function for the standard logistic distribution instead. Since we have the values of X, Y and Z for the data and the likelihood that $(Y = 1|X, Z)$, we can rearrange the above equation into:

$$Pr\left(Y = 1|X, Z\right) = \Phi(-D + \psi Z + \omega X) \tag{A.2}$$

where $D = \frac{C}{\sigma}$, $\psi = \frac{\gamma}{\sigma}$, and $\omega = \frac{\beta}{\sigma}$. We can use the above to find maximum likelihood estimates of D, ψ and ω, which are scaled versions of γ, β and C. This is essentially the probit regression model. However, we can never recover the original parameters γ and β (or C). Again, if e was logistically distributed then we can derive the logistic regression model in the same way.

The Problem

Let's compare two linear regression models for the same type of outcome Y for two different groups (i.e. group 1 and 2):

$$Y_1^* = \beta_1 X + e_1$$

$$Y_2^* = \beta_1 X + e_2$$

Where Y_1^* is the outcome for group 1, β_1 is change in Y_1^* associated with X for group 1, and e_1 is the error term for group 1. We have follow the same logical for group 2. For the sake of argument again, assume that e_1 and e_2 are both normally distributed with standard errors of σ_1 and σ_2 respectively. It is perfectly possible obtain estimates of β_1 and β_2 using a linear regression and to judge if the effects of X on Y_1^* and Y_2^* is the same. To clarify, if Y_1^* was hourly wages for biological sciences graduates and Y_2^* was hourly wages for other STEM graduates then we would be able to compare the size and direction of the relationship between X and hourly wages between these two groups of graduates.

Now let's say we only observe Y_1 and Y_2 instead where:

$$Y_1 = \begin{cases} 1, & \text{if } Y_1^* > C \\ 0, & \text{otherwise} \end{cases}$$

and

$$Y_2 = \begin{cases} 1, & \text{if } Y_2^* > C \\ 0, & \text{otherwise} \end{cases}$$

Since Y_1 and Y_2 are discrete variables, we may wish to use a probit regression model to find the $Pr(Y_1 = 1|X)$ and $Pr(Y_2 = 1|X)$. If the resulting parameter estimate from the probit are ω_1 and ω_2 then:

$$\omega_1 = \frac{\beta_1}{\sigma_1} \text{ and } \omega_2 = \frac{\beta_2}{\sigma_2}$$

It is clear that ω_1 and ω_2 are partly determined by the standard deviation of e_1 (σ_1) and e_2 (σ_2). Therefore it does not follow that:

$$\text{if } \omega_1 > \omega_2 \text{ then } \beta_1 > \beta_2$$

Believing that this would be the case can lead to an erroneous inferences. This may not seem particularly insightful at first so I will a concrete example.

Imagine again that Y_1^* was hourly wages for biological sciences graduates and Y_2^* was hourly wages for other STEM graduates with β_1 and β_2 being the effects of X on wages with $\beta_1 = 10$ and $\beta_2 = 5$. Now for argument's sake say that we only know if a graduates' hourly wage was over £10 or not, so in effect we observe $Y_1 = 1$ and $Y_2 = 1$ when $Y_1^* > 10$ and $Y_2^* > 10$ respectively. Since Y_1 and Y_2 are discrete variables we may use a probit regression to find ω_1 and ω_1, where:

$$\omega_1 = \frac{10}{\sigma_1} \text{ and } \omega_2 = \frac{5}{\sigma_2}$$

For argument's sake let's say that the wages of biological science graduates are more varied than other STEM graduates such that their standard deviation given X is twice as great as those in other STEM subjects (i.e. $\sigma_1 = 2\sigma_2$). In this case we would expect our estimates of ω_1 and ω_2 to be the same. We would correctly infer that the impact of X on the probability that an individual earns over £10 is the same for both biological sciences and STEM graduates.

However, we would usually be more interested to know if the effects of X on wages in general was the same across the two groups and we simply cannot know this from comparing ω_1 and ω_2 alone. We cannot naively say that the effects of X (i.e. β) on mean wages was the same for both groups of graduates. It should also be clear then that if we were interested in skills utilisation then simply modelling the probability of whether a graduate was underemployed or not using a probit or logit model, and comparing the results would not be sufficient.

Proposed solution using partial correlation coefficients

Proposed methods to extract and compare β_1 and β_2 rely on making additional untestable assumptions about the data generating process and/or are also shown to be biased and inconsistent under less than ideal circumstance (Allison 1999, William 2009; see Keele and Park 2006 for Monte Carlo simulations). However, it is moderately easy to obtain estimates of the partial correlation between the latent outcome Y^* and X in equation A.1 without making any further assumptions beyond those already stated. The partial correlation ($\rho_{Y^*,X|Z}$) is the correlation between X and Y^* conditional on other predictors. In the next example I will introduce only one other predictor Z. The relationship between β and $\rho_{Y^*,X|Z}$, in equation A.1, is:

$$\beta = \rho_{Y^*,X|Z} \frac{\sigma_{Y|Z}}{\sigma_{X|Z}}$$

Let's assume the error term in equation A.1 is normally distributed (i.e. $e \sim N(0, \sigma)$).Since the parameter estimate from a probit regression with Y is $\omega = \frac{\beta}{\sigma}$ (equation A.2), we can re-write and arrange the above into:

$$\rho_{Y^*,X|Z} = (\omega\sigma) \frac{\sigma_{X|Z}}{\sigma_{Y^*|Z}} \tag{A.3}$$

Now the variance of Y^* given Z is:

$$\sigma^2_{Y^*|Z} = \beta^2 \sigma^2_{X|Z} + \sigma^2_{Y^*|Z,X} = (\omega\ \sigma)^2 \sigma^2_{X|Z} + \sigma^2 = \sigma^2(\omega^2 \sigma^2_{X|Z} + 1)$$

The values of X given Z can be found in a regression of X on Z (i.e. they are the residuals from the resulting regression model). Now we can express equation A.3 as:

$$\rho_{Y^*,X|Z} = \frac{(\omega\sigma)(\sigma_{X|Z})}{\sigma\sqrt{(\omega^2\sigma^2_{X|Z} + 1)}} \tag{A.4}$$

Now since σ appears in the numerator and denominator of the above fraction, we can now express $\rho_{Y^*,X|Z}$ without σ.

$$\rho_{Y^*,X|Z} = \frac{(\omega\sigma)(\sigma_{X|Z})}{\sigma\sqrt{(\omega^2\sigma^2_{X|Z} + 1)}} \tag{A.5}$$

In equation A.5 all the quantities need to calculate $\rho_{Y^*,X|Z}$ can be estimated; to re-iterate $\sigma_{X|Z}$ is simply the variance of the residual term in an OLS regression of X on Z and ω is the parameter estimate for X in a probit regression. If we assume the error term e in equation A.1 was logistically distributed then we would only need to make minor alterations to equation A.5. First we substitute ω for the parameter estimate for X in a logistic regression and the number 1 in the denominator for $\frac{\pi^2}{3}$ which is the variance of the standard logistic distribution. The full explanation of the method, the method to extract additional statistics and standard errors (without resorting to resampling methods) are given in Breen, Holm and Karlson (2013). It should be noted however that the distribution of estimates for $\rho_{Y^*,X|Z}$ is not normally distributed but atanh($\rho_{Y^*,X|Z}$) is approximately normally distributed. In reality since $\rho_{Y^*,X|Z} \sim$ atanh($\rho_{Y^*,X|Z}$) for low value of $|\rho_{Y^*,X|Z}|$ (<0.2, see figure A.1). As such, I will present the standard errors for atanh($\rho_{Y^*,X|Z}$) as approximate standard error for $\rho_{Y^*,X|Z}$ in tables. p values are still derived using atanh($\rho_{Y^*,X|Z}$).

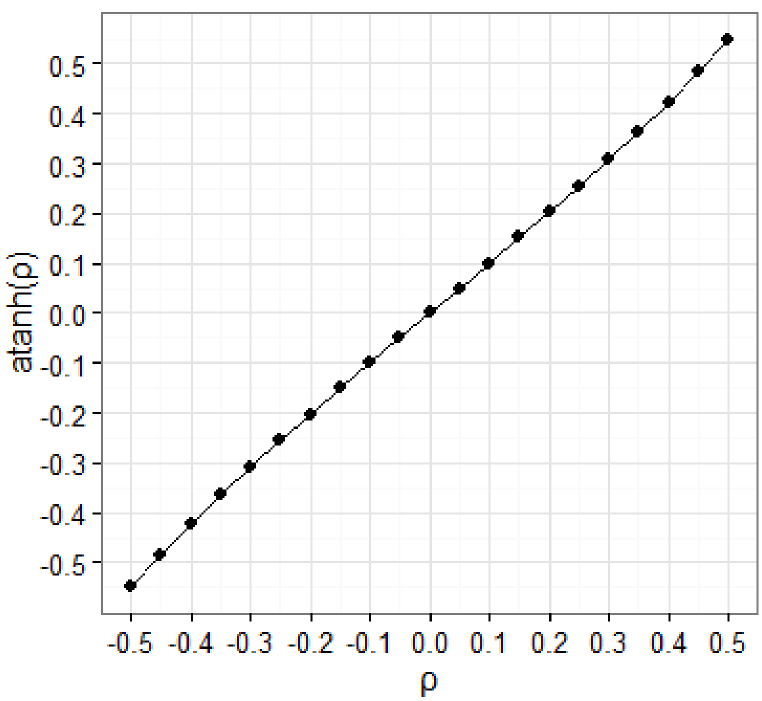

Figure A.1: Relationship between ρ and atanh(ρ)

Since $\rho_{Y^*,X|Z}$ is scale free (i.e. not affect by values of σ), it can be compared across different regression models to draw inferences about the strength of association between an outcome Y^* and a predictor X, accounting for other factors. This is particularly useful for comparing the strength of association between factors, such as gender, and job prestige or skills use between graduates from different fields of study. One caveat is that is if X is a dummy variable then $\rho_{Y^*,X|Z}$ is slightly sensitive to the distribution of X across different datasets. There is little that can be done to adjust for this.

A.2.2 Adjusting for multiple comparisons in hypothesis testing

In many studies, researchers commonly use interaction terms to detect test for variations in parameter estimates by field of study. The other common strategy is to run separate regression models for each field of study and compare parameter estimates for the same predictors across models. The two methods are related since estimating a separate model for each group is akin to estimating one model using all the data and interaction terms between group and all the other predictors (plus dummy variables for group membership itself).

$$Y_1 = \alpha_1 + \beta_1 X + \gamma_1 Z + e_1, \tag{A.6}$$

$$Y_2 = \alpha_2 + \beta_2 X + \gamma_2 Z + e_2, \tag{A.7}$$

$$Y_{1+2} = \alpha + \hat{\alpha} G + \beta X + \hat{\beta} XG + \gamma Z + \hat{\gamma} ZG + e \tag{A.8}$$

For sake of example, equations A.6 and A.7 denote the same model estimated separately for groups 1 and 2 respectively (i.e. β_1 is the parameter estimate for X for group 1 and so forth). Equation A.8 denotes model estimated using data from both group 1 and 2. In equation A.8 there is an interaction term between every predictor and G where G is a dummy variable indicating group membership indicator, $G = 1$ when a case is in group 2 else it is 0. e, with and without subscripts, denotes the error term in all the model. The term α in equation A.8 will be *identical* to α_1, β will be identical to β_1 and so forth. The term $\hat{\alpha}$ will be *identical* to $\alpha_2 - \alpha_1$ and so forth for the other parameter estimates. In the simple case of equation A.8, we can test if β_1 is different from β_2 through a t test on $\hat{\beta}$.

When the number of group increase beyond 2 we need to account for the fact that we are making multiple comparisons and adjust our statistical tests appropriately. For instance, If we are doing sub-group analysis looking at the effects of X on Y like in equations A.6 and A.7 for K number of groups, we can end up making $\frac{K(K-1)}{2}$ pairwise comparisons! For instance, if β_1, $\beta_2 \ldots \beta_K$ are our parameter estimate for X for group 1,2 ... K, we could test the difference between $\beta_1$and β_2, β_1 and β_3, and so forth. A similar issue exists with interaction terms. It is easy to see that as the number of groups K increases the chance of findings at least one statistically significant result. In this case it would be problematic to reject the null hypothesis that there is no variation in the effects of X on Y across groups (i.e. $\beta_1 = \beta_2 = \ldots \beta_K$) on the account of one statistically significant pairwise comparison test without adjusting for multiple comparisons.

However, this is precisely what happens in the literature looking at levels of stratification by fields of study. This is particularly problematic as field of study can be divided up into many groups. This can lead to over-exaggerated claims and misleading results which may drive the odd findings and patterns observed across studies. I will demonstrate by reanalysing the Hansen's (2001) results looking at the relationship between socio-economic background and income across different fields of study.

The Problem

Hansen used Norwegian tax return data to test for the existence of variations in stratification by socioeconomic background across different field of study. The regression model she used can be simplified into this form:

$$\log\left(\text{income}_h\right) = \delta_{\text{base}} + \beta_{\text{base}} X + \sum_{1}^{K} \delta_k \text{field}_k + \sum_{1}^{K} \beta_k X(field_k) + \sum_{1}^{j=J} \gamma_j Z_j \tag{A.9}$$

Where X is a dummy variable denoting a socioeconomic background category, the baseline comparison group are those with working class backgrounds. There were three other socio-economic background categories (Managerial, Higher, Medium) used in this study, equation 9 only has one X dummy variable for simplicity. field_k are dummy variables denoting one of nine fields of study, the baseline comparison group is teaching and social work. β_{base} is the size of the difference in $log(income)$ between those from working class backgrounds and another background category for those who studied teaching and social work. $\beta_{\text{base}} + \beta_k$ is the size of this difference for field of study k, where $k = 1$ may stand for law and so forth. Finally Z_j denotes the other J number of regressors in the model, including age and other interaction terms. Hansen actually estimated the models for three types of income; employed income; combined self-employed and employed income; and combined self-employed and employed income plus capital income (including stock returns).

What is fundamentally of interest in Hansen's analysis is whether we can reject the null hypothesis that the interaction effects β_k are all zero. However there are nine different interaction terms and the more statistical tests we do the higher the chances are that one of them will be statistically significant. This greatly raises the probability that we will reject the null hypothesis, when the null hypothesis is true (Type 1 error).

Tables A.1 and A.3 shows the results of Hansen's analysis for combined employed and self-employed incomes, and employed and self-employed incomes plus capital income. The table shows the interaction effects across fields of study and shows the p values for these effects. These results are taken from Table A1 from Hansen's paper (p. 230-1, 2001). Results for employed income only and females do not show a greater degree of heterogeneity and are left out. Tables A.2 and A.4 shows the number of statistically significant interaction terms from the model before and after taking multiple comparisons into account using the Holm-Bonferroni correction (HB) (Holm 1979).

Table A.1: Results of Hansen's Analysis on Employed and Self-employed income

Field of study	Managerial	p value	Higher	p value	Medium	p value
Health	0.094 (0.095)	0.322	0.104 (0.06)	0.083	0.002 (0.045)	0.965
Law	0.224 (0.101)	0.027	0.181 (0.079)	0.022	0.031 (0.068)	0.648
Economics	0.216 (0.093)	0.020	-0.02 (0.074)	0.787	0.073 (0.055)	0.184
Admin	0.086 (0.076)	0.258	0.103 (0.056)	0.066	-0.019 (0.034)	0.576
Engineering	0.049 (0.074)	0.508	0.033 (0.048)	0.492	-0.019 (0.031)	0.540
Natural Sciences	0.059 (0.091)	0.517	0.088 (0.061)	0.149	0.03 (0.043)	0.485
Agriculture	0.145 (0.088)	0.099	0.033 (0.066)	0.617	-0.031 (0.036)	0.389
Social Sciences	0.227 (0.089)	0.011	0.117 (0.067)	0.081	0.051 (0.37)	0.890
Humanities	0.11 (0.085)	0.196	0.142 (0.058)	0.014	0.045 (0.041)	0.272

Focussing on combined employed and self-employed data only, we find that there are three

Table A.2: Number of statistically significant interaction terms (Employed and Self-employed income)

Socioeconomic background	alpha level=0.05 (Original)	alpha level=0.1 (HB)	alpha level=0.05 (HB)
Managerial	3	1	0
Higher	2	0	0
Medium	0	0	0

Table A.3: Results of Hansen's Analysis on Employed, Self-employed and Capital income

Field of study	Managerial	p value	Higher	p value	Medium	p value
Health	0.074 (0.101)	0.464	0.105 (0.064)	0.101	-0.002 (0.048)	0.967
Law	0.222 (0.107)	0.038	0.188 (0.084)	0.025	0.038 (0.072)	0.598
Economics	0.334 (0.099)	0.001	0.052 (0.079)	0.510	0.1 (0.059)	0.090
Admin	0.138 (0.081)	0.088	0.106 (0.059)	0.072	-0.008 (0.037)	0.829
Engineering	0.078 (0.079)	0.323	0.037 (0.051)	0.468	-0.028 (0.033)	0.396
Natural Sciences	0.068 (0.097)	0.483	0.092 (0.065)	0.157	0.027 (0.046)	0.557
Agriculture	0.144 (0.094)	0.126	0.043 (0.07)	0.539	-0.031 (0.038)	0.415
Social Sciences	0.283 (0.095)	0.003	0.176 (0.072)	0.015	0.052 (0.054)	0.336
Humanities	0.23 (0.091)	0.011	0.145 (0.062)	0.019	0.042 (0.043)	0.329

(two) statistically significant interactions for Managerial (Higher) compared to working class. However, after correcting for multiple comparisons, there are no statistically significant interaction effects at the conventional $p<0.05$ level and only one significant comparison at the higher $p<0.1$ level. There is a similar picture for on combined employed and self-employed data plus capital income, we find four (three) statistically significant interactions for Managerial (Higher). After correcting for multiple comparisons there is only one significant interaction term for Managerial at the conventional $p<0.05$ level. This is driven by the extremely large income differences between those from managerial and working class backgrounds who studied a field related to economics. As pointed out in chapter 4, capital income does not distinguish between income that is earned through employment and income derived from inherited wealth such as property rents and so forth. As such, after correcting for multiple comparison, the strongest evidence that any variation in stratification exists by fields of study rests upon a generous interpretation of income (and even then only for males).

Proposed solution using the Holm-Bonferroni method and simulated chi-squared distributions

The number of significant statistically interaction effects in models represented by equation A.8 and A.9 is also a poor indicator of heterogeneity. This is because this number is highly sensitive to what group is set as the reference (or baseline) category. In theory, using this method, one can set up favourable results for tests of heterogeneity by switching the baseline group.

When we wish to test for variations using interaction terms, it is better to do an F ratio test for

Table A.4: Number of statistically significant interaction terms (All income types)

Socioeconomic background	alpha level=0.05 (Original)	alpha level=0.1 (HB)	alpha level=0.05 (HB)
Managerial	4	1	1
higher	3	0	0
medium	0	0	0

model fit comparing a model with interaction effects and one without (or an equivalent for non-linear models). However, when our model is like equation A.8, where there are two interaction effects (one for X and one for Z), we can test whether including both interactions will improve model fit compared to using no interactions. However, we cannot test which interaction effect is driving improvements in model fit. I propose two different methods for testing for variations in estimates by field of study in this case; one using the Holm-Bonferroni correction and another using the chi-squared distribution. First let us formally state the null hypothesis H_0:

$$\beta_1 = \beta_2 = \ldots \beta_k = \beta$$

Where $\beta_1 \ldots \beta_k$ denotes the effects of our predictor of interest for groups $1 \ldots k$, much like in equations A.6 and A.7.

Method 1: Pairwise comparison tests using the Holm-Bonferroni method

As mentioned the null hypothesis can be reduced to $\frac{K(K-1)}{2}$ pairwise comparisons, where we compare β_1 and β_2, β_1 and β_3, $\ldots$ β_{k-1} and β_k. One way to test the null hypothesis is to test every possible pairwise comparison and see how many are statistically significant after correcting for multiple comparisons using the Holm-Bonferroni correction. Under the null hypothesis, the probability of finding one or more statistically significant result should be around 5 percent (if $p<0.05$ was the level of statistical significance used) (Holm 1979, Dunn 1961). The number of statistically significant comparisons also gives us a rough idea of how unlikely our results are under the null hypothesis—this is a substitute for an actual p value. There are no further assumption involved in the test.

Method 2: Hypothesis testing using simulated chi-squared distributions

Under the null hypothesis, $\beta_1 \ldots \beta_k$ can all be considered estimates of β and if we assume estimates of β are at least approximately normally distributed, as they are under OLS and a host of other estimators, then we can test the null hypothesis using the chi-squared distribution. For instance, if β_1 was an estimate of β with a variance of σ_1^2 then $\frac{\left(\beta_1 - \beta\right)^2}{\sigma_1^2}$ will be chi-squared distributed with a 1 degrees of freedom. By extension:

$$\sum_{1}^{k=K} \frac{\left(\beta_k - \beta\right)^2}{\sigma_k^2} \sim \chi^2(K) \tag{A.10}$$

That is the sum of $\left(\beta_k - \beta\right)^2 / \sigma_k^2$ across all of our K groups will be chi-squared distributed with K degrees of freedom. Unfortunately we do not know the true value of β and as such we must replace it with an estimate of β. One such estimate is the weighted mean of $\beta_1 \ldots \beta_k$. We must also replace σ_k^2 with estimates, for instance if β_k was estimated using OLS then an estimate of σ_k^2 is the square of the standard error of β_k. If $\sigma_1^2 = \sigma_2^2 = \ldots \sigma_k^2$ then the statistic in equation A.10 would have $K - 1$ degrees of freedom. This is unlikely to be the case for practical applications (i.e. comparing results across regression models); least of all because different sample sizes across each of the K groups will cause the standard errors of β_k to vary.

In the case described above, the degrees of freedom become harder to calculate. In such cases however we can derive the distribution of our test statistics using Monte Carlo simulations. In the simulations I assume that $\beta_1 = \beta_2 \ldots = \beta_k = 0$ and we use estimates of σ_k^2 to generate the appropriate distribution for the chi-squared statistic. We can generate an arbitrarily precise distribution by increasing the number of simulations; all subsequent analyses are based on distribution obtained from 1,000 simulations. This method allows us to also derive arbitrarily precise p values. The simulations account for the uncertainty in estimates of β but cannot account for uncertainity in estimates of σ_k^2, which in any case can be very small.

Simulation results

I test both methods (Holm-Bonferroni and chi-squared) under the situation where there are $K = 10$ groups and for each group $y_k = \beta_k X + e$. Both X and e are independent draws from the standard normal distribution ($\sim N(0,1)$). Furthermore the true values of β_k are drawn from the normal distribution $N(0, \sigma_\beta)$. The size of group 1 is 100 and increases by 200 (i.e. group 2 is 300) until we have 1,900 cases in group 10. This is to allow for different variances in the estimate of β_k. I estimate β_k using OLS separately for each group k.

Table A.5: Null hypothesis rejection rate (based on 2000 simulated datasets)

Method	σ_β=0	σ_β=0.025	σ_β=0.05
Holm Bonferroni*	3.35%	30.25%	84.50%
Simulated chi-squared	5.20%	20.35%	72.80%

*At least one statistically significant (p<0.05) pairwise comparison

Table A.5 shows how many times both the methods rejects the null hypothesis, at the conventional p<0.05 level, for 2,000 simulated datasets where σ_β is 0 (no variations), 0.025 and 0.05. The results show that under the null hypothesis the Holm-Bonferroni method is a little bit more conservative than the simulated chi-square test. The latter has a type I error rate of 5.2 percent under the null hypothesis whilst the former has a type I error rate of 3.35 percent. Both are able are fairly sensitive, rejecting the null hypothesis over 70 percent of the time when $\sigma_\beta = 0.05$. It should be noted that for most of the analyses in this thesis, we are actually dealing with sub-sample sizes (i.e. in each field of study) larger than those in the simulation. Since we can derive p values from the chi-squared method, I will primarily report the results of that test in the rest of the study.

Finally I will demonstrate methods with Hansen's results for incomes including self-employed and capital incomes. Referring back to equation A.9, the estimate for predictor X in field of study k is equal to $\beta_{\text{base}} + \beta_k$. The approximate variance of $\beta_{\text{base}} + \beta_k$ can be easily derived from Hansen's results tables[1]. I will only examine the differences in incomes between those from Managerial and Working class socioeconomic backgrounds by field of study since these results were the most extreme.

A chi squared test shows that the variations in these differences across fields of study are not significant (p=0.616) when we look at employed incomes only but is significant when we use the combined self-employed and employed income (p=0.035) and all income types, including capital income, combined (p<0.01).

[1] $\text{var}(\beta_{\text{base}} + \beta_k) = var(\beta_{\text{base}}) + var(\beta_k) + 2cov(\beta_{\text{base}}, \beta_k)$ since β_k is an interaction term in a linear regression then $\text{var}(\beta_{\text{base}}) = -\text{cov}(\beta_{\text{base}}, \beta_k)$. Therefore $\text{var}(\beta_{\text{base}} + \beta_k) = var(\beta_k) - \text{var}(\beta_{\text{base}})$.

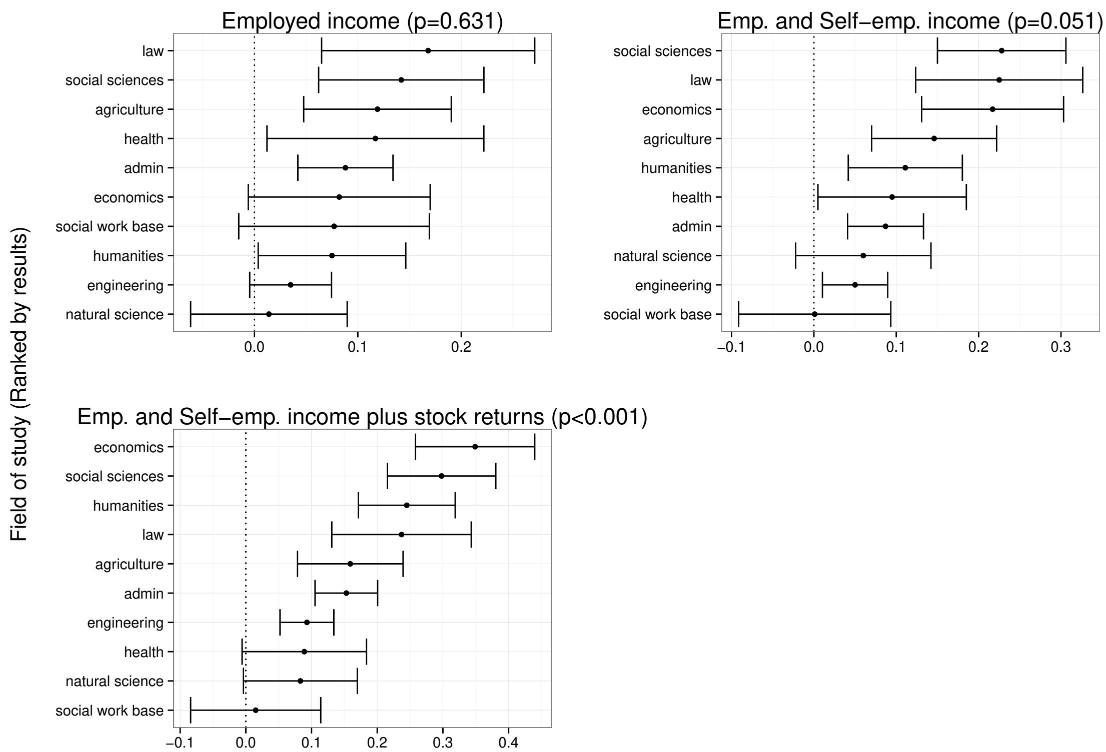

Figure A.2: Difference in log(income) between graduates from Managerial and Working class socioeconomic backgrounds (Source: Hansen 2001, p. 230, table A1)

Figure A.2 displays the differences graphically across fields of study for each of the three income types. In figure A.2 the error bars are arranged so to facilitate pairwise comparisons. If the error bars do not overlap then a pairwise comparison of the two parameter estimates would, on average, be statistically significant (p<0.05, Goldstein and Healy 1995, hence why the error bars are also called comparison intervals). This convention for graphically representing results to facilitate comparisons across fields of study is also retained for the rest of the thesis.

A.3 Sample selection bias

A.3.1 Sample selection bias in regression analysis

Introduction

The problem of sample selection bias in regression models is well known but there is often little that can be done about it. For instance we may wish to know the impact of getting a degree on earnings but we can only observe earnings for individuals who are employed. If we simply run an OLS regression of earnings, our results may not give us an unbiased estimate of the effects of getting a degree. I will demonstrate this formally first using the original proof given by Heckman and later using an intuitive example. It is surprisingly common for research papers in sociology to routinely misapply methods for dealing with sample selection bias or to omit important details about how the method was applied in the first place (see Bushway, Johnson and Slocum 2007). As such, it is worth providing details about how sample selection was dealt with in this thesis.

The Problem

Say that S^* and Y^* are two continuous latent variables that we do not observe. For individual *(i)* in the data we may assume that:

$$S^* = \sum_{k=1}^{K} \omega_k Z_k + u$$

Where Z_k are regressors in the model (e.g. $Z_{k=1}$ stands for age etc.) and $\omega_k$are the parameters for Z_k. u is the error term with an expected value of 0. Y^* is also defined in a similar fashion:

$$Y^* = \sum_{j=1}^{J} \beta_j X_j + e$$

Where X_j are regressors in the model and $\beta_j$are the parameters to be estimated. Again e is the error term with an expected value of 0. For the sake of argument, both the error terms—u and e—are normally distributed with covariance σ_{ue}. This is an important assumption in the original Heckman correction.

$$\begin{pmatrix} u \\ e \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \sigma_{ue} \\ \sigma_{ue} & \sigma_e^2 \end{pmatrix}\right]$$

Let's imagine that $S^*$is a latent term that stands for the propensity for an individual to be full-time employed. This may be determined by various things such as their human capital, the state of demand and supply for their skills in the labour market, or an individual's desire to do other activities instead of entering the labour market.

S is an indicator for being full-time employed; if an individual i was employed full time then $s_i = 1$ else it is equal to 0. We will observe if an individual is full-time employed if their propensity to be employed (S^*) is great enough. As such that we may say that:

$$S = \begin{cases} 1, & \text{if } S^* > c \\ 0, & \text{otherwise} \end{cases}$$

Where c is the threshold value that S^* must be above in order for an individual to be full-time employed. We can state the above as:

$$\text{if } \sum_{k=1}^{K} \omega_k Z_{\text{ik}} + u > c \; then \; S = 1 \; else \; S = 0$$

Note that we can set c to be of any value with no loss of generalisability later on (as long as we have an intercept in the model). Let's assume that $c = 0$ for convenience. The above can be rearranged like so into equation A.11:

$$S = \begin{cases} 1, & \text{if } u > -\sum_{k=1}^{K} \omega_k Z_k \\ 0, & \text{otherwise} \end{cases} \tag{A.11}$$

Turning to the outcome Y^*, let us assume that Y^* represented the hourly wages for that an individual would receive if they were employed full-time. Much like with S^*, we do not observe Y^* either. Instead we observe Y where Y is the observed hourly wage for individuals who are actually employed full-time employed in the data. The relationship between Y^* and Y is as follows:

$$Y = \begin{cases} Y^*, & \text{if } S = 1 \\ \text{Unobserved}, & \text{otherwise} \end{cases} \tag{A.12}$$

It follows then that:

$$E\left(Y|X\right) = E\left(Y^*|X, S=1\right) = \sum_{j=1}^{J} \beta_j X_j + E(e|S=1) \tag{A.13}$$

Which we will note as equation A.13.The $E(e|S_i = 1)$ term is especially important as

$$\text{if } \sigma_{\text{ue}} \neq 0 \textit{ then } E(e|S=1) \neq E(e) \neq 0$$

Which essentially means that if we naively regress Y on X (i.e. hourly wages on predictors for full time employed individuals) when $E(e|S_i = 1) \neq 0$, then our estimates of β_j may be biased. We will call this potentially biased estimate $\tilde{\beta}_j$. $\tilde{\beta}_j$ is *not* an accurate estimate of the differences in hourly wages associated with a change in predictor X.

Informal statement of the problem

An intuitive way to understand the problem is to use another example. Say that degree holders with a first class honours degree would receive higher wages in the labour market (i.e. our hypothetical Y^*) if they were offered and accepted a job. However, these individual may be more likely to pursue further studies for various reasons. They may see the potential for greater future earnings by acquiring further qualifications or just enjoy learning for its own sake. Those with first class honours who do not go on to further study may have different preferences, or are otherwise compelled to go into paid employment for reasons that we do not observe. For example, family crises or dependent children may compel these individuals to find work immediately. Further these circumstance may compel these individuals to also accept lower wages—individuals who urgently need to find employment may forgo searching for better job offers in exchange for lower paying but immediately available work.

In this example, individuals with first class honours degrees who are employed will have an average wage that is actually *lower* than the average wage that first class honours degree holders in general would have received if they had gone into paid employment. This occurs as a results of unobserved, and perhaps unobservable, factors that affect both the chances of employment and people's wage.

Proposed solution using control functions

Heckman proposed a solution to the problem of sample selection. The method has been extended for a variety of selection situations and there are semi-parametric versions as well. However, in the thesis I will deal with the simple binary selection model with a continuous outcome as originally outlined by Heckman. In equation A.13 we know all the X predictors in the data but $E(e|S_i = 1)$ is unknown. However, we can estimate it if e and u are assumed to be normally distributed.

First we note that:

$$E\left(e|S=1\right) = E(e|u > \; -\sum_{k=1}^{K} \omega_k Z_k) \tag{A.14}$$

If e and u are correlated in a bivariate normal distribution then the expected values of e given a value of u is

$$E(e|u) = \rho_{\text{ue}} \frac{\sigma_e}{\sigma_u}(u)$$

Where ρ_{ue} is simply the correlation between u and e. If we substitute u in equation A.14 then we get:

$$E\left(e|S=1\right) = \rho_{\text{ue}} \frac{\sigma_e}{\sigma_u} E(u|u > \; -\sum_{k=1}^{K} \omega_k Z_k)$$

$E(u|u > \; -\sum_{k=1}^{K} \omega_k Z_k)$ is the expected value of a truncated normal distribution and is given by:

$$E\left(e|S=1\right) = E(u|u > \; -\sum_{k=1}^{K} \omega_k Z_k) = \sigma_u \frac{\phi\left(\sum_{k=1}^{K} \frac{\omega_k}{\sigma_u} Z_{\text{ik}}\right)}{\Phi\left(\sum_{k=1}^{K} \frac{\omega_k}{\sigma_u} Z_{\text{ik}}\right)} = \sigma_u \lambda \tag{A.15}$$

Where ϕ is the probability density function of the standard normal distribution and Φ is the cumulative distribution function of the standard normal distribution. We can estimate $\frac{\omega_k}{\sigma_u}$ by running a probit regression of S with Z as predictors (see previous appendix sections). The estimated parameter estimates $\psi_k$is equal to $\frac{\omega_k}{\sigma_u}$. So effectively given that Z is known and $\frac{\omega_k}{\sigma_u}$ can be estimated we can derive λ which is also known as the inverse mills ratio (IMR). Therefore if we put the results of equation A.13 and A.15 together we get:

$$E\left(Y|X\right) = \sum_{j=1}^{J} \beta_j X_j + \left(\rho_{\text{ue}} \sigma_e\right) \lambda$$

Where both X and λ are either known or can be estimated. Values of λ will vary across individuals. β_j and $(\rho_{\text{ue}} \sigma_e)$ are unknown constants. In short, the equation effectively boils down to a linear regression that can be estimated by OLS:

$$Y = \sum_{j=1}^{J} \beta_j X_j + \left(\rho_{\text{ue}} \sigma_e\right) \lambda + \tau$$

Where τ is the error term with expect value of 0 but its variance term is unknown and heteroskedastic.

However, one issue is that it is beneficial to have at least one predictor in the selection equation (Z) that does not feature in the outcome equation (i.e. $Z_{1...K}$ is not a subset of $X_{1...J}$). These predictors are also known as exclusion restrictions. Whilst it is not essential for estimation, without exclusion restrictions we will be relying on distributional assumptions alone to identify our parameters of interest (i.e. β_j). Furthermore the standard errors of our estimates will also be far larger if we do not use exclusion restrictions. In fact, the standard errors can be so large as to render the whole routine pointless.

Knowing what predictors serve as appropriate exclusion restrictions means assuming things about the selection and outcome processes that we are trying to model. This requires the analyst to make some assumptions that are worth explaining in detail—if any attempts to deal with sample selection is to be taken seriously. I will detail how I dealt with sample selection for wage analyses done in later chapters. I will deal with sample selection due to full-time employment and attrition in the longitudinal DLHE survey. I will examine the set of the results that account for sample selection and compare them to results found elsewhere in the thesis that do not account for sample selection.

Dealing with selection bias when the outcome only has discrete variables is slightly more complicated and is very sensitive to distributional assumptions. In such situation the 'cure' may be worse than the 'disease' and as such I do not attempt such analyses in the thesis.

A.3.2 Selection bias due to full-employment status in the DLHE

The problem

In the DLHE and longitudinal DLHE, graduates' annual salaries are the main indicators of earnings. However, until recently, the DLHE surveys did not contain questions asking individuals about their hours worked. As such, we cannot accurate compare earnings between part-time and full-time workers. Furthermore, we do not observe earnings for those that are not in work. This issue is particularly severe for the DLHE which capture graduates' destinations approximately six months after leaving HE. In this period, a substantial proportion are in part-time work or further study. This is less of an issue for the longitudinal DLHE which captures graduate destinations three and a half years after leaving HE—although the longitudinal DLHE suffers from another problem: sample attrition.

In this thesis I have dealt with sample selection in the DLHE by using information about where graduates were domiciled prior to HE and the location of their current employers. In the DLHE data, we can imagine that the domicile of the individual prior to university, which I will call this *domicile* for short, will affect their chances of being employed. After their studies graduates have a tendency to migrate back home and stay with their parents before continuing their job searches (Sage, Evandrou and Falkingham 2012, Tucker 2013). They may also prefer to find work closer to their hometowns to stay closer to friends and family, or want to save money by moving back in with their parents. This preference will have an impact on graduates' chances of finding work as the regional economies of the UK are very different. Also if short-term employment prospects are particularly poor then graduates may opt to go into further study. I propose that:

Assumption 1: Domicile should not affect the wages of an employed individual after other predictors including the location of their employer have been accounted for.

We can imagine that the wages that an employer offers is conditional on factors like the level of competition for work and the cost of living in the area that they are based. Furthermore employer location may also be a sign of job quality and firm size as the headquarters of many large firms are based in London and other major cities. However:

Assumption 2: Employers are unlikely to offer their employees wages based on the UK region their workers originally came from[2]*.*

Taking assumption 1 and 2 as given, if *domicile* is associated with employer location then it will be associated with earnings unless employer location was accounted for. After *employer location* and other covariates (such as family background) are accounted for, *domicile* ought to have no impact on wages. We can graphically represent our model using a path diagram (figure A.3).

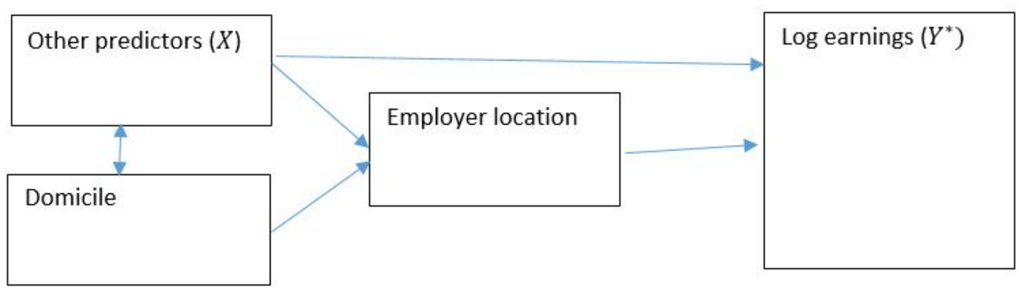

Figure A.3: Path diagram of factors associated with earnings

Empirical strategy

Following the arguments outlined so far we should be able to get results from this model using the control function approach. The observed earnings of individual who are working full-time is estimated (Y) as:

$$Y = (Y^* \,|FT = 1) = \sum_{j=1}^{J} \hat{\gamma}_j X_j + \hat{\gamma}_{\text{emp}}\,(\text{Employer Location}) + \gamma_{\text{mills}}\lambda + \tau \tag{A.16}$$

Where FT is an indicator of whether an individual was working full-time. λ is the estimated value of the inverse mill ratios for each individual. However, as previously explained, $\hat{\gamma}_j$ and $\hat{\gamma}_{\text{emp}}$ are estimates for γ_j and γ_{emp} in a model of hypothetical earnings (Y^*) where:

$$Y^* = \sum_{j=1}^{J} \gamma_j X_j + \gamma_{\text{emp}}\,(\text{Employer Location}) + e \tag{A.17}$$

[2]One could argue that employers may discriminate on the basis of regional accents or other particular factors that are related to region but are not already picked up by personal characteristics like family background. However, we may plausibly that the effects of these factors are likely to be pretty low and so low that they may as well not affect wages.

Where γ_j is the effect of X_j on (observed or unobserved) earnings (Y^*) condition on other factors including employer location.

The estimates of γ_j in equation A.17 are not actually our parameters of interest. In chapter 7 and 8, we want to know the relationship between X_j and graduates' earnings conditional on other human capital factors and background characteristics. We did not wish to know the effects of X_j on earnings *conditional* on employer location. There are clear practical reasons why, the most obvious one being that if we can imagine that X_j is the *treatment* then employer location would be a post-treatment result. For instance, if X_j stood for degree classification; we would be interested in the effects of degree classification on earnings. People with higher degree classifications may go work in bigger cities like London and earn more in these locations. We would wish to capture this relationship in our estimates instead of conditioning it away. In general, we should not condition on post-treatment results (but see chapter 8 for exceptions). Ideally we would wish to get estimates from the following model:

$$Y^* = \sum_{j=1}^{J} \beta_j X_j + \beta_{\mathrm{dom}}(\mathit{Domicile}) + v \tag{A.18}$$

Domicile is in the model because it is clearly a pre-treatment variable. Estimates of β_j are exact the thing that we are interested in—the effects of X_j on earnings conditional on other factors including *domicile* but not employment location. However, as I previously pointed out this would mean all the variables in the wages regression would also be used in the selection equation.

However, if we simply look at our model with employer location (equation A.17) again we can see that we can rewrite it as:

$$Y^* = \sum_{j=1}^{J} \gamma_j X_j + \gamma_{\mathrm{emp}}\,(\text{Employer Location}) + \gamma_{\mathrm{dom}}\,(\text{Domicile}) + e \tag{A.19}$$

here it important to note that:

$$\gamma_{\mathrm{dom}} = 0$$

Here we can see that equation A.18 and A.19 are almost identical. The model represented by equation A.18 is the same as equation A.19 with omitted variables for *Employer Location.* As such, we can easily estimate β_j from γ_j by using a simple result about path analysis (or omitted variable bias in linear regression models).

If we only have one variable for Employer Location then:

$$\beta_j = \gamma_j + \gamma_{\mathrm{emp}}\delta_j$$

Where δ_j is simply the results of a regression of *Employer Location* on all the other predictors in the model represented by equation A.19. For example, employer location is represented as one dummy variable London (e.g. if employer location is in London then London=1 else London=0) then we would estimate δ_j using the following linear regression model:

$$\beta_{\text{London}} = \sum_{j=1}^{J} \delta_j X_j + \delta_{\text{dom}} domicile + \varepsilon \tag{A.20}$$

We can easily extend the method to cases where employer location is captured by several dummy variables to obtain estimates for β_j.

In summary, in order to obtain unbiased estimates of the relationship between predictor X_j on (log) earnings (i.e. β_j) we need to take the following steps:

1) Use a probit model to estimate the probability of graduates being in full-time employment. The model includes *domicile* and predictors X_j.

2) Use the results of the probit model in step one to calculate the inverse mills ratio.

3) Regress (log) earnings on predictors X_j, the inverse mills ratio, and dummy variables for *Employer Location* using OLS.

4) Regress the dummy variables for *Employer location* onto X_j and *domicile*.

5) Use the results of step 3 and 4 to compute estimates of β_j using equation A.20.

Standard errors for estimates of β_j were obtained by bootstrapping from 1,000 resamples.

Simulation results

In order to ascertain whether the Heckman type estimator is correct I have simulated datasets where the variables S^* and Y^* are:

$$S^* = 0.5 \cdot X_1 - X_2 + u$$
$$Y^* = 1.5 \cdot X_1 - 2 \cdot X_3 + e$$

Where u and e are draws from a bivariate normal distribution with means 0, standard deviations of 1, and a covariance of 0.7. The variables X_1 to X_3 are draws from a multivariate normal distribution:

$$\begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.3 & 0.6 \\ 0.3 & 1 & 0.3 \\ 0.6 & 0.3 & 1 \end{pmatrix} \right]$$

The parameters of interest, β_1 and β_2, come from a regression of Y^* on X_1 and X_2. The model is as follows:

$$Y^* = \alpha + \beta_1 X_1 - \beta_2 X_2 + v \tag{A.21}$$

I compare three different estimates of β_1 and β_2 in equation A.21. The first estimate comes from a regression of Y^* on X_1 and X_2. This is the estimate that we would prefer to use if there was no sample selection issues. The second estimate is obtained from a regression of Y on X_1 and X_2 where:

$$Y = \begin{cases} Y^*, & \text{if } S^* > 0 \\ Missing, & \text{otherwise} \end{cases}$$

Due to the sample selection mechanism, half of the values of Y will be missing and any estimates are likely to be biased. The third estimate of β_1 and β_2 is obtained using the Heckman type estimator mentioned in the previous section. The simulated datasets have 200 cases each and I obtain estimates from 5,000 simulations. The results are report in table A.6. The regression estimates on Y are clearly biased whilst the estimates from the Heckman type estimator are not. Furthermore the Heckman type estimator is efficient, the standard deviations for estimates of β_1 are not substantially higher than estimates obtained from a regression on Y^*. Standard deviations for estimates of β_2 are actually *lower* when using the Heckman type estimator compared to the regression on Y^*. This may seem surprising at first but this is because the Heckman type estimator assumes that X_2 has no relationship with Y^* conditional on X_1 and X_3. Effectively the extra precision comes because we have used prior (assumed) information in the estimate.

Table A.6: Estimates of β_1 and β_2 from 5,000 simulated datasets

	β_1		β_2	
	Mean	Std. Dev.	Mean	Std. Dev.
Regression on Y^*	0.382	0.141	-0.261	0.141
Regression on Y	0.218	0.202	0.073	0.238
Heckman type estimator	0.383	0.155	-0.261	0.120

Results

Sample selection in the DLHE can be an issue in general however it is particularly problematic for the analysis in chapter 7 where I compare earnings differences before and after the recession. Since the proportion of graduates in full-time employment fell during the recession this causes whereby sample selection bias could be much worse for any results obtained using post-recession data.

Table A.7 look at the results of regression models for earnings used in chapter 6 and 7. The results show the relationship between certain predictors and earnings in an analysis using all graduates (with dummy variables for field of study). The table shows compares the results of the analysis adjusting for sample selection to the results obtained by OLS.

Estimates of the gender earnings gap reduces after we account for sample selection from men earning 6.4 percent more than women to 4.5 percent in the 2006/07 cohort. This is a statistically significant difference (p=0.03). For the 2008/09 cohort the difference in the two estimates are even large; the gap reduces from 5.6 percent to 1.7 percent (p<0.01). The earnings gap between privately educated and state educated graduates also reduces for the 2008/09 cohort from 5.7 percent to 2.7 percent (p=0.02). Finally there are statistically significant and substantial reductions in the earnings gap between graduates from Russell group universities and those from post-1992 universities: from

Table A.7: Results for models of (log) earning using graduates from all fields of study (6 months)

Predictor	2006/07		2008/09	
	OLS	Adjusted	OLS	Adjusted
Intercept	9.540 (0.012)*	9.362 (0.074)*	9.498 (0.013)*	9.113 (0.096)*
Age (Base=18)	0.036 (0.002)*	0.043 (0.004)*	0.042 (0.002)*	0.063 (0.005)*
Non-white ethnicity	0.018 (0.006)*	-0.039 (0.016)*	0.006 (0.007)	-0.103 (0.023)*
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.016 (0.006)*	0.012 (0.005)*	0.019 (0.006)*	0.02 (0.006)*
–Managerial or professional	0.021 (0.005)*	0.015 (0.005)*	0.022 (0.006)*	0.018 (0.006)*
Has a known disability	0.008 (0.007)	-0.03 (0.013)*	-0.009 (0.007)	-0.044 (0.011)*
Male	0.062 (0.004)*	0.044 (0.007)*	0.055 (0.004)*	0.017 (0.01)
Domicile prior to HE				
(Ref: London)				
–North England	-0.154 (0.007)*	-0.192 (0.004)*	-0.125 (0.007)*	-0.168 (0.005)*
–Northern Ireland	-0.238 (0.012)*	-0.283 (0.01)*	-0.226 (0.012)*	-0.287 (0.013)*
–Scotland	-0.141 (0.008)*	-0.184 (0.007)*	-0.104 (0.010)*	-0.163 (0.009)*
–SE and East England	-0.057 (0.006)*	-0.086 (0.003)*	-0.048 (0.007)*	-0.077 (0.003)*
–SW and Mid England	-0.128 (0.006)*	-0.158 (0.003)*	-0.096 (0.007)*	-0.132 (0.004)*
–Wales	-0.150 (0.010)*	-0.194 (0.007)*	-0.108 (0.011)*	-0.164 (0.007)*
UCAS tariff quartile				
(Ref: 1st Quartile)				
–2nd Quartile	0.017 (0.005)*	0.023 (0.005)*	0.029 (0.005)*	0.041 (0.006)*
–3rd Quartile	0.034 (0.006)*	0.041 (0.006)*	0.046 (0.006)*	0.057 (0.007)*
–4th Quartile	0.038 (0.006)*	0.028 (0.008)*	0.030 (0.006)*	0.022 (0.007)*
Privately educated	0.065 (0.005)*	0.05 (0.009)*	0.055 (0.006)*	0.027 (0.01)*
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.066 (0.005)*	0.051 (0.007)*	0.077 (0.005)*	0.07 (0.006)*
–Other degree class	-0.055 (0.004)*	-0.045 (0.005)*	-0.051 (0.005)*	-0.056 (0.005)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.071 (0.005)*	0.061 (0.005)*	0.063 (0.005)*	0.04 (0.007)*
–Russell group university	0.094 (0.005)*	0.057 (0.011)*	0.090 (0.005)*	0.047 (0.011)*
Field of study [Ref: Biological sciences]				
–Business	0.162 (0.007)*	0.246 (0.03)*	0.138 (0.007)*	0.269 (0.031)*
–Creative arts	-0.023 (0.008)*	-0.023 (0.008)*	-0.038 (0.009)*	-0.073 (0.012)*
–Education	0.225 (0.010)*	0.291 (0.024)*	0.282 (0.010)*	0.427 (0.034)*
–Engineering and computer science	0.228 (0.007)*	0.301 (0.027)*	0.222 (0.008)*	0.318 (0.024)*
–Humanities and languages	0.018 (0.007)*	0.013 (0.007)	-0.013 (0.007)	-0.031 (0.009)*
–Law	0.078 (0.010)*	-0.001 (0.03)	0.055 (0.012)*	-0.041 (0.024)
–Other STEM	0.144 (0.008)*	0.151 (0.009)*	0.121 (0.009)*	0.107 (0.01)*
–Social studies	0.140 (0.007)*	0.171 (0.015)*	0.147 (0.008)*	0.189 (0.015)*
–Subjects allied to medicine	0.147 (0.008)*	0.243 (0.031)*	0.222 (0.008)*	0.426 (0.045)*
N	23889		20564	

*p<0.05

9.9 percent to 5.9 percent for the 2006/07 cohort (p<0.01) and from 9.4 percent to 4.8 percent for the 2008/09 cohort.

Looking at the results from the sample selection model we still come to the same conclusion as that in chapter 7. There are no statistically significant changes in stratification before and after the recession. However it is worth noting that the gender earnings gap between male and female actually reduced between the two cohorts from 4.1 percent to 1.7 percent (p=0.06).

The results adjusted for sample selection bias by field of study are contained in tables D.25 and D.26. On the whole the results seem to support the conclusions of chapter 6; there are variations in stratification by sex; HEI type; private education and degree classification across fields of study. There is little evidence of any variations in stratification by socioeconomic background.

A.3.3 Sample selection bias in the longitudinal DLHE due to sample attrition

The problem

The issue of sample selection due to full-time employment is less of an issue in the longitudinal DLHE where the majority of graduates are in full-time employment (>70%). However the response rates for the longitudinal DLHE are far worse than the initial DLHE. The possibility remains that those who responded to the longitudinal DLHE may also have higher or lower earnings than those that did not.

Fortunately we can take advantage of the sampling method of the longitudinal DLHE to adjust for selection bias. The sampling frame for the longitudinal DLHE was split into two different sub-samples: A and B (see chapter 4). Those in sample A were contacted more persistently and had much higher response rates than those in sample B (see table 4.3). Selection into Sample A was done to oversample certain graduate groups and the sampling criteria is known (IFF 2011, 2013). After we take into account the variables used in the sample criteria (Z_k) then membership of sample A or B is random and thus independent of labour market outcomes in the longitudinal DLHE.

Empirical strategy

For example, let Y^* be hypothetical earnings, we would say that the probability that an individual is in sample A is independent of earnings conditional on Z_k. Where Z_k includes all relevant the information that IFF used to draw individuals into sample A: ethnicity, domicile and employment status in the DLHE (p. 8, IFF 2011; p. 10, IFF 2013). After conditioning on Z_k we know those in sample A are more likely to respond to the longitudinal DLHE compared to those in sample B due to IFF's data collection strategy. Therefore we can model the outcome using control functions:

$$Y^*|(S=1) = \sum_{j=1}^{J} \gamma_j X_j + \sum_{k=1}^{K} \gamma_k Z_k + \gamma_{\text{mills}}\lambda + \tau \tag{A.22}$$

Where $S=1$ when respondent i is in the longitudinal DLHE and 0 otherwise. λ is the inverse mills ratios, and is estimated from a probit regression using Z_k and a dummy variable indicating whether the individual is in sample A or not as predictors. However, the indicator for sample A or B does not appear as a predictors in the outcome model.

There is some overlap between elements of X_j and Z_k (i.e. ethnicity and domicile). We also do not want to estimate the relationship between Y^* and X_j conditional on one element of Z_k: employment status in the DLHE. In order to eliminate the effects of employment status in the DLHE from the estimates I simply use the same strategy that I outlined in the previous section for eliminating employer location.

One alternative approach would be to model a double selection mechanism. For example modelling the chances of responding to the longitudinal DLHE then the chances of being full-time employed (see Chevalier 2012 for an example). However, the method used in Chevalier's paper is reliant on even more parametric assumptions and will have such inflated standard errors that it would hardly be worth the effort.

Results

I will only note the results of the analysis using data with all graduates to model earnings. This is because analyses by field of study for the 42 month data uses much smaller sample sizes compared to the 6 month data. In some cases this leads the results to be suspect due to overfitting or standard errors to be far too large to be of use. Full results are displayed in table A.8.

After adjusting for sample selection bias, the estimated earnings gap between those with first and upper second class honours increased from 8 percent to 13.2 percent for the 2006/07 cohort (p=0.04). The gap increase from 8.2 percent to 14.9 percent for the 2008/09 cohort (p=0.02). The gap between those with upper second class honours and other degree classifications also increased for the 2006/07 cohort (p=0.05). After adjusting for sample selection the earning gap between graduates who attended different HEIs also increased but these changes were only significant for graduates in the 2008/09 cohort. The gap between graduates from pre- and post-1992 universities increased from 2.9 percent to 9.4 percent (p<0.01). The gap between those from Russell group and post-1992 universities also grew substantially from 11.2 percent to 21 percent (p<0.01). There were no statistically significant differences between the OLS and sample bias adjusted estimates for other predictors.

Table A.8: Results for models of (log) earning using graduates from all fields of study (42 months)

Predictor	2006/07 OLS	2006/07 Adjusted	2008/09 OLS	2008/09 Adjusted
Intercept	9.863 (0.027)*	9 (0.308)*	9.854 (0.023)*	8.664 (0.382)*
Age (Base=18)	0.025 (0.005)*	0.045 (0.009)*	0.030 (0.004)*	0.066 (0.012)*
Non-white ethnicity	-0.012 (0.012)	0.125 (0.051)*	0.003 (0.011)	0.097 (0.036)*
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.003 (0.012)	0.012 (0.016)	0.034 (0.010)*	0.056 (0.016)*
–Managerial or professional	0.022 (0.011)*	0.042 (0.016)*	0.050 (0.010)*	0.073 (0.014)*
Has a known disability	-0.067 (0.013)*	0.03 (0.04)	-0.019 (0.011)	0.061 (0.032)
Male	0.078 (0.008)*	0.06 (0.013)*	0.072 (0.007)*	0.054 (0.012)*
Domicile prior to HE				
(Ref: London)				
–North England	-0.125 (0.015)*	-0.105 (0.02)*	-0.145 (0.013)*	-0.124 (0.019)*
–Northern Ireland	-0.250 (0.018)*	0.021 (0.099)	-0.257 (0.017)*	0.055 (0.103)
–Scotland	-0.093 (0.017)*	0.012 (0.042)	-0.117 (0.016)*	0.016 (0.048)
–SE and East England	-0.038 (0.014)*	-0.024 (0.018)	-0.039 (0.012)*	0.003 (0.022)
–SW and Mid England	-0.097 (0.014)*	-0.073 (0.02)*	-0.098 (0.012)*	-0.049 (0.023)*
–Wales	-0.150 (0.019)*	0.062 (0.077)	-0.140 (0.017)*	0.061 (0.069)
UCAS tariff quartile				
(Ref: 1st Quartile)				
–2nd Quartile	0.027 (0.009)*	0.037 (0.014)*	0.028 (0.008)*	0.043 (0.013)*
–3rd Quartile	0.071 (0.012)*	0.098 (0.019)*	0.056 (0.010)*	0.09 (0.017)*
–4th Quartile	0.057 (0.012)*	0.071 (0.018)*	0.021 (0.011)*	0.01 (0.015)
Privately educated	0.075 (0.011)*	0.059 (0.016)*	0.057 (0.010)*	0.031 (0.016)
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.077 (0.010)*	0.124 (0.021)*	0.079 (0.009)*	0.139 (0.023)*
–Other degree class	-0.088 (0.009)*	-0.129 (0.019)*	-0.094 (0.008)*	-0.119 (0.014)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.070 (0.010)*	0.073 (0.013)*	0.029 (0.009)*	0.09 (0.023)*
–Russell group university	0.101 (0.010)*	0.067 (0.017)*	0.106 (0.009)*	0.191 (0.03)*
Field of study [Ref: Biological sciences]				
–Business	0.129 (0.015)*	0.143 (0.02)*	0.161 (0.014)*	0.141 (0.02)*
–Creative arts	-0.093 (0.017)*	-0.134 (0.029)*	-0.070 (0.016)*	-0.159 (0.037)*
–Education	0.133 (0.026)*	0.044 (0.046)	0.151 (0.021)*	0.074 (0.036)*
–Engineering and computer science	0.161 (0.015)*	0.192 (0.022)*	0.176 (0.014)*	0.223 (0.025)*
–Humanities and languages	-0.036 (0.014)*	-0.072 (0.022)*	-0.019 (0.012)	-0.043 (0.019)*
–Law	0.080 (0.018)*	-0.013 (0.042)	0.090 (0.017)*	-0.004 (0.039)
–Other STEM	0.097 (0.015)*	0.113 (0.02)*	0.105 (0.013)*	0.256 (0.051)*
–Social studies	0.086 (0.016)*	0.051 (0.025)*	0.098 (0.015)*	0.023 (0.032)
–Subjects allied to medicine	0.207 (0.018)*	0.169 (0.028)*	0.236 (0.016)*	0.18 (0.028)*
Has postgraduate qualifications	0.011 (0.009)	0.03 (0.014)*	0.001 (0.008)	0.009 (0.01)
N	8104		11922	

*p<0.05

Appendix B

Qualitative study documents

Participant Information Sheet

Study Title: Graduating into Unemployment? A Study of Early Career Graduate Trajectories

You are being invited to take part in a research study. Before you decide whether or not to take part, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully.

What is the study about?
This study aims to explore the experiences and activities of young graduates from a range of subject disciplines after university. Since the early 1990s there has been a large expansion of participation in Higher Education with an increasing concern by policy makers and educationalists regarding the future of these new graduates. The current study aims to look at what graduates have done after university, their future plans and their experiences along the way. The findings from the project will contribute to academic and public debates regarding graduate employability and go on to help future graduates. The study consists of two interviews, one initial interview and one follow-up interview around a year later.

It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and be asked to sign a consent form. If you decide to take part you are still free to withdraw at any time and without giving a reason.

What do I have to do?
If you choose to take part, you may be invited to participate in an individual interview. The discussion will be guided around topics such as what you have done since graduating (including your work history), your current activities and your plans for the future. The interview will be held in a convenient location for you, this may be a quiet public place or your own home if you wish. If securing an appropriate location is a problem then, a phone interview can be arranged. Interviews may take around 20 minutes to an hour. Note that the interview will be tape-recorded and transcribed as part of the research.

As part of the research you will be contacted 12 months later for a follow-up interview regarding your activities and experience since the initial interview. You may choose not to do a follow-up interview however your continued participation would be extremely appreciated and would add much to the scope of the research.

If you wish to participate in the study then please fill out the attached contact and consent forms and send them by post or email to the address given on the forms. You will be contacted by email or telephone to arrange the time, date and location of the interview.

Will my details be safe?
All your personal details will be stored safely and be kept confidential. Names and any identifying details (such as the name of your employers) will be given pseudonyms or left out of the final research report to preserve anonymity. Should you wish to opt out of the research at any time and withdraw any materials collected on yourself, you may do so at any time.

Why should I participate in the research?
Your participation would go on to inform our understanding of why people choose to work or do further studies after their first degrees and in particular how they gained their current jobs. This information will go on to help universities and educationalists, as well as students themselves, as they learn from your experiences after university. £10 will be given to you or a charity of your choice as a thank-you for participating in the research. An additional £30 will be given to those who complete a follow-up interview as a further gesture of gratitude.

Any further questions or enquiries about the study, please don't hesitate to contact me at Zhangm19@cf.ac.uk.

Thank You

Participant Contact Details

(Highlight or Delete as Appropriate)

Study Title: Graduating into Unemployment? A Study of Early Career Graduate Trajectories

Name:

Contact Number:

Email:

Sex: ☐ **Male** ☐ **Female**

Type and Class of Degree:

Degree Subject Studied:

Institution Attended:

Current Activities (e.g. further study, full-time work etc):

Could you give any further details about your current activities (e.g. place of work or study, role):

Could you briefly describe what you have been up to since graduation:

Additional Contact Detail

Permanent or Home Address:

Addition Contact Number:

Additional Email Address :

Interview Protocol: Interview one

Things to check beforehand: Read and signed consent form; Read through background information; Ask for permission to record the interview;

Introduction

I'm interested in what you have been up to since you have left your university and your thoughts on your experiences so far. Can I start by asking you to tell me a little about your choice to go to university? Why your current subject?

Topics

1) Past: Can you tell me a bit about your final year at university? What were your expectations of life after university? Did you have a career in mind? Work experience during study?
2) Life after university: Can you tell me about what has happened since then? Can you tell me a bit about the story behind that? Why did you choose to study? (if applicable) Try to elucidate the event details (Length of each role, Type of contract, How they came across work etc)
3) Work: What sort of tasks do you do in your current role (in a normal given day)? How do you feel about your work? Does it utilise your skills as a graduate? Why did you go with that role? What sort of job searching strategies did you use? Were you constrained in the jobs that you could take?
4) Workplace: Within the organisation you are in what are your employers looking for? How do people normally enter the organisation?
5) Current situation: How do you feel about where you are now one year on? Has it met your expectations? What do you hope to do in the future/ one year from now? Do they plan to do any further training? What career aspirations do they have? What is important for them to achieve in the future? Have you changed since the last year?
6) We've spoken a bit about what you've been up to and your thoughts so far. Has there been anything else that you would like to add? Anything else that happened since living university that was important.

Conclusion

Thank participants for their participation. Check family background details before the end. Ask if they are willing to be contacted one year onwards for a follow-up interview. Take down contact details. Sort out details for payment for participation.

Second interview procedure

Sub-session one

Starting line: ‘I would like you to tell me the story of what has happened since we last met, including all of the events and experiences which were important to you. Start wherever you like. Please take all the time you need, we have plenty of time. I’ll listen first and I won’t interrupt. I’ll just take some notes for afterwards.’

If they fail to start then assure them you don’t mind how they start/ No special questions at this time. ‘Start wherever you wish’; ‘It’s okay, just start wherever you feel comfortable.’

During narrative: Non-directional support; Empathetic, allow people to get there in their own time (‘You seem upset/angry’); Appreciative (‘I know this is difficult but what you’re saying is very helpful’); Active listening (‘Hmmmm’, ‘Okay’, ‘I understand’); Repeat key terms and phrases back

If narrative seems to be ending: ‘Is there anymore stories you can tell’; ‘Is there any other things you can remember happening?’

Sub-session two

Go through notes for topics; feel free to skip topics but never return back to a previous topic in a narrative.

Work from more general questions to specific ones; each time create questions aimed at inducing narratives each time

Use participants’ own words to prompt narratives, even if you do not understand them yet yourself. Save questions about their meaning in final part.

Cross out any central research questions still to be answered in sub-section three that is already answered by now.

Sub-session three

Ask specific/ contingency questions that I had for participants based on their previous interviews if they have not been answered already.

General questions:

1) Have your views on careers or your future expectations changed at all since we last met? What thoughts have you had about the topic since last time?
2) Have you changed jobs? If so, can you tell me more about that?
3) What is important to you in your personal life right now? Has it changed since the last time we met?
4) In retrospect, how did you feel about our last interview?

Clarify any key terms that I do not yet already understand

Thank participants for their participation and check details for payment.

Appendix C

Conversion of the SOC2000 to SOC(HE)2010

Table C.1: Conversion of the SOC2000 to the SOC(HE)2000 including skills scores and type of job

SOC code	Occupational group	Exp.	Orch.	Com.	Type of job
11110	(11110) Senior officials in national government	5.43	7.83	5.57	Orchestrator
11120	(11120) Directors and chief executives of major organisations	6.03	8.58	5.06	Orchestrator
11130	(11130) Senior officials in local government	5.34	6.71	5.73	Orchestrator
11140	(11140) Senior officials of special interest organisations	6.09	8.03	4.91	Orchestrator
11141	(11141) Senior officials of trade unions	6.09	8.03	4.91	Orchestrator
11142	(11142) Senior officials of employers, trades and professional associations	6.09	8.03	4.91	Orchestrator
11143	(11143) Senior officials of charities	6.09	8.03	4.91	Orchestrator
11144	(11144) Senior officials of political parties	6.09	8.03	4.91	Orchestrator
11210	(11210) Production, works and maintenance managers	6.00	8.00	5.00	Orchestrator
11220	(11220) Managers in construction	6.19	7.63	5.00	Orchestrator
11230	(11230) Managers in mining and energy	6.08	6.99	4.40	Orchestrator
11231	(11231) Mining, quarrying and drilling managers	6.08	6.99	4.40	Orchestrator
11232	(11232) Gas, water and electricity supply managers	6.08	6.99	4.40	Orchestrator
11310	(11310) Financial managers and chartered secretaries	5.71	7.26	4.56	Orchestrator
11311	(11311) Finance managers and directors	5.71	7.26	4.56	Orchestrator
11312	(11312) Investment/merchant bankers	5.71	7.26	4.56	Orchestrator
11313	(11313) Chartered company secretaries, treasurers, company registrars	5.71	7.26	4.56	Orchestrator
11320	(11320) Marketing and sales managers	4.18	3.08	6.18	Communicator
11321	(11321) Marketing managers	4.18	3.08	6.18	Communicator

11322	(11322) Sales managers	4.18	3.08	6.18	Communicator
11323	(11323) Market research managers	4.18	3.08	6.18	Communicator
11324	(11324) Export and import managers	4.18	3.08	6.18	Communicator
11330	(11330) Purchasing managers	6.03	7.97	4.97	Orchestrator
11340	(11340) Advertising and public relations managers	5.55	6.36	8.09	Communicator
11341	(11341) Advertising managers	5.55	6.36	8.09	Communicator
11342	(11342) Public affairs and publicity managers	5.55	6.36	8.09	Communicator
11350	(11350) Personnel, training and industrial relations managers	6.67	7.18	6.67	Orchestrator
11351	(11351) Personnel managers	6.67	7.18	6.67	Orchestrator
11352	(11352) Industrial relations managers	6.67	7.18	6.67	Orchestrator
11353	(11353) Training managers	6.67	7.18	6.67	Orchestrator
11354	(11354) Operational research, organisation and methods managers	6.67	7.18	6.67	Orchestrator
11360	(11360) Information and communication technology managers	7.22	5.06	4.28	Expert
11361	(11361) Information managers	7.22	5.06	4.28	Expert
11362	(11362) Computer operations managers	7.22	5.06	4.28	Expert
11363	(11363) Telecommunications managers	7.22	5.06	4.28	Expert
11370	(11370) Research and development managers	7.38	7.31	5.00	Expert
11410	(11410) Quality assurance managers	7.00	4.00	4.00	Expert
11420	(11420) Customer care managers	3.00	3.00	5.00	Non-graduate
11510	(11510) Financial institution managers	5.07	5.63	3.82	Orchestrator
11511	(11511) Bank managers	5.07	5.63	3.82	Orchestrator
11512	(11512) Building society managers	5.07	5.63	3.82	Orchestrator
11513	(11513) Post Office and postal service managers	5.07	5.63	3.82	Orchestrator
11514	(11514) Insurance office managers	5.07	5.63	3.82	Orchestrator
11515	(11515) Stockbroking managers	5.07	5.63	3.82	Orchestrator
11520	(11520) Office managers	3.31	2.41	2.85	Non-graduate
11521	(11521) Reservations and booking office managers	3.31	2.41	2.85	Non-graduate
11522	(11522) Administration and records managers	3.31	2.41	2.85	Non-graduate
11523	(11523) Payroll and pensions managers	3.31	2.41	2.85	Non-graduate
11524	(11524) Invoice, costs and accounts managers	3.31	2.41	2.85	Non-graduate
11610	(11610) Transport and distribution managers	6.00	8.00	5.00	Orchestrator
11620	(11620) Storage and warehouse managers	4.80	7.30	4.60	Orchestrator
11630	(11630) Retail and wholesale managers	4.75	7.43	5.00	Orchestrator
11710	(11710) Officers in armed forces	5.00	8.00	5.00	Orchestrator
11711	(11711) Army officers	5.00	8.00	5.00	Orchestrator
11712	(11712) Navy officers	5.00	8.00	5.00	Orchestrator
11713	(11713) Air Force officers	5.00	8.00	5.00	Orchestrator
11720	(11720) Police officers (Inspectors and above)	5.00	8.00	5.00	Orchestrator
11730	(11730) Senior officers in Fire, Ambulance, Prison and related services	5.00	8.00	5.00	Orchestrator
11740	(11740) Security managers	4.35	3.05	4.17	Non-graduate
11810	(11810) Hospital and health service managers	6.19	7.10	5.00	Orchestrator

11820	(11820) Pharmacy managers	8.81	2.32	5.00	Expert
11830	(11830) Healthcare practice managers	5.00	5.00	5.00	Non-graduate
11840	(11840) Social services managers	6.00	8.00	6.00	Orchestrator
11850	(11850) Residential and day care managers	5.00	4.00	5.00	Non-graduate
11851	(11851) Residential care managers	5.00	4.00	5.00	Non-graduate
11852	(11852) Day care managers	5.00	4.00	5.00	Non-graduate
12110	(12110) Farm managers	5.00	6.00	5.00	Orchestrator
12120	(12120) Natural environment, conservation and heritage managers	6.96	2.79	4.44	Expert
12190	(12190) Managers in animal husbandry, forestry and fishing n.e.c.	4.85	5.39	4.39	Orchestrator
12191	(12191) Animal establishment (not livestock) managers	4.85	5.39	4.39	Orchestrator
12192	(12192) Forestry and tree felling managers	4.85	5.39	4.39	Orchestrator
12210	(12210) Hotel and accommodation managers	5.00	6.00	5.00	Orchestrator
12211	(12211) Hotel managers	5.00	6.00	5.00	Orchestrator
12212	(12212) Wardens of hostels, halls of residences, nurses homes and other communal accommodation	5.00	6.00	5.00	Orchestrator
12213	(12213) Managers of guest houses, caravan sites and other holiday accommodation	5.00	6.00	5.00	Orchestrator
12220	(12220) Conference, events and exhibition managers	4.06	5.00	6.88	Communicator
12221	(12221) Conference managers	4.06	5.00	6.88	Communicator
12222	(12222) Exhibition managers	4.06	5.00	6.88	Communicator
12230	(12230) Restaurant and catering managers	4.41	4.12	5.00	Non-graduate
12240	(12240) Publicans and managers of licensed premises	4.56	5.12	5.00	Non-graduate
12250	(12250) Leisure and sports managers	5.00	5.00	5.00	Non-graduate
12251	(12251) Recreation and sports facilities managers	5.00	5.00	5.00	Non-graduate
12252	(12252) Entertainment managers	5.00	5.00	5.00	Non-graduate
12253	(12253) Cultural and leisure establishment managers	5.00	5.00	5.00	Non-graduate
12260	(12260) Travel agency managers	5.00	5.00	5.00	Non-graduate
12310	(12310) Property, housing and land managers	4.90	3.90	4.90	Non-graduate
12311	(12311) Property agency managers and landlords etc.	4.90	3.90	4.90	Non-graduate
12312	(12312) Estates and facilities managers	4.90	3.90	4.90	Non-graduate
12320	(12320) Garage managers and proprietors	4.85	4.55	3.85	Non-graduate
12330	(12330) Hairdressing and beauty salon managers and proprietors	5.00	4.00	5.00	Non-graduate
12340	(12340) Shopkeepers	5.00	4.00	5.00	Non-graduate
12350	(12350) Recycling and refuse disposal managers	6.00	5.00	3.00	Expert
12390	(12390) Managers and proprietors in other services n.e.c.	5.24	4.88	5.28	Non-graduate
21110	(21110) Chemists	9.00	2.00	3.00	Expert
21111	(21111) Research/development chemists	9.00	2.00	3.00	Expert
21112	(21112) Analytical chemists	9.00	2.00	3.00	Expert
21120	(21120) Biological scientists and biochemists	9.00	2.00	3.00	Expert

21121	(21121) Biochemists, medical scientists	9.00	2.00	3.00	Expert
21122	(21122) Biologists	9.00	2.00	3.00	Expert
21123	(21123) Bacteriologists, microbiologists etc.	9.00	2.00	3.00	Expert
21124	(21124) Botanists	9.00	2.00	3.00	Expert
21125	(21125) Pathologists	9.00	2.00	3.00	Expert
21126	(21126) Agricultural scientists	9.00	2.00	3.00	Expert
21127	(21127) Physiologists	9.00	2.00	3.00	Expert
21130	(21130) Physicists, geologists and meteorologists	9.00	2.00	3.00	Expert
21131	(21131) Physicists	9.00	2.00	3.00	Expert
21132	(21132) Geophysicists	9.00	2.00	3.00	Expert
21133	(21133) Geologists, mineralogists etc.	9.00	2.00	3.00	Expert
21134	(21134) Meteorologists	9.00	2.00	3.00	Expert
21135	(21135) Astronomers	9.00	2.00	3.00	Expert
21136	(21136) Mathematicians	9.00	2.00	3.00	Expert
21210	(21210) Civil engineers	9.00	3.00	4.00	Expert
21211	(21211) Water, sanitation, drainage and public health engineers	9.00	3.00	4.00	Expert
21212	(21212) Mining, quarrying and drilling engineers	9.00	3.00	4.00	Expert
21213	(21213) Construction engineers	9.00	3.00	4.00	Expert
21220	(21220) Mechanical engineers	9.00	2.00	4.00	Expert
21221	(21221) Aeronautical engineers	9.00	2.00	4.00	Expert
21222	(21222) Automobile engineers	9.00	2.00	4.00	Expert
21223	(21223) Marine engineers	9.00	2.00	4.00	Expert
21224	(21224) Plant and maintenance engineers	9.00	2.00	4.00	Expert
21230	(21230) Electrical engineers	9.00	2.00	4.00	Expert
21231	(21231) Electricity generation and supply engineers	9.00	2.00	4.00	Expert
21232	(21232) Telecommunications engineers	9.00	2.00	4.00	Expert
21240	(21240) Electronic engineers	9.00	2.00	4.00	Expert
21241	(21241) Broadcasting engineers	9.00	2.00	4.00	Expert
21242	(21242) Avionics, radar and communications engineers	9.00	2.00	4.00	Expert
21250	(21250) Chemical engineers	9.00	2.00	3.00	Expert
21260	(21260) Design and development engineers	9.00	2.00	4.00	Expert
21270	(21270) Production and process engineers	8.80	1.96	2.96	Expert
21280	(21280) Planning and quality control engineers	6.46	3.14	3.45	Expert
21281	(21281) Planning engineers	6.46	3.14	3.45	Expert
21282	(21282) Quality control engineers	6.46	3.14	3.45	Expert
21290	(21290) Engineering professionals n.e.c.	8.90	2.10	4.00	Expert
21291	(21291) Metallurgists and material scientists	8.90	2.10	4.00	Expert
21292	(21292) Patents examiners, agents and officers	8.90	2.10	4.00	Expert
21293	(21293) Heating and ventilating engineers	8.90	2.10	4.00	Expert
21294	(21294) Food and drink technologists (including brewers)	8.90	2.10	4.00	Expert
21295	(21295) Acoustic engineers	8.90	2.10	4.00	Expert
21310	(21310) IT strategy and planning professionals	7.29	2.09	3.18	Expert

21311	(21311) IT consultants and planners	7.29	2.09	3.18	Expert
21312	(21312) Telecommunications consultants and planners	7.29	2.09	3.18	Expert
21320	(21320) Software professionals	8.35	2.26	3.79	Expert
21321	(21321) Software designers and engineers	8.35	2.26	3.79	Expert
21322	(21322) Computer analysts and programmers	8.35	2.26	3.79	Expert
21323	(21323) Network/systems designers and engineers	8.35	2.26	3.79	Expert
21324	(21324) Web developers and producers	8.35	2.26	3.79	Expert
22110	(22110) Medical practitioners	9.00	3.00	5.00	Expert
22111	(22111) Pre-registration house officers	9.00	3.00	5.00	Expert
22112	(22112) Senior house officers	9.00	3.00	5.00	Expert
22113	(22113) Specialist registrars, consultants and general practitioners	9.00	3.00	5.00	Expert
22120	(22120) Psychologists	9.00	1.00	6.00	Expert
22121	(22121) Education psychologists	9.00	1.00	6.00	Expert
22122	(22122) Clinical psychologists	9.00	1.00	6.00	Expert
22123	(22123) Occupational psychologists	9.00	1.00	6.00	Expert
22130	(22130) Pharmacists/pharmacologists	9.00	2.00	5.00	Expert
22131	(22131) Pharmacists	9.00	2.00	5.00	Expert
22132	(22132) Pharmacologists	9.00	2.00	5.00	Expert
22140	(22140) Ophthalmic opticians	9.00	2.00	4.00	Expert
22150	(22150) Dental practitioners	9.00	2.00	4.00	Expert
22151	(22151) General practice dentists	9.00	2.00	4.00	Expert
22152	(22152) Hospital dentists, house officers (dental)	9.00	2.00	4.00	Expert
22160	(22160) Veterinarians	9.00	1.00	4.00	Expert
23110	(23110) Higher education teaching professionals	9.00	3.00	8.00	Expert
23111	(23111) University and higher education professors	9.00	3.00	8.00	Expert
23112	(23112) University and higher education lecturers	9.00	3.00	8.00	Expert
23113	(23113) Teacher training establishment lecturers	9.00	3.00	8.00	Expert
23114	(23114) University tutorial and teaching assistants	9.00	3.00	8.00	Expert
23120	(23120) Further education teaching professionals	6.97	2.08	7.97	Expert
23130	(23130) Education officers, school inspectors	7.00	6.00	6.00	Expert
23131	(23131) Education officers	7.00	6.00	6.00	Expert
23132	(23132) Education advisors	7.00	6.00	6.00	Expert
23133	(23133) Education inspectors	7.00	6.00	6.00	Expert
23140	(23140) Secondary education teaching professionals	7.00	2.00	8.00	Expert
23141	(23141) Secondary head teachers	7.00	2.00	8.00	Expert
23142	(23142) Secondary teachers	7.00	2.00	8.00	Expert
23150	(23150) Primary and nursery education teaching professionals	6.00	2.42	7.86	Communicator
23151	(23151) Primary head teachers	6.00	2.42	7.86	Communicator
23152	(23152) Primary teachers	6.00	2.42	7.86	Communicator
23160	(23160) Special needs education teaching professionals	6.00	2.15	7.95	Communicator

23170	(23170) Registrars and senior administrators of educational establishments	6.00	5.00	7.00	Expert
23190	(23190) Teaching professionals n.e.c	6.93	1.97	7.90	Expert
23191	(23191) Music, dance and drama teachers (private/pedagogical)	6.93	1.97	7.90	Expert
23192	(23192) Language assistants and tutors, TEFL	6.93	1.97	7.90	Expert
23193	(23193) Tutors and teachers at adult education centres	6.93	1.97	7.90	Expert
23194	(23194) Examiners and moderators	6.93	1.97	7.90	Expert
23210	(23210) Scientific researchers	9.00	2.00	4.00	Expert
23220	(23220) Social science researchers	9.00	2.00	5.00	Expert
23290	(23290) Researchers n.e.c.	8.45	3.09	4.00	Expert
23291	(23291) Researchers (media)	8.45	3.09	4.00	Expert
23292	(23292) Researchers (university - unspecified discipline)	8.45	3.09	4.00	Expert
24110	(24110) Solicitors and lawyers, judges and coroners	8.81	4.09	6.05	Expert
24111	(24111) Barristers and advocates	8.81	4.09	6.05	Expert
24112	(24112) Solicitors	8.81	4.09	6.05	Expert
24113	(24113) Judges, magistrates, coroners and sheriffs	8.81	4.09	6.05	Expert
24190	(24190) Legal professionals n.e.c.	7.00	5.00	5.00	Expert
24191	(24191) Clerks of court, officers of court	7.00	5.00	5.00	Expert
24192	(24192) Legal advisers in non-law firms	7.00	5.00	5.00	Expert
24210	(24210) Chartered and certified accountants	7.00	4.00	3.00	Expert
24211	(24211) Chartered accountants	7.00	4.00	3.00	Expert
24212	(24212) Certified accountants	7.00	4.00	3.00	Expert
24213	(24213) Public finance accountants	7.00	4.00	3.00	Expert
24214	(24214) Examiners/auditors	7.00	4.00	3.00	Expert
24220	(24220) Management accountants	7.00	4.00	3.00	Expert
24230	(24230) Management consultants, actuaries, economists and statisticians	7.16	8.19	5.52	Orchestrator
24231	(24231) Management consultants	7.16	8.19	5.52	Orchestrator
24232	(24232) Business analysts	7.16	8.19	5.52	Orchestrator
24233	(24233) Economists	7.16	8.19	5.52	Orchestrator
24234	(24234) Statisticians	7.16	8.19	5.52	Orchestrator
24235	(24235) Actuaries	7.16	8.19	5.52	Orchestrator
24310	(24310) Architects	9.00	6.00	5.00	Expert
24311	(24311) Landscape architects	9.00	6.00	5.00	Expert
24320	(24320) Town planners	7.00	6.00	6.00	Expert
24330	(24330) Quantity surveyors	7.00	4.00	3.00	Expert
24340	(24340) Chartered surveyors (not quantity surveyors)	7.00	4.00	4.00	Expert
24341	(24341) General practice surveyors	7.00	4.00	4.00	Expert
24342	(24342) Land surveyors	7.00	4.00	4.00	Expert
24343	(24343) Building surveyors	7.00	4.00	4.00	Expert
24344	(24344) Hydrographic surveyors	7.00	4.00	4.00	Expert

24410	(24410) Public service administrative professionals	7.00	6.00	5.00	Expert
24411	(24411) Local government area and divisional officers	7.00	6.00	5.00	Expert
24412	(24412) Registrars of births, marriages and deaths	7.00	6.00	5.00	Expert
24413	(24413) National government administrative professionals (grades 5/6/7)	7.00	6.00	5.00	Expert
24420	(24420) Social workers	7.00	4.86	5.86	Expert
24421	(24421) Social workers (medical, mental health, rehab)	7.00	4.86	5.86	Expert
24422	(24422) Social workers (children, fostering, adoption)	7.00	4.86	5.86	Expert
24423	(24423) Social Workers (family)	7.00	4.86	5.86	Expert
24430	(24430) Probation officers	7.00	3.00	6.00	Expert
24440	(24440) Clergy	6.84	3.16	7.52	Communicator
24510	(24510) Librarians	7.00	2.00	5.00	Expert
24520	(24520) Archivists and curators	9.00	2.00	5.00	Expert
24521	(24521) Archivists	9.00	2.00	5.00	Expert
24522	(24522) Curators (museum etc.)	9.00	2.00	5.00	Expert
31110	(31110) Laboratory technicians	4.00	1.00	2.00	Non-graduate
31111	(31111) Laboratory technicians (non-medical)	4.00	1.00	2.00	Non-graduate
31112	(31112) Medical laboratory technicians	4.00	1.00	2.00	Non-graduate
31120	(31120) Electrical/electronic technicians	4.00	1.00	2.00	Non-graduate
31130	(31130) Engineering technicians	4.00	1.00	2.00	Non-graduate
31140	(31140) Building and civil engineering technicians	4.00	1.00	2.00	Non-graduate
31150	(31150) Quality assurance technicians	4.00	1.00	2.00	Non-graduate
31190	(31190) Science and engineering technicians n.e.c.	4.08	1.03	2.03	Non-graduate
31210	(31210) Architectural and town planning technicians	4.51	1.68	2.17	Non-graduate
31211	(31211) Town planning assistants, technicians	4.51	1.68	2.17	Non-graduate
31212	(31212) Architectural technicians, assistants	4.51	1.68	2.17	Non-graduate
31220	(31220) Draughtspersons	4.00	1.00	2.00	Non-graduate
31221	(31221) Design Draughtsperson	4.00	1.00	2.00	Non-graduate
31222	(31222) Mechanical engineering draughtsperson	4.00	1.00	2.00	Non-graduate
31223	(31223) Cartographical draughtsperson	4.00	1.00	2.00	Non-graduate
31224	(31224) Drawing office assistants, tracers	4.00	1.00	2.00	Non-graduate
31230	(31230) Building inspectors	6.00	2.00	3.00	Expert
31310	(31310) IT operations technicians (network support)	4.61	1.14	2.06	Non-graduate
31320	(31320) IT User support technicians (help desk support)	5.00	1.00	5.00	Non-graduate
32110	(32110) Nurses	7.00	3.00	5.00	Expert
32111	(32111) Hospital matrons and nurse administrators	7.00	3.00	5.00	Expert
32112	(32112) Staff nurses (adult)	7.00	3.00	5.00	Expert
32113	(32113) Staff nurses (children)	7.00	3.00	5.00	Expert
32114	(32114) Staff nurses (mental health)	7.00	3.00	5.00	Expert
32115	(32115) Non-hospital Nurses (e.g. general practice, community, clinics etc.)	7.00	3.00	5.00	Expert

32120	(32120) Midwives	7.00	2.00	5.00	Expert
32130	(32130) Paramedics	5.00	4.00	5.00	Non-graduate
32140	(32140) Medical radiographers	7.00	1.00	4.00	Expert
32150	(32150) Chiropodists	7.00	1.00	4.00	Expert
32160	(32160) Dispensing opticians	5.00	1.00	5.00	Non-graduate
32170	(32170) Pharmaceutical dispensers	3.81	1.59	2.59	Non-graduate
32180	(32180) Medical and dental technicians	5.06	1.00	2.12	Non-graduate
32181	(32181) Medical technicians	5.06	1.00	2.12	Non-graduate
32182	(32182) Audiologists	5.06	1.00	2.12	Non-graduate
32183	(32183) Dental technicians	5.06	1.00	2.12	Non-graduate
32210	(32210) Physiotherapists	7.00	1.00	4.00	Expert
32220	(32220) Occupational therapists	7.00	1.00	4.00	Expert
32230	(32230) Speech and language therapists	7.00	1.00	4.00	Expert
32290	(32290) Therapists n.e.c.	6.45	1.00	4.03	Expert
32291	(32291) Acupuncturists, reflexologists	6.45	1.00	4.03	Expert
32292	(32292) Dieticians	6.45	1.00	4.03	Expert
32293	(32293) Osteopaths, hydrotherapists, massage therapists, chiropractors	6.45	1.00	4.03	Expert
32294	(32294) Psychotherapists	6.45	1.00	4.03	Expert
32295	(32295) Homeopaths	6.45	1.00	4.03	Expert
32310	(32310) Youth and community workers	5.38	3.94	4.94	Non-graduate
32311	(32311) Youth workers	5.38	3.94	4.94	Non-graduate
32312	(32312) Community workers	5.38	3.94	4.94	Non-graduate
32320	(32320) Housing and welfare officers	5.45	3.08	4.99	Non-graduate
32321	(32321) Housing/homeless officers	5.45	3.08	4.99	Non-graduate
32322	(32322) Education/learning support worker	5.45	3.08	4.99	Non-graduate
32323	(32323) Drug worker	5.45	3.08	4.99	Non-graduate
32324	(32324) Counsellors	5.45	3.08	4.99	Non-graduate
33110	(33110) Armed forces: NCOs and other ranks	4.00	3.00	2.00	Non-graduate
33120	(33120) Police officers (Sergeant and below)	4.00	3.00	4.00	Non-graduate
33130	(33130) Fire Service officers (Leading Fire Officer and below)	4.00	3.00	4.00	Non-graduate
33140	(33140) Prison Service Officers (below Principal Officer)	4.00	3.00	4.00	Non-graduate
33190	(33190) Protective service associate professionals n.e.c.	4.00	2.00	4.00	Non-graduate
33191	(33191) Customs, excise and duty officers	4.00	2.00	4.00	Non-graduate
33192	(33192) Immigration officers	4.00	2.00	4.00	Non-graduate
34110	(34110) Artists (fine art)	7.00	1.00	6.00	Expert
34120	(34120) Authors, writers	7.00	3.00	9.00	Communicator
34121	(34121) Authors	7.00	3.00	9.00	Communicator
34122	(34122) Technical authors	7.00	3.00	9.00	Communicator
34123	(34123) Translators	7.00	3.00	9.00	Communicator
34124	(34124) Interpreters	7.00	3.00	9.00	Communicator
34125	(34125) Literary agents	7.00	3.00	9.00	Communicator

34130	(34130) Performing artists	6.00	1.00	9.00	Communicator
34131	(34131) Actors	6.00	1.00	9.00	Communicator
34132	(34132) Vocalists	6.00	1.00	9.00	Communicator
34133	(34133) Entertainers	6.00	1.00	9.00	Communicator
34134	(34134) Disc jockeys (not broadcasting)	6.00	1.00	9.00	Communicator
34140	(34140) Dancers and choreographers	5.00	1.00	5.00	Non-graduate
34150	(34150) Musicians	7.00	1.00	6.00	Expert
34151	(34151) Composers, arrangers, conductors and musical directors	7.00	1.00	6.00	Expert
34152	(34152) Musical instrument players	7.00	1.00	6.00	Expert
34160	(34160) Arts officers, producers and directors	7.00	6.00	9.00	Communicator
34161	(34161) Directors, producers	7.00	6.00	9.00	Communicator
34162	(34162) Stage and studio managers	7.00	6.00	9.00	Communicator
34163	(34163) Arts officers, advisers and consultants	7.00	6.00	9.00	Communicator
34164	(34164) Entertainment agents	7.00	6.00	9.00	Communicator
34210	(34210) Graphic artists and designers	7.00	1.45	7.11	Communicator
34211	(34211) Commercial artists	7.00	1.45	7.11	Communicator
34212	(34212) Web designers	7.00	1.45	7.11	Communicator
34213	(34213) Exhibition, multi-media designers	7.00	1.45	7.11	Communicator
34214	(34214) Desk top publishers, assistants and operators	7.00	1.45	7.11	Communicator
34220	(34220) Product, clothing and related designers	7.00	1.00	4.00	Expert
34221	(34221) Interior decoration designers	7.00	1.00	4.00	Expert
34222	(34222) Set designers (stage etc.)	7.00	1.00	4.00	Expert
34223	(34223) Industrial designers	7.00	1.00	4.00	Expert
34224	(34224) Textile designers	7.00	1.00	4.00	Expert
34225	(34225) Clothing designers	7.00	1.00	4.00	Expert
34226	(34226) Clothing advisers, consultants	7.00	1.00	4.00	Expert
34310	(34310) Journalists, newspaper and periodical editors	7.00	4.00	9.00	Communicator
34311	(34311) Editors	7.00	4.00	9.00	Communicator
34312	(34312) Journalists	7.00	4.00	9.00	Communicator
34320	(34320) Broadcasters (announcers, disc jockeys, news readers)	6.88	5.10	9.00	Communicator
34330	(34330) Public relations officers	6.00	5.00	9.00	Communicator
34340	(34340) Photographers and audio-visual equipment operators	7.00	1.00	6.00	Expert
34341	(34341) Photographers	7.00	1.00	6.00	Expert
34342	(34342) TV and film camera operators	7.00	1.00	6.00	Expert
34343	(34343) Audio-visual effects designers and operators	7.00	1.00	6.00	Expert
34344	(34344) Video, telecine and film recorder operators	7.00	1.00	6.00	Expert
34345	(34345) Sound recordists, technicians, assistants	7.00	1.00	6.00	Expert
34410	(34410) Sports players	5.00	2.00	4.00	Non-graduate
34420	(34420) Sports coaches, instructors and officials	5.00	5.00	5.00	Non-graduate
34421	(34421) Sports coaches, instructors	5.00	5.00	5.00	Non-graduate

34422	(34422) Sports officials	5.00	5.00	5.00	Non-graduate
34430	(34430) Fitness instructors	5.00	2.00	5.00	Non-graduate
34490	(34490) Sports and fitness occupations n.e.c.	4.91	4.82	5.00	Non-graduate
34491	(34491) Outdoor pursuits instructors	4.91	4.82	5.00	Non-graduate
35110	(35110) Air traffic controllers	4.60	2.95	3.60	Expert
35120	(35120) Aircraft pilots and flight engineers	6.00	3.00	4.00	Expert
35121	(35121) Aircraft pilots and instructors	6.00	3.00	4.00	Expert
35122	(35122) Aircraft flight engineers, navigators	6.00	3.00	4.00	Expert
35130	(35130) Ship and hovercraft officers	6.00	3.00	4.00	Expert
35140	(35140) Train drivers	4.00	1.00	1.00	Non-graduate
35200	(35200) Legal associate professionals	5.00	2.00	5.00	Non-graduate
35201	(35201) Legal executives and paralegals	5.00	2.00	5.00	Non-graduate
35202	(35202) Clerks to judges and barristers (not solicitors)	5.00	2.00	5.00	Non-graduate
35203	(35203) Adjudicators, tribunal and panel members	5.00	2.00	5.00	Non-graduate
35310	(35310) Estimators, valuers and assessors	5.00	2.00	3.00	Non-graduate
35311	(35311) Insurance surveyors, inspectors	5.00	2.00	3.00	Non-graduate
35312	(35312) Insurance claims officials, adjusters	5.00	2.00	3.00	Non-graduate
35313	(35313) Estimators	5.00	2.00	3.00	Non-graduate
35314	(35314) Rating, valuation and rent officers	5.00	2.00	3.00	Non-graduate
35320	(35320) Brokers	6.00	4.00	3.00	Expert
35321	(35321) Stockbrokers	6.00	4.00	3.00	Expert
35322	(35322) Share dealers	6.00	4.00	3.00	Expert
35323	(35323) Insurance brokers	6.00	4.00	3.00	Expert
35324	(35324) Air, commodity and ship brokers	6.00	4.00	3.00	Expert
35325	(35325) Finance, money and foreign exchange brokers	6.00	4.00	3.00	Expert
35330	(35330) Insurance underwriters	6.00	4.00	3.00	Expert
35340	(35340) Finance and investment analysts/advisers	6.00	4.00	5.00	Expert
35341	(35341) Investment advisers	6.00	4.00	5.00	Expert
35342	(35342) Pension advisers	6.00	4.00	5.00	Expert
35343	(35343) Mortgage consultants	6.00	4.00	5.00	Expert
35344	(35344) Independent financial advisers	6.00	4.00	5.00	Expert
35345	(35345) Financial analysts	6.00	4.00	5.00	Expert
35350	(35350) Taxation experts	6.00	3.00	4.00	Expert
35351	(35351) Tax inspectors	6.00	3.00	4.00	Expert
35352	(35352) Tax consultants, advisers	6.00	3.00	4.00	Expert
35360	(35360) Importers, exporters	5.00	5.00	5.00	Non-graduate
35370	(35370) Financial and accounting technicians	4.00	1.00	1.00	Non-graduate
35371	(35371) Accounting technicians	4.00	1.00	1.00	Non-graduate
35372	(35372) Trust administrators and officers	4.00	1.00	1.00	Non-graduate
35390	(35390) Business and related associate professionals n.e.c.	5.53	2.71	5.47	Expert
35391	(35391) Organisation, methods and business systems analysts	5.53	2.71	5.47	Expert

35392	(35392) Conference, exhibition and events co-ordinators and consultants	5.53	2.71	5.47	Expert
35393	(35393) Contract officers (building and manufacturing contracting)	5.53	2.71	5.47	Expert
35394	(35394) Transport and traffic advisors	5.53	2.71	5.47	Expert
35410	(35410) Buyers and purchasing officers	4.00	3.00	6.00	Communicator
35411	(35411) Buyers and purchasing officers	4.00	3.00	6.00	Communicator
35412	(35412) Contract officers (purchasing)	4.00	3.00	6.00	Communicator
35420	(35420) Sales representatives	3.73	1.77	5.38	Communicator
35421	(35421) Sales representatives and agents	3.73	1.77	5.38	Communicator
35422	(35422) Technical sales representatives	3.73	1.77	5.38	Communicator
35423	(35423) Sales controllers, administrators and co-ordinators	3.73	1.77	5.38	Communicator
35430	(35430) Marketing associate professionals	3.97	1.00	5.90	Communicator
35431	(35431) Advertising and marketing executives	3.97	1.00	5.90	Communicator
35432	(35432) Media planners	3.97	1.00	5.90	Communicator
35433	(35433) Market research analysts	3.97	1.00	5.90	Communicator
35434	(35434) Advertising and publicity writers	3.97	1.00	5.90	Communicator
35435	(35435) Fundraising, campaigns and appeals organisers	3.97	1.00	5.90	Communicator
35440	(35440) Estate agents, auctioneers	4.00	2.00	5.00	Non-graduate
35441	(35441) Estate agents	4.00	2.00	5.00	Non-graduate
35442	(35442) Land agents	4.00	2.00	5.00	Non-graduate
35443	(35443) Letting agents	4.00	2.00	5.00	Non-graduate
35444	(35444) Auctioneers	4.00	2.00	5.00	Non-graduate
35510	(35510) Conservation, heritage and environmental protection officers	7.00	2.62	4.38	Expert
35520	(35520) Countryside and park rangers	5.01	2.92	4.78	Non-graduate
35610	(35610) Public service associate professionals (HEOs, SEOs)	4.95	1.20	4.87	Non-graduate
35611	(35611) Public service associate professionals in central government departments and local offices	4.95	1.20	4.87	Non-graduate
35612	(35612) Public service associate professionals in local government	4.95	1.20	4.87	Non-graduate
35620	(35620) Personnel and industrial relations officers	6.63	2.81	5.81	Expert
35621	(35621) Employment agency consultants	6.63	2.81	5.81	Expert
35622	(35622) Personnel and recruitment consultants/advisers	6.63	2.81	5.81	Expert
35623	(35623) Personnel officers	6.63	2.81	5.81	Expert
35624	(35624) Industrial relations, equal opportunities and conciliation officers	6.63	2.81	5.81	Expert
35630	(35630) Vocational and industrial trainers and instructors	4.94	2.94	4.97	Non-graduate
35640	(35640) Careers advisers and vocational guidance specialists	6.00	3.00	5.00	Expert

35650	(35650) Inspectors of factories, utilities and trading standards	6.00	2.00	3.00	Expert
35660	(35660) Other statutory inspectors	6.00	2.00	3.00	Expert
35670	(35670) Occupational hygienists and safety officers (health and safety)	4.22	1.89	4.89	Non-graduate
35671	(35671) Health and safety officers	4.22	1.89	4.89	Non-graduate
35672	(35672) Occupational hygienists	4.22	1.89	4.89	Non-graduate
35680	(35680) Environmental health officers	6.87	2.87	5.62	Expert
41110	(41110) Civil service executive officers	5.00	1.00	5.00	Non-graduate
41120	(41120) Civil service administrative officers and assistants	4.00	6.00	4.00	Orchestrator
41130	(41130) Local government clerical officers and assistants	4.03	5.74	4.03	Orchestrator
41140	(41140) Officers of non-governmental organisations	3.99	4.98	3.99	Non-graduate
41141	(41141) Charity officers	3.99	4.98	3.99	Non-graduate
41142	(41142) Trade union officers	3.99	4.98	3.99	Non-graduate
41143	(41143) Employers, trade and professional association officers	3.99	4.98	3.99	Non-graduate
41144	(41144) Officers of political parties	3.99	4.98	3.99	Non-graduate
41210	(41210) Credit controllers	3.00	1.03	3.97	Non-graduate
41220	(41220) Accounts and wages clerks, book-keepers, other financial clerks	3.00	1.00	2.27	Non-graduate
41221	(41221) Accounts clerks	3.00	1.00	2.27	Non-graduate
41222	(41222) Wages clerks	3.00	1.00	2.27	Non-graduate
41223	(41223) Book-keepers	3.00	1.00	2.27	Non-graduate
41224	(41224) Financial administrators	3.00	1.00	2.27	Non-graduate
41230	(41230) Counter clerks (banks, building societies, Post Offices)	3.00	1.00	3.00	Non-graduate
41310	(41310) Filing and other records assistants/clerks	3.00	1.03	1.25	Non-graduate
41311	(41311) University, college clerks	3.00	1.03	1.25	Non-graduate
41312	(41312) Personnel and staff clerks	3.00	1.03	1.25	Non-graduate
41313	(41313) Marketing assistants and advertising clerks	3.00	1.03	1.25	Non-graduate
41314	(41314) Solicitors' assistants and court officers	3.00	1.03	1.25	Non-graduate
41315	(41315) Hospital clerks and clerical officers	3.00	1.03	1.25	Non-graduate
41316	(41316) Production, quality control and work study assistants (clerical)	3.00	1.03	1.25	Non-graduate
41320	(41320) Pensions and insurance clerks	3.00	1.00	1.00	Non-graduate
41321	(41321) Pensions clerks	3.00	1.00	1.00	Non-graduate
41322	(41322) Insurance clerks	3.00	1.00	1.00	Non-graduate
41330	(41330) Stock control clerks	3.00	1.00	1.00	Non-graduate
41340	(41340) Transport and distribution clerks	3.10	1.17	1.19	Non-graduate
41350	(41350) Library assistants/clerks	3.00	1.00	2.00	Non-graduate
41360	(41360) Database assistants/clerks	2.22	1.01	1.08	Non-graduate
41370	(41370) Market research interviewers	3.00	1.00	5.00	Non-graduate
41410	(41410) Telephonists	2.03	1.07	3.07	Non-graduate

41420	(41420) Communication operators	2.00	1.00	3.00	Non-graduate
41500	(41500) General office assistants/clerks n.e.c.	3.00	1.05	3.00	Non-graduate
42110	(42110) Medical secretaries	3.00	1.00	3.00	Non-graduate
42120	(42120) Legal secretaries	3.00	1.00	3.00	Non-graduate
42130	(42130) School secretaries	2.00	1.00	3.00	Non-graduate
42140	(42140) Company secretaries (also see 11313)	3.00	1.00	2.00	Non-graduate
42150	(42150) Personal assistants and other secretaries	4.00	1.00	3.00	Non-graduate
42151	(42151) Secretaries	4.00	1.00	3.00	Non-graduate
42152	(42152) Personal assistants	4.00	1.00	3.00	Non-graduate
42153	(42153) Secretary-typists	4.00	1.00	3.00	Non-graduate
42160	(42160) Receptionists	2.00	1.00	4.00	Non-graduate
42170	(42170) Typists	2.01	1.01	1.01	Non-graduate
51110	(51110) Farmers	4.00	4.00	1.00	Non-graduate
51120	(51120) Horticultural trades	4.00	2.00	1.00	Non-graduate
51130	(51130) Gardeners and groundsmen/groundswomen	3.72	2.00	1.00	Non-graduate
51131	(51131) Garden designers	3.72	2.00	1.00	Non-graduate
51190	(51190) Agricultural and fishing trades n.e.c.	3.56	2.13	1.88	Non-graduate
52110	(52110) Smiths and forge workers	4.00	2.00	1.00	Non-graduate
52120	(52120) Moulders, core makers, die casters	4.00	2.00	1.12	Non-graduate
52130	(52130) Sheet metal workers	4.00	2.00	1.00	Non-graduate
52140	(52140) Metal plate workers, shipwrights, riveters	4.00	2.00	1.19	Non-graduate
52150	(52150) Welding trades	4.00	2.00	1.00	Non-graduate
52160	(52160) Pipe fitters	2.23	2.00	1.23	Non-graduate
52210	(52210) Metal machining setters and setter-operators	2.05	2.00	1.05	Non-graduate
52220	(52220) Tool makers, tool fitters and markers-out	4.00	2.00	1.00	Non-graduate
52230	(52230) Metal working production and maintenance fitters	3.98	2.00	1.22	Non-graduate
52240	(52240) Precision instrument makers and repairers	4.00	2.00	1.00	Non-graduate
52310	(52310) Motor mechanics	3.92	1.96	1.17	Non-graduate
52320	(52320) Vehicle body builders and repairers	4.00	2.00	1.00	Non-graduate
52330	(52330) Auto electricians	4.00	2.00	1.00	Non-graduate
52340	(52340) Vehicle spray painters	2.00	2.00	1.00	Non-graduate
52410	(52410) Electricians, electrical fitters	4.00	2.00	1.15	Non-graduate
52411	(52411) Production fitters (electrical/electronic)	4.00	2.00	1.15	Non-graduate
52412	(52412) Electricians, electrical maintenance fitters	4.00	2.00	1.15	Non-graduate
52413	(52413) Electrical engineers (not professional)	4.00	2.00	1.15	Non-graduate
52420	(52420) Telecommunications engineers	4.00	2.00	3.00	Non-graduate
52430	(52430) Lines repairers and cable jointers	4.00	2.00	2.59	Non-graduate
52440	(52440) TV, video and audio engineers	4.00	2.00	1.00	Non-graduate
52450	(52450) Computer engineers, installation and maintenance	4.11	1.89	1.56	Non-graduate
52490	(52490) Electrical/electronics engineers n.e.c.	4.00	2.00	1.08	Non-graduate
53110	(53110) Steel erectors	4.00	2.00	1.00	Non-graduate
53120	(53120) Bricklayers, masons	4.00	2.00	1.00	Non-graduate

53130	(53130) Roofers, roof tilers and slaters	4.00	2.00	1.00	Non-graduate
53140	(53140) Plumbers, heating and ventilating engineers	4.00	2.00	1.25	Non-graduate
53150	(53150) Carpenters and joiners	4.00	2.00	1.11	Non-graduate
53160	(53160) Glaziers, window fabricators and fitters	4.00	2.00	1.00	Non-graduate
53190	(53190) Construction trades n.e.c.	4.00	2.00	1.07	Non-graduate
53210	(53210) Plasterers	4.00	2.00	1.00	Non-graduate
53220	(53220) Floorers and wall tilers	4.00	2.00	1.00	Non-graduate
53230	(53230) Painters and decorators	3.83	1.94	1.00	Non-graduate
54110	(54110) Weavers and knitters	4.00	2.00	1.00	Non-graduate
54120	(54120) Upholsterers	4.00	2.00	1.00	Non-graduate
54130	(54130) Leather and related trades	4.00	2.00	1.00	Non-graduate
54140	(54140) Tailors and dressmakers	4.00	2.00	1.00	Non-graduate
54190	(54190) Textiles, garments and related trades n.e.c.	4.00	2.00	1.00	Non-graduate
54210	(54210) Originators, compositors and print preparers	4.00	2.00	1.00	Non-graduate
54220	(54220) Printers	4.00	2.00	1.00	Non-graduate
54230	(54230) Bookbinders and print finishers	3.85	1.93	1.00	Non-graduate
54240	(54240) Screen printers	4.00	2.00	1.00	Non-graduate
54310	(54310) Butchers, meat cutters	4.00	2.00	1.00	Non-graduate
54320	(54320) Bakers, flour confectioners	4.00	2.00	1.00	Non-graduate
54330	(54330) Fishmongers, poultry dressers	4.00	2.00	1.00	Non-graduate
54340	(54340) Chefs, cooks	3.92	2.00	1.84	Non-graduate
54910	(54910) Glass and ceramics makers, decorators and finishers	4.00	2.00	1.00	Non-graduate
54920	(54920) Furniture makers, other craft woodworkers	4.00	2.00	1.00	Non-graduate
54930	(54930) Pattern makers (moulds)	4.00	2.00	1.00	Non-graduate
54940	(54940) Musical instrument makers and tuners	4.00	2.00	1.00	Non-graduate
54950	(54950) Goldsmiths, silversmiths, precious stone workers	4.00	2.00	1.00	Non-graduate
54960	(54960) Floral arrangers, florists	4.00	2.00	3.00	Non-graduate
54990	(54990) Hand craft occupations n.e.c.	4.00	2.00	1.00	Non-graduate
61110	(61110) Nursing auxiliaries and assistants	3.00	2.00	4.00	Non-graduate
61111	(61111) Nursing auxiliaries and ward attendants	3.00	2.00	4.00	Non-graduate
61112	(61112) Surgery, theatre and sterile services assistants	3.00	2.00	4.00	Non-graduate
61113	(61113) Occupational therapy and physiotherapy assistants	3.00	2.00	4.00	Non-graduate
61120	(61120) Ambulance staff (excl. paramedics)	3.00	2.00	4.00	Non-graduate
61130	(61130) Dental nurses	2.00	1.00	3.00	Non-graduate
61140	(61140) Houseparents and residential wardens	3.00	2.00	3.00	Non-graduate
61150	(61150) Care assistants and home carers (elderly and infirm)	3.00	1.18	5.06	Non-graduate
61151	(61151) Care assistants (residential)	3.00	1.18	5.06	Non-graduate
61152	(61152) Home carers	3.00	1.18	5.06	Non-graduate
61210	(61210) Nursery nurses	3.00	2.00	5.00	Non-graduate

61211	(61211) Nursery nurses and assistants	3.00	2.00	5.00	Non-graduate
61212	(61212) Creche attendants	3.00	2.00	5.00	Non-graduate
61220	(61220) Childminders and related occupations	3.00	2.00	5.00	Non-graduate
61230	(61230) Playgroup leaders/assistants	3.00	2.00	5.00	Non-graduate
61240	(61240) Educational assistants (excl. HE/FE tutors and language assistants)	3.00	2.00	5.00	Non-graduate
61310	(61310) Veterinary nurses and assistants	3.58	2.00	3.00	Non-graduate
61390	(61390) Animal care occupations n.e.c.	3.00	2.00	3.00	Non-graduate
62110	(62110) Sports and leisure assistants	3.00	2.00	3.00	Non-graduate
62111	(62111) Museum assistants	3.00	2.00	3.00	Non-graduate
62112	(62112) Bookmakers	3.00	2.00	3.00	Non-graduate
62113	(62113) Leisure centre, gym and swimming pool attendants	3.00	2.00	3.00	Non-graduate
62120	(62120) Travel agents	4.00	2.00	5.00	Non-graduate
62130	(62130) Travel and tour guides	2.63	1.63	3.00	Non-graduate
62140	(62140) Air travel assistants	3.00	2.00	3.00	Non-graduate
62141	(62141) Cabin crew	3.00	2.00	3.00	Non-graduate
62142	(62142) Passenger services assistants	3.00	2.00	3.00	Non-graduate
62150	(62150) Rail travel assistants	3.00	2.00	3.00	Non-graduate
62190	(62190) Leisure and travel service occupations n.e.c.	2.89	1.92	2.94	Non-graduate
62191	(62191) Ship stewards	2.89	1.92	2.94	Non-graduate
62210	(62210) Hairdressers, barbers	3.00	1.00	3.00	Non-graduate
62220	(62220) Beauticians and related occupations	2.83	1.00	2.83	Non-graduate
62310	(62310) Housekeepers and related occupations	2.86	2.00	3.29	Non-graduate
62311	(62311) Domestic housekeepers	2.86	2.00	3.29	Non-graduate
62312	(62312) Non-domestic housekeepers	2.86	2.00	3.29	Non-graduate
62320	(62320) Caretakers	2.00	1.00	1.00	Non-graduate
62910	(62910) Undertakers and mortuary assistants	3.00	2.00	5.00	Non-graduate
62920	(62920) Pest control officers	4.00	2.00	3.00	Non-graduate
71110	(71110) Sales and retail assistants	2.00	1.00	3.14	Non-graduate
71120	(71120) Retail cashiers and check-out operators	2.00	1.00	3.00	Non-graduate
71130	(71130) Telephone salespersons	2.00	1.00	5.00	Non-graduate
71210	(71210) Collector salespersons and credit agents	2.00	1.00	3.00	Non-graduate
71220	(71220) Debt, rent and other cash collectors	2.00	1.00	3.00	Non-graduate
71230	(71230) Roundsmen/women and van salespersons	2.00	1.00	3.00	Non-graduate
71240	(71240) Market and street traders and assistants	2.00	1.00	3.00	Non-graduate
71250	(71250) Merchandisers and window dressers	3.00	2.00	3.00	Non-graduate
71251	(71251) Merchandisers	3.00	2.00	3.00	Non-graduate
71252	(71252) Window dressers	3.00	2.00	3.00	Non-graduate
71290	(71290) Sales related occupations n.e.c	2.52	1.26	3.58	Non-graduate
71291	(71291) Property negotiators	2.52	1.26	3.58	Non-graduate
71292	(71292) Insurance sales representatives	2.52	1.26	3.58	Non-graduate
71293	(71293) Demonstrators and promoters (sales)	2.52	1.26	3.58	Non-graduate
71294	(71294) Sales representatives (retail)	2.52	1.26	3.58	Non-graduate
72110	(72110) Call centre agents/operators	2.08	1.17	3.17	Non-graduate

72120	(72120) Customer care occupations	2.07	1.14	3.14	Non-graduate
81110	(81110) Food, drink and tobacco process operatives	2.00	1.00	1.00	Non-graduate
81120	(81120) Glass and ceramics process operatives	2.00	1.00	1.00	Non-graduate
81130	(81130) Textile process operatives	2.00	1.00	1.00	Non-graduate
81140	(81140) Chemical and related process operatives	2.00	1.00	1.00	Non-graduate
81150	(81150) Rubber process operatives	2.00	1.00	1.00	Non-graduate
81160	(81160) Plastics process operatives	2.00	1.00	1.00	Non-graduate
81170	(81170) Metal making and treating process operatives	2.00	1.00	1.00	Non-graduate
81180	(81180) Electroplaters	2.00	1.00	1.00	Non-graduate
81190	(81190) Process operatives n.e.c.	2.00	1.00	1.00	Non-graduate
81210	(81210) Paper and wood machine operatives	2.00	1.00	1.00	Non-graduate
81220	(81220) Coal mine operatives	2.00	1.00	1.00	Non-graduate
81230	(81230) Quarry workers and related operatives	2.00	1.00	1.00	Non-graduate
81240	(81240) Energy plant operatives	2.00	1.00	1.00	Non-graduate
81250	(81250) Metal working machine operatives	2.27	1.13	1.07	Non-graduate
81260	(81260) Water and sewerage plant operatives	2.00	1.00	1.00	Non-graduate
81290	(81290) Plant and machine operatives n.e.c	2.00	1.00	1.00	Non-graduate
81310	(81310) Assemblers (electrical products)	2.00	1.00	1.00	Non-graduate
81320	(81320) Assemblers (vehicles and metal goods)	2.00	1.00	1.00	Non-graduate
81330	(81330) Routine inspectors and testers	2.00	1.00	1.00	Non-graduate
81340	(81340) Weighers, graders, sorters	2.00	1.00	1.00	Non-graduate
81350	(81350) Tyre, exhaust and windscreen fitters	2.00	1.00	1.00	Non-graduate
81360	(81360) Clothing cutters	4.00	2.00	1.00	Non-graduate
81370	(81370) Sewing machinists	2.00	1.00	1.00	Non-graduate
81380	(81380) Routine laboratory testers	3.86	1.00	1.93	Non-graduate
81390	(81390) Assemblers and routine operatives n.e.c.	2.17	1.09	1.00	Non-graduate
81410	(81410) Scaffolders, stagers, riggers	2.06	1.03	1.06	Non-graduate
81420	(81420) Road construction operatives	2.09	1.05	1.09	Non-graduate
81430	(81430) Rail construction and maintenance operatives	3.09	1.55	2.09	Non-graduate
81490	(81490) Construction operatives n.e.c	2.87	1.43	1.87	Non-graduate
82110	(82110) Heavy goods vehicle drivers	3.00	2.00	1.00	Non-graduate
82120	(82120) Van drivers	3.00	2.00	1.00	Non-graduate
82130	(82130) Bus and coach drivers	3.00	2.00	2.00	Non-graduate
82140	(82140) Taxi, cab drivers and chauffeurs	2.93	1.00	2.07	Non-graduate
82150	(82150) Driving instructors	4.00	1.00	3.00	Non-graduate
82160	(82160) Rail transport operatives	2.00	1.00	1.00	Non-graduate
82170	(82170) Seafarers (Merchant Navy); barge, lighter and boat operatives	2.09	1.05	1.00	Non-graduate
82180	(82180) Air transport operatives	2.00	1.00	1.00	Non-graduate
82190	(82190) Transport operatives n.e.c.	2.00	1.00	1.00	Non-graduate
82210	(82210) Crane drivers	2.00	1.00	1.00	Non-graduate
82220	(82220) Fork-lift truck drivers	2.00	1.00	1.00	Non-graduate
82230	(82230) Agricultural machinery drivers	2.00	1.00	1.00	Non-graduate

82290	(82290) Mobile machine drivers and operatives n.e.c.	3.00	1.00	1.00	Non-graduate
91110	(91110) Farm workers	2.00	1.00	1.00	Non-graduate
91120	(91120) Forestry workers	2.00	1.00	1.00	Non-graduate
91190	(91190) Fishing and agriculture related occupations n.e.c.	2.00	1.00	1.00	Non-graduate
91210	(91210) Labourers in building and woodworking trades	2.00	1.00	1.00	Non-graduate
91290	(91290) Labourers in other construction trades n.e.c.	2.40	1.20	1.00	Non-graduate
91310	(91310) Labourers in foundries	1.00	1.00	1.00	Non-graduate
91320	(91320) Industrial cleaning process occupations	1.97	1.00	1.00	Non-graduate
91330	(91330) Printing machine minders and assistants	2.29	1.15	1.00	Non-graduate
91340	(91340) Packers, bottlers, canners, fillers	1.00	1.00	1.00	Non-graduate
91390	(91390) Labourers in process and plant operations n.e.c.	1.00	1.00	1.00	Non-graduate
91410	(91410) Stevedores, dockers and slingers	1.00	1.00	1.00	Non-graduate
91490	(91490) Other goods handling and storage occupations n.e.c.	1.00	1.00	1.00	Non-graduate
91491	(91491) Storekeepers, warehousemen/women	1.00	1.00	1.00	Non-graduate
91492	(91492) Goods collectors, assemblers, dispatchers and porters	1.00	1.00	1.00	Non-graduate
92110	(92110) Postal workers, mail sorters, messengers, couriers	1.00	1.00	1.00	Non-graduate
92111	(92111) Postal workers	1.00	1.00	1.00	Non-graduate
92112	(92112) Messengers	1.00	1.00	1.00	Non-graduate
92113	(92113) Couriers, deliverers and distributors	1.00	1.00	1.00	Non-graduate
92190	(92190) Elementary office occupations n.e.c.	2.00	1.00	1.00	Non-graduate
92191	(92191) Reprographics, print room and office machine operators	2.00	1.00	1.00	Non-graduate
92192	(92192) Office juniors	2.00	1.00	1.00	Non-graduate
92210	(92210) Hospital porters	1.00	1.00	2.00	Non-graduate
92220	(92220) Hotel porters	1.00	1.00	1.00	Non-graduate
92230	(92230) Kitchen and catering assistants	1.00	1.00	1.00	Non-graduate
92231	(92231) Kitchen porters, hands	1.00	1.00	1.00	Non-graduate
92232	(92232) Counterhands, catering assistants	1.00	1.00	1.00	Non-graduate
92240	(92240) Waiters, waitresses	1.00	1.00	4.00	Non-graduate
92250	(92250) Bar staff	1.00	1.00	4.00	Non-graduate
92260	(92260) Leisure and theme park attendants	1.00	1.00	1.00	Non-graduate
92290	(92290) Elementary personal services occupations n.e.c.	1.00	1.00	1.00	Non-graduate
92310	(92310) Window cleaners	1.00	1.00	1.00	Non-graduate
92320	(92320) Road sweepers	1.00	1.00	1.00	Non-graduate
92330	(92330) Cleaners, domestics	1.06	1.06	1.24	Non-graduate
92340	(92340) Launderers, dry cleaners, pressers	1.03	1.03	1.13	Non-graduate
92350	(92350) Refuse and salvage occupations	1.00	1.00	1.00	Non-graduate
92390	(92390) Elementary cleaning occupations n.e.c.	1.10	1.00	1.00	Non-graduate

92410	(92410) Security guards and related occupations	1.00	1.00	1.00	Non-graduate
92411	(92411) Detectives and investigators (security services)	1.00	1.00	1.00	Non-graduate
92412	(92412) Security guards, wardens and watchmen	1.00	1.00	1.00	Non-graduate
92420	(92420) Traffic wardens	1.00	1.00	3.00	Non-graduate
92430	(92430) School crossing patrol attendants	1.00	1.00	3.00	Non-graduate
92440	(92440) School midday assistants	1.00	1.00	3.00	Non-graduate
92450	(92450) Car park attendants	1.00	1.00	3.00	Non-graduate
92490	(92490) Elementary security occupations n.e.c.	1.00	1.00	1.00	Non-graduate
92510	(92510) Shelf fillers	1.00	1.00	1.00	Non-graduate
92590	(92590) Elementary sales occupations n.e.c.	1.00	1.00	2.00	Non-graduate
92591	(92591) Trolley attendant	1.00	1.00	2.00	Non-graduate
92592	(92592) Advertisement hand	1.00	1.00	2.00	Non-graduate

Appendix D

Additional tables

Table D.1: Percentage 18-20 participating in higher education

Year	% Participation rate	Source
1960	5	Greenaway and Haynes (2000)
1962	6	Greenaway and Haynes (2000)
1964	8	Greenaway and Haynes (2000)
1966	10	Greenaway and Haynes (2000)
1968	13	Greenaway and Haynes (2000)
1970	14	Greenaway and Haynes (2000)
1972	14	Greenaway and Haynes (2000)
1974	13.5	Greenaway and Haynes (2000)
1976	13	Greenaway and Haynes (2000)
1978	12.5	Greenaway and Haynes (2000)
1980	13	Greenaway and Haynes (2000)
1982	13	Greenaway and Haynes (2000)
1984	14	Greenaway and Haynes (2000)
1986	14.5	Greenaway and Haynes (2000)
1988	17	Greenaway and Haynes (2000)
1990	24	Greenaway and Haynes (2000)
1992	30	Greenaway and Haynes (2000)
1994	33	Greenaway and Haynes (2000)
1996	33	Greenaway and Haynes (2000)
1998	34	Mayhew, Deer and Dua (2004)
1999	31.3	DBIS (Supplementary table A, 2014)
2000	31.9	DBIS (Supplementary table A, 2014)
2001	32.5	DBIS (Supplementary table A, 2014)
2002	32.7	DBIS (Supplementary table A, 2014)
2003	31.8	DBIS (Supplementary table A, 2014)
2004	32.1	DBIS (Supplementary table A, 2014)
2005	34	DBIS (Supplementary table A, 2014)
2006	33.6	DBIS 2014 (Supplementary table B, 2014)
2007	35	DBIS 2014 (Supplementary table B, 2014)
2008	36.7	DBIS 2014 (Supplementary table B, 2014)
2009	37.4	DBIS 2014 (Supplementary table B, 2014)
2010	37.8	DBIS 2014 (Supplementary table B, 2014)
2011	41.6	DBIS 2014 (Supplementary table B, 2014)
2012	36.2	DBIS 2014 (Supplementary table B, 2014)

Table D.2: Descriptive summary for the DLHE sample used

	Variable	2006/07	2008/09	2006/07 prop.	2008/09 prop.
SOC(HE)2010 job	Non-graduate	8964	7923	37.5%	38.5%
	Graduate	14925	12641	62.5%	61.5%
Age on entry to HE	16	19	9	0.1%	0.0%
	17	593	510	2.5%	2.5%
	18	15030	13663	62.9%	66.4%
	19	6739	5212	28.2%	25.3%
	20	1508	1170	6.3%	5.7%
Ethnicity	White	21139	18431	88.5%	89.6%
	Non-white	2750	2133	11.5%	10.4%
Degree classification	Upper second class honours	13011	11326	54.5%	55.1%
	First class honours	3599	3789	15.1%	18.4%
	Other degree class	7279	5449	30.5%	26.5%
Type of HEI attended	Post-1992	10180	8802	42.6%	42.8%
	Pre-1992	5254	4516	22.0%	22.0%
	Russell group	8455	7246	35.4%	35.2%
Socioeconomic background	Semi-routine or routine	3363	3046	14.1%	14.8%
	Intermediate	6525	5548	27.3%	27.0%
	Managerial or professional	14001	11970	58.6%	58.2%
UCAS tariff on entry (relative to entire cohort of leavers)	1st quartile	9860	7765	41.3%	37.8%
	2nd quartile	7172	6382	30.0%	31.0%
	3rd quartile	3900	3518	16.3%	17.1%
	4th quartile	2957	2899	12.4%	14.1%
Disability status	No known disabilities	22354	18981	93.6%	92.3%
	Disabled	1535	1583	6.4%	7.7%
Sex	Female	13540	11976	56.7%	58.2%
	Male	10349	8588	43.3%	41.8%
Education prior to HE	State school/ college	20881	18084	87.4%	87.9%
	Privately educated	3008	2480	12.6%	12.1%
Domicile prior to HE	London	2937	2229	12.3%	10.8%
	N England	4691	4420	19.6%	21.5%
	Northern Ireland	596	671	2.5%	3.3%
	Scotland	1629	1298	6.8%	6.3%
	SE and E England	6751	5760	28.3%	28.0%
	SW and Mid England	6302	5313	26.4%	25.8%
	Wales	983	873	4.1%	4.2%
Employer location	London	5891	4513	24.7%	21.9%
	N England	4605	4340	19.3%	21.1%
	Northern Ireland	464	488	1.9%	2.4%
	Scotland	1631	1339	6.8%	6.5%
	SE and E England	5137	4541	21.5%	22.1%
	SW and Mid England	5337	4630	22.3%	22.5%
	Wales	824	713	3.4%	3.5%
Field of study	Biological sciences	2766	2295	11.6%	11.2%
	Business	3849	3398	16.1%	16.5%
	Creative arts	1735	1279	7.3%	6.2%
	Education	944	1038	4.0%	5.0%
	Engineering and computer science	3592	2788	15.0%	13.6%
	Humanities and languages	3852	3123	16.1%	15.2%
	Law	826	637	3.5%	3.1%
	Other STEM	2074	1821	8.7%	8.9%
	Social studies	2433	1949	10.2%	9.5%
	Subjects allied to medicine	1818	2236	7.6%	10.9%
Employer size	1 to 49	4847	4571	20.3%	22.2%
	250 or more	15020	12546	62.9%	61.0%
	50 to 249	4022	3447	16.8%	16.8%
Annual salary	Mean	18,694	18,842		
	Std. deviation	5,948	6,011		
Total N		23889	20564		

Table D.3: Descriptive summary for the Longitudinal DLHE sample used

	Variable	2006/07	2008/09	2006/07 prop.	2008/09 prop.
SOC(HE)2010 job	Non-graduate	2548	3471	31.4%	29.1%
	Graduate	5556	8451	68.6%	70.9%
Age on entry to HE	16	5	7	0.1%	0.1%
	17	247	338	3.0%	2.8%
	18	5308	8083	65.5%	67.8%
	19	2152	2919	26.6%	24.5%
	20	392	575	4.8%	4.8%
Ethnicity	White	7096	10468	87.6%	87.8%
	Non-white	1008	1454	12.4%	12.2%
Degree classification	Upper second class honours	4392	6565	54.2%	55.1%
	First class honours	1362	2121	16.8%	17.8%
	Other degree class	2350	3236	29.0%	27.1%
Type of HEI attended	Post-1992	2753	4161	34.0%	34.9%
	Pre-1992	2166	2996	26.7%	25.1%
	Russell group	3185	4765	39.3%	40.0%
Socioeconomic background	Semi-routine or routine	1059	1693	13.1%	14.2%
	Intermediate	2270	3192	28.0%	26.8%
	Managerial or professional	4775	7037	58.9%	59.0%
UCAS tariff on entry (relative to entire cohort of leavers)	1st quartile	3049	4326	37.6%	36.3%
	2nd quartile	2586	3736	31.9%	31.3%
	3rd quartile	1445	2244	17.8%	18.8%
	4th quartile	1024	1616	12.6%	13.6%
Disability status	No known disabilities	7429	10848	91.7%	91.0%
	Disabled	675	1074	8.3%	9.0%
Sex	Female	4474	6671	55.2%	56.0%
	Male	3630	5251	44.8%	44.0%
Education prior to HE	State school/ college	7085	10473	87.4%	87.8%
	Privately educated	1019	1449	12.6%	12.2%
Domicile prior to HE	London	862	1296	10.6%	10.9%
	England	1519	2382	18.7%	20.0%
	Northern Ireland	628	733	7.7%	6.1%
	Scotland	719	973	8.9%	8.2%
	SE and E England	2050	3045	25.3%	25.5%
	SW and Mid England	1793	2801	22.1%	23.5%
	Wales	533	692	6.6%	5.8%
Employer location	England	6537	10019	80.7%	84.0%
	Northern Ireland	485	523	6.0%	4.4%
	Scotland	705	909	8.7%	7.6%
	Wales	377	471	4.7%	4.0%
Field of study	Biological sciences	913	1273	11.3%	10.7%
	Business	1138	1507	14.0%	12.6%
	Creative arts	578	825	7.1%	6.9%
	Education	178	373	2.2%	3.1%
	Engineering and computer science	1324	1672	16.3%	14.0%
	Humanities and languages	1402	2234	17.3%	18.7%
	Law	464	634	5.7%	5.3%
	Other STEM	863	1579	10.6%	13.2%
	Social studies	765	1044	9.4%	8.8%
	Subjects allied to medicine	479	781	5.9%	6.6%
Employer size	1 to 49	1501	2405	18.5%	20.2%
	250 or more	5104	7197	63.0%	60.4%
	50 to 249	1499	2320	18.5%	19.5%
Highest qualification	Postgraduate degree	1665	2973	20.5%	24.9%
	Undergraduate degree	6439	8949	79.5%	75.1%
Annual salary	Mean	25,083	25,949		
	Std. deviation	9,526	11,398		
Total N		8104	11922		

Table D.4: Partial correlations with skills utilisation using graduates from all fields of study (6 months) (2006/07)

Predictor	Models		
	Basic covariates	Pre-HE covariates	HE covariates
Age (Base=18)	0.125 (0.008)*	0.128 (0.008)*	0.082 (0.008)*
Non-white ethnicity	0.001 (0.007)	0.008 (0.007)	-0.013 (0.008)
Socioeconomic background (Ref: Routine and semi-routine)			
–Intermediate	0.024 (0.007)*	0.020 (0.007)*	0.018 (0.008)*
–Managerial or professional	0.044 (0.007)*	0.030 (0.007)*	0.028 (0.008)*
Has a known disability	-0.015 (0.007)*	-0.014 (0.007)	-0.007 (0.008)
Male	0.086 (0.007)*	0.088 (0.008)*	0.055 (0.008)*
Domicile prior to HE (Ref: London)			
–North England	-0.012 (0.007)	-0.013 (0.007)	-0.025 (0.008)*
–Northern Ireland	0.019 (0.008)*	0.023 (0.008)*	-0.004 (0.008)
–Scotland	0.034 (0.008)*	0.033 (0.008)*	0.009 (0.008)
–SE and East England	0.009 (0.007)	0.007 (0.007)	0.005 (0.008)
–SW and Mid England	0.002 (0.007)	0.003 (0.007)	-0.008 (0.008)
–Wales	-0.015 (0.007)*	-0.010 (0.007)	-0.021 (0.008)*
UCAS tariff quartile (Ref: 1st Quartile)			
–2nd Quartile		0.081 (0.007)*	0.031 (0.008)*
–3rd Quartile		0.111 (0.008)*	0.046 (0.008)*
–4th Quartile		0.049 (0.008)*	0.024 (0.008)*
Privately educated		0.034 (0.008)*	0.031 (0.008)*
Degree classification (Ref: Upper second class honours)			
–First class honours			0.090 (0.009)*
–Other degree class			-0.102 (0.008)*
Type of HEI (Ref: Post-1992 university)			
–Pre-1992 university			0.082 (0.008)*
–Russell group university			0.086 (0.008)*
Field of study [Ref: Biological sciences]			
–Business			0.141 (0.008)*
–Creative arts			0.061 (0.007)*
–Education			0.189 (0.009)*
–Engineering and computer science			0.198 (0.008)*
–Humanities and languages			0.044 (0.007)*
–Law			-0.008 (0.008)
–Other STEM			0.102 (0.008)*
–Social studies			0.072 (0.007)*
–Subjects allied to medicine			0.228 (0.009)*
R-square (MacFadden)	0.02	0.03	0.1
N		23889	

*p<0.05

Table D.5: Partial correlations with skills utilisation using graduates from all fields of study (42 months) (2006/07)

Predictor	Models		
	Basic covariates	Pre-HE covariates	HE covariates
Age (Base=18)	0.039 (0.013)*	0.041 (0.013)*	0.026 (0.014)
Non-white ethnicity	-0.065 (0.013)*	-0.057 (0.013)*	-0.058 (0.013)*
Socioeconomic background			
(Ref: Routine and semi-routine)			
–Intermediate	0.015 (0.013)	0.012 (0.013)	0.008 (0.013)
–Managerial or professional	0.043 (0.013)*	0.031 (0.013)*	0.020 (0.013)
Has a known disability	-0.041 (0.013)*	-0.040 (0.013)*	-0.036 (0.013)*
Male	0.026 (0.013)	0.029 (0.013)*	0.023 (0.014)
Domicile prior to HE			
(Ref: London)			
–North England	-0.016 (0.013)	-0.015 (0.013)	-0.020 (0.014)
–Northern Ireland	-0.047 (0.013)*	-0.036 (0.013)*	-0.062 (0.014)*
–Scotland	-0.025 (0.013)	-0.027 (0.013)*	-0.030 (0.014)*
–SE and East England	-0.013 (0.013)	-0.014 (0.014)	-0.015 (0.014)
–SW and Mid England	-0.023 (0.013)	-0.023 (0.013)	-0.030 (0.014)*
–Wales	-0.045 (0.013)*	-0.036 (0.013)*	-0.045 (0.013)*
UCAS tariff quartile			
(Ref: 1st Quartile)			
–2nd Quartile		0.080 (0.013)*	0.021 (0.014)
–3rd Quartile		0.100 (0.014)*	0.027 (0.014)
–4th Quartile		0.066 (0.013)*	0.020 (0.014)
Privately educated		0.046 (0.014)*	0.038 (0.015)*
Degree classification			
(Ref: Upper second class honours)			
–First class honours			0.077 (0.015)*
–Other degree class			-0.092 (0.013)*
Type of HEI			
(Ref: Post-1992 university)			
–Pre-1992 university			0.023 (0.013)
–Russell group university			0.067 (0.014)*
Field of study [Ref: Biological sciences]			
–Business			0.012 (0.013)
–Creative arts			0.034 (0.013)*
–Education			0.080 (0.015)*
–Engineering and computer science			0.103 (0.014)*
–Humanities and languages			-0.011 (0.013)
–Law			0.018 (0.013)
–Other STEM			0.046 (0.014)*
–Social studies			0.003 (0.013)
–Subjects allied to medicine			0.164 (0.016)*
Has postgraduate qualifications			-0.158 (0.015)*
R-square (MacFadden)	0.01	0.02	0.07
N		8104	

*p<0.05

Table D.6: Partial correlations with skills utilisation by fields of study (6 months) (2006/07)

Predictor	Bio. Sci.	Business	C. Arts	Fields of study Eng. Comp.	Human. Lang.	Other STEM	Soc. Studies	Chi-sq. p value
Age (Base=18)	0.066 (0.022)*	0.115 (0.019)*	0.076 (0.027)*	0.143 (0.024)*	0.046 (0.018)*	0.055 (0.027)*	0.056 (0.024)*	0.021
Non-white ethnicity	0.025 (0.022)	-0.045 (0.019)*	0.013 (0.027)	-0.069 (0.022)*	-0.015 (0.018)	-0.006 (0.027)	0.055 (0.024)*	<0.001
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	0.041 (0.022)	0.009 (0.019)	-0.024 (0.027)	0.019 (0.023)	0.034 (0.018)	0.016 (0.026)	0.006 (0.023)	0.531
–Managerial or professional	0.033 (0.022)	0.034 (0.019)	-0.011 (0.027)	0.024 (0.023)	0.011 (0.018)	0.038 (0.026)	0.046 (0.023)*	0.700
Has a known disability	-0.004 (0.022)	-0.034 (0.019)	0.003 (0.027)	-0.002 (0.025)	-0.020 (0.018)	0.024 (0.028)	0.021 (0.024)	0.461
Male	0.025 (0.022)	0.037 (0.019)	0.116 (0.027)*	0.042 (0.024)	0.040 (0.018)*	0.065 (0.027)*	0.101 (0.024)*	0.044
Domicile prior to HE								
(Ref: London)								
–North England	-0.020 (0.022)	-0.061 (0.019)*	0.019 (0.027)	-0.012 (0.023)	-0.025 (0.018)	-0.030 (0.027)	-0.029 (0.024)	0.366
–Northern Ireland	-0.001 (0.021)	-0.031 (0.020)	0.038 (0.030)	0.010 (0.028)	-0.016 (0.018)	-0.019 (0.026)	0.014 (0.023)	0.500
–Scotland	0.006 (0.022)	-0.032 (0.020)	0.045 (0.027)	0.053 (0.026)*	-0.032 (0.018)	0.024 (0.027)	-0.029 (0.024)	0.027
–SE and East England	0.014 (0.022)	-0.023 (0.020)	0.028 (0.027)	0.020 (0.024)	-0.022 (0.018)	0.030 (0.027)	0.002 (0.024)	0.403
–SW and Mid England	0.000 (0.022)	-0.044 (0.020)*	0.032 (0.027)	0.008 (0.024)	-0.001 (0.018)	0.005 (0.027)	-0.028 (0.024)	0.292
–Wales	-0.025 (0.022)	-0.053 (0.019)*	0.011 (0.027)	-0.002 (0.024)	-0.015 (0.018)	0.008 (0.027)	-0.048 (0.023)*	0.297
UCAS tariff quartile								
(Ref: 1st Quartile)								
–2nd Quartile	0.000 (0.022)	0.058 (0.020)*	0.067 (0.027)*	-0.034 (0.025)	0.036 (0.018)*	0.031 (0.026)	0.019 (0.023)	0.044
–3rd Quartile	0.011 (0.022)	0.059 (0.021)*	-0.016 (0.027)	0.060 (0.030)*	0.050 (0.018)*	0.056 (0.027)*	0.046 (0.024)	0.249
–4th Quartile	-0.007 (0.022)	0.028 (0.019)	-0.005 (0.027)	0.017 (0.024)	0.037 (0.018)*	0.090 (0.027)*	0.049 (0.024)*	0.100
Privately educated	0.053 (0.021)*	0.008 (0.020)	0.001 (0.027)	-0.062 (0.026)*	0.069 (0.018)*	-0.008 (0.028)	0.088 (0.025)*	<0.001
Degree classification								
(Ref: Upper second class honours)								
–First class honours	0.075 (0.021)*	0.074 (0.021)*	0.120 (0.028)*	0.153 (0.031)*	0.045 (0.018)*	0.084 (0.029)*	0.094 (0.026)*	0.053
–Other degree class	-0.106 (0.022)*	-0.133 (0.018)*	-0.076 (0.027)*	-0.164 (0.022)*	-0.069 (0.018)*	-0.110 (0.026)*	-0.076 (0.023)*	0.009
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	0.082 (0.022)*	0.079 (0.020)*	0.071 (0.028)*	0.198 (0.025)*	0.008 (0.018)	0.146 (0.026)*	0.113 (0.023)*	<0.001
–Russell group university	0.115 (0.022)*	0.116 (0.021)*	-0.027 (0.027)	0.246 (0.025)*	0.018 (0.018)	0.160 (0.025)*	0.108 (0.023)*	<0.001
R-square (MacFadden)	0.04	0.06	0.04	0.13	0.02	0.07	0.07	
N	2766	3849	1735	3592	3852	2074	2433	

*p<0.05

Table D.7: Partial correlations with skills utilisation by fields of study (42 months) (2006/07)

Predictor	Fields of study							Chi-sq.
	Bio. Sci.	Business	C. Arts	Eng. Comp.	Human. Lang.	Other STEM	Soc. Studies	p value
Age (Base=18)	-0.021 (0.040)	0.064 (0.035)	-0.003 (0.050)	0.083 (0.037)*	0.011 (0.032)	0.032 (0.044)	-0.015 (0.044)	0.373
Non-white ethnicity	-0.032 (0.040)	-0.104 (0.034)*	-0.060 (0.048)	-0.062 (0.035)	-0.021 (0.032)	-0.051 (0.043)	0.007 (0.045)	0.524
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	0.043 (0.039)	0.009 (0.034)	0.022 (0.050)	-0.037 (0.037)	0.006 (0.031)	-0.001 (0.043)	-0.018 (0.043)	0.850
–Managerial or professional	0.015 (0.039)	0.035 (0.034)	-0.002 (0.049)	-0.035 (0.038)	0.012 (0.031)	0.018 (0.043)	0.024 (0.043)	0.906
Has a known disability	-0.016 (0.039)	-0.002 (0.035)	-0.015 (0.050)	-0.018 (0.037)	-0.058 (0.031)	-0.028 (0.043)	-0.081 (0.042)	0.788
Male	0.003 (0.039)	0.030 (0.035)	0.067 (0.050)	0.037 (0.037)	-0.026 (0.032)	0.032 (0.044)	0.077 (0.044)	0.528
Domicile prior to HE								
(Ref: London)								
–North England	-0.064 (0.043)	-0.048 (0.035)	0.026 (0.049)	0.046 (0.037)	-0.067 (0.033)*	-0.045 (0.045)	-0.008 (0.044)	0.239
–Northern Ireland	-0.119 (0.040)*	-0.052 (0.034)	-0.006 (0.049)	-0.057 (0.036)	-0.092 (0.032)*	-0.084 (0.042)*	-0.035 (0.042)	0.573
–Scotland	-0.108 (0.041)*	-0.037 (0.035)	0.010 (0.050)	0.046 (0.038)	-0.089 (0.032)*	-0.052 (0.043)	0.001 (0.044)	0.053
–SE and East England	-0.108 (0.042)*	0.015 (0.035)	0.018 (0.049)	0.007 (0.036)	-0.050 (0.034)	-0.043 (0.045)	0.055 (0.045)	0.096
–SW and Mid England	-0.083 (0.043)	-0.053 (0.035)	0.045 (0.049)	0.043 (0.036)	-0.074 (0.033)*	0.019 (0.046)	-0.060 (0.043)	0.069
–Wales	-0.076 (0.041)	-0.055 (0.034)	-0.010 (0.049)	0.019 (0.037)	-0.100 (0.032)*	-0.057 (0.043)	-0.013 (0.044)	0.237
UCAS tariff quartile								
(Ref: 1st Quartile)								
–2nd Quartile	-0.020 (0.039)	0.053 (0.035)	0.032 (0.051)	0.026 (0.039)	0.048 (0.031)	0.038 (0.043)	-0.016 (0.043)	0.728
–3rd Quartile	0.029 (0.041)	0.005 (0.035)	-0.070 (0.049)	-0.061 (0.039)	0.094 (0.032)*	0.018 (0.043)	0.084 (0.045)	0.017
–4th Quartile	-0.040 (0.040)	0.010 (0.035)	-0.014 (0.049)	-0.016 (0.037)	0.043 (0.032)	0.078 (0.045)	0.093 (0.047)*	0.224
Privately educated	0.061 (0.042)	0.021 (0.035)	0.040 (0.054)	0.012 (0.042)	0.063 (0.034)	0.021 (0.047)	0.064 (0.047)	0.935
Degree classification								
(Ref: Upper second class honours)								
–First class honours	0.050 (0.043)	0.103 (0.037)*	0.120 (0.055)*	0.046 (0.041)	0.050 (0.035)	0.148 (0.049)*	-0.028 (0.046)	0.120
–Other degree class	-0.102 (0.039)*	-0.137 (0.033)*	-0.104 (0.048)*	-0.122 (0.036)*	-0.076 (0.030)*	-0.024 (0.042)	0.005 (0.043)	0.109
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	0.037 (0.039)	-0.053 (0.035)	0.052 (0.051)	0.101 (0.036)*	-0.024 (0.031)	0.042 (0.041)	0.081 (0.042)*	0.024
–Russell group university	0.091 (0.040)*	-0.039 (0.035)	0.034 (0.053)	0.234 (0.039)*	-0.019 (0.032)	0.089 (0.042)*	0.130 (0.042)*	<0.001
Has postgraduate qualifications	-0.290 (0.042)*	-0.103 (0.038)*	-0.160 (0.055)*	0.003 (0.037)	-0.219 (0.034)*	-0.175 (0.047)*	-0.177 (0.047)*	<0.001
R-square (MacFadden)	0.09	0.06	0.06	0.07	0.07	0.06	0.08	
N	913	1138	578	1324	1402	863	765	

*p<0.05

Table D.8: Results for models of (log) earning using graduates from all fields of study (6 months)

Predictor	Models		
	Basic covariates	Pre-HE covariates	HE covariates
Intercept	9.627 (0.011)*	9.583 (0.011)*	9.540 (0.012)*
Age (Base=18)	0.050 (0.002)*	0.049 (0.002)*	0.036 (0.002)*
Non-white ethnicity	0.033 (0.006)*	0.041 (0.006)*	0.018 (0.006)*
Socioeconomic background			
(Ref: Routine and semi-routine)			
–Intermediate	0.027 (0.006)*	0.020 (0.006)*	0.016 (0.006)*
–Managerial or professional	0.046 (0.006)*	0.028 (0.005)*	0.021 (0.005)*
Has a known disability	-0.001 (0.008)	-0.004 (0.007)	0.008 (0.007)
Male	0.105 (0.004)*	0.105 (0.004)*	0.062 (0.004)*
Domicile prior to HE			
(Ref: London)			
–North England	-0.153 (0.007)*	-0.151 (0.007)*	-0.154 (0.007)*
–Northern Ireland	-0.198 (0.013)*	-0.178 (0.013)*	-0.238 (0.012)*
–Scotland	-0.110 (0.009)*	-0.109 (0.009)*	-0.141 (0.008)*
–SE and East England	-0.059 (0.007)*	-0.059 (0.007)*	-0.057 (0.006)*
–SW and Mid England	-0.133 (0.007)*	-0.128 (0.007)*	-0.128 (0.006)*
–Wales	-0.157 (0.011)*	-0.141 (0.011)*	-0.150 (0.010)*
UCAS tariff quartile			
(Ref: 1st Quartile)			
–2nd Quartile		0.062 (0.004)*	0.017 (0.005)*
–3rd Quartile		0.108 (0.005)*	0.034 (0.006)*
–4th Quartile		0.067 (0.006)*	0.038 (0.006)*
Privately educated		0.080 (0.006)*	0.065 (0.005)*
Degree classification			
(Ref: Upper second class honours)			
–First class honours			0.066 (0.005)*
–Other degree class			-0.055 (0.004)*
Type of HEI			
(Ref: Post-1992 university)			
–Pre-1992 university			0.071 (0.005)*
–Russell group university			0.094 (0.005)*
Field of study [Ref: Biological sciences]			
–Business			0.162 (0.007)*
–Creative arts			-0.023 (0.008)*
–Education			0.225 (0.010)*
–Engineering and computer science			0.228 (0.007)*
–Humanities and languages			0.018 (0.007)*
–Law			0.078 (0.010)*
–Other STEM			0.144 (0.008)*
–Social studies			0.140 (0.007)*
–Subjects allied to medicine			0.147 (0.008)*
Residual SD	0.285	0.28	0.261
R-square	0.09	0.12	0.24
N		23889	

*p<0.05

Table D.9: Results for models of (log) earning using graduates from all fields of study (42 months) (2006/07)

Predictor	Models		
	Basic covariates	Pre-HE covariates	HE covariates
Intercept	9.944 (0.025)*	9.867 (0.025)*	9.863 (0.027)*
Age (Base=18)	0.038 (0.005)*	0.039 (0.005)*	0.025 (0.005)*
Non-white ethnicity	-0.026 (0.013)*	-0.011 (0.012)	-0.012 (0.012)
Socioeconomic background			
(Ref: Routine and semi-routine)			
–Intermediate	0.017 (0.013)	0.010 (0.013)	0.003 (0.012)
–Managerial or professional	0.053 (0.012)*	0.030 (0.012)*	0.022 (0.011)*
Has a known disability	-0.090 (0.014)*	-0.087 (0.014)*	-0.067 (0.013)*
Male	0.110 (0.008)*	0.112 (0.008)*	0.078 (0.008)*
Domicile prior to HE			
(Ref: London)			
–North England	-0.126 (0.015)*	-0.121 (0.015)*	-0.125 (0.015)*
–Northern Ireland	-0.225 (0.019)*	-0.192 (0.019)*	-0.250 (0.018)*
–Scotland	-0.078 (0.018)*	-0.080 (0.018)*	-0.093 (0.017)*
–SE and East England	-0.037 (0.015)*	-0.036 (0.014)*	-0.038 (0.014)*
–SW and Mid England	-0.097 (0.015)*	-0.094 (0.015)*	-0.097 (0.014)*
–Wales	-0.176 (0.020)*	-0.145 (0.020)*	-0.150 (0.019)*
UCAS tariff quartile			
(Ref: 1st Quartile)			
–2nd Quartile		0.084 (0.009)*	0.027 (0.009)*
–3rd Quartile		0.155 (0.011)*	0.071 (0.012)*
–4th Quartile		0.096 (0.012)*	0.057 (0.012)*
Privately educated		0.096 (0.012)*	0.075 (0.011)*
Degree classification			
(Ref: Upper second class honours)			
–First class honours			0.077 (0.010)*
–Other degree class			-0.088 (0.009)*
Type of HEI			
(Ref: Post-1992 university)			
–Pre-1992 university			0.070 (0.010)*
–Russell group university			0.101 (0.010)*
Field of study [Ref: Biological sciences]			
–Business			0.129 (0.015)*
–Creative arts			-0.093 (0.017)*
–Education			0.133 (0.026)*
–Engineering and computer science			0.161 (0.015)*
–Humanities and languages			-0.036 (0.014)*
–Law			0.080 (0.018)*
–Other STEM			0.097 (0.015)*
–Social studies			0.086 (0.016)*
–Subjects allied to medicine			0.207 (0.018)*
Has postgraduate qualifications			0.011 (0.009)
Residual SD	0.343	0.336	0.318
R-square	0.07	0.11	0.20
N		8104	

*p<0.05

Table D.10: Results for models of earnings by fields of study (6 months) (2006/07)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	9.551 (0.034)*	9.667 (0.027)*	9.525 (0.039)*	9.854 (0.045)*	9.717 (0.028)*	9.551 (0.027)*
Age (Base=18)	0.038 (0.007)*	0.053 (0.005)*	0.034 (0.008)*	0.027 (0.009)*	0.034 (0.005)*	0.034 (0.006)*
Non-white ethnicity	0.042 (0.019)*	0.021 (0.012)	0.010 (0.028)	-0.089 (0.045)*	0.013 (0.013)	0.015 (0.018)
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.031 (0.017)	-0.002 (0.013)	0.016 (0.019)	-0.011 (0.021)	0.007 (0.012)	0.033 (0.015)*
–Managerial or professional	0.024 (0.015)	0.026 (0.012)*	0.017 (0.018)	-0.002 (0.019)	0.005 (0.011)	0.032 (0.014)*
Has a known disability	0.038 (0.019)	0.005 (0.018)	-0.009 (0.020)	0.008 (0.031)	0.017 (0.015)	-0.004 (0.018)
Male	0.058 (0.012)*	0.066 (0.008)*	0.071 (0.013)*	-0.046 (0.021)*	0.077 (0.011)*	0.043 (0.009)*
Domicile prior to HE						
(Ref: London)						
–North England	-0.164 (0.020)*	-0.204 (0.016)*	-0.143 (0.024)*	-0.177 (0.031)*	-0.113 (0.016)*	-0.127 (0.015)*
–Northern Ireland	-0.249 (0.041)*	-0.337 (0.027)*	-0.200 (0.070)*	-0.020 (0.071)	-0.185 (0.025)*	-0.303 (0.036)*
–Scotland	-0.111 (0.028)*	-0.214 (0.019)*	-0.165 (0.040)*	-0.009 (0.035)	-0.060 (0.019)*	-0.183 (0.024)*
–SE and East England	-0.072 (0.019)*	-0.081 (0.015)*	-0.062 (0.023)*	-0.076 (0.030)*	-0.038 (0.016)*	-0.056 (0.013)*
–SW and Mid England	-0.149 (0.019)*	-0.170 (0.015)*	-0.127 (0.023)*	-0.136 (0.030)*	-0.095 (0.015)*	-0.121 (0.014)*
–Wales	-0.144 (0.028)*	-0.218 (0.025)*	-0.122 (0.035)*	-0.162 (0.037)*	-0.116 (0.023)*	-0.159 (0.025)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.001 (0.013)	0.031 (0.011)*	0.045 (0.016)*	0.033 (0.018)	0.001 (0.011)	0.037 (0.012)*
–3rd Quartile	0.022 (0.018)	0.052 (0.016)*	0.056 (0.024)*	0.028 (0.031)	0.017 (0.013)	0.051 (0.014)*
–4th Quartile	0.029 (0.019)	0.030 (0.015)*	-0.003 (0.015)	-0.027 (0.021)	0.004 (0.012)	0.075 (0.017)*
Privately educated	0.075 (0.017)*	0.061 (0.014)*	0.067 (0.026)*	-0.025 (0.034)	0.030 (0.013)*	0.074 (0.012)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.049 (0.016)*	0.063 (0.012)*	0.080 (0.019)*	0.034 (0.032)	0.068 (0.010)*	0.015 (0.014)
–Other degree class	-0.050 (0.012)*	-0.075 (0.009)*	-0.013 (0.013)	-0.033 (0.015)*	-0.088 (0.009)*	-0.015 (0.011)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.062 (0.014)*	0.105 (0.011)*	0.031 (0.019)	0.008 (0.024)	0.133 (0.011)*	0.056 (0.013)*
–Russell group university	0.068 (0.014)*	0.121 (0.013)*	-0.017 (0.023)	-0.053 (0.026)*	0.184 (0.011)*	0.071 (0.012)*
Residual SD	0.269	0.249	0.245	0.204	0.234	0.261
R-square	0.12	0.22	0.10	0.11	0.23	0.13
N	2766	3849	1735	944	3592	3852

*$p<0.05$

Results for models of earnings by fields of study (6 months) (2006/07) cont.

Predictor	Models				Chi-sq.
	Law	Other STEM	Soc. Studies	Sub. Med.	p value
Intercept	9.710 (0.063)*	9.659 (0.043)*	9.665 (0.040)*	9.708 (0.036)*	>0.001
Age (Base=18)	0.021 (0.014)	0.028 (0.008)*	0.020 (0.008)*	0.043 (0.007)*	0.029
Non-white ethnicity	-0.013 (0.032)	0.107 (0.024)*	0.107 (0.019)*	-0.076 (0.016)*	>0.001
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.035 (0.031)	0.029 (0.022)	0.025 (0.021)	0.005 (0.017)	0.597
–Managerial or professional	0.039 (0.029)	0.030 (0.020)	0.023 (0.020)	0.014 (0.016)	0.840
Has a known disability	0.030 (0.048)	0.022 (0.026)	-0.002 (0.024)	0.015 (0.024)	0.870
Male	0.060 (0.021)*	0.067 (0.012)*	0.091 (0.012)*	-0.016 (0.014)	>0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.236 (0.039)*	-0.192 (0.024)*	-0.171 (0.022)*	-0.044 (0.022)*	>0.001
–Northern Ireland	-0.308 (0.061)*	-0.168 (0.049)*	-0.173 (0.047)*	-0.159 (0.031)*	>0.001
–Scotland	-0.239 (0.052)*	-0.152 (0.032)*	-0.228 (0.032)*	-0.034 (0.028)	>0.001
–SE and East England	-0.063 (0.036)	-0.081 (0.023)*	-0.037 (0.019)	-0.007 (0.022)	0.189
–SW and Mid England	-0.173 (0.037)*	-0.147 (0.023)*	-0.121 (0.020)*	-0.032 (0.021)	>0.001
–Wales	-0.265 (0.058)*	-0.122 (0.036)*	-0.159 (0.037)*	-0.034 (0.032)	>0.001
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	-0.016 (0.027)	0.048 (0.018)*	0.009 (0.017)	-0.027 (0.013)*	0.001
–3rd Quartile	0.015 (0.034)	0.078 (0.019)*	0.045 (0.020)*	-0.060 (0.016)*	>0.001
–4th Quartile	0.080 (0.037)*	0.110 (0.021)*	0.132 (0.023)*	-0.018 (0.021)	>0.001
Privately educated	0.146 (0.034)*	0.063 (0.017)*	0.114 (0.016)*	0.004 (0.017)	>0.001
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.057 (0.060)	0.071 (0.015)*	0.102 (0.020)*	0.038 (0.016)*	0.007
–Other degree class	-0.022 (0.021)	-0.089 (0.015)*	-0.071 (0.015)*	-0.028 (0.012)*	>0.001
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.031 (0.028)	0.112 (0.021)*	0.101 (0.019)*	-0.024 (0.015)	>0.001
–Russell group university	0.056 (0.030)	0.122 (0.020)*	0.119 (0.019)*	0.011 (0.013)	>0.001
Residual SD	0.274	0.273	0.299	0.225	
R-square	0.16	0.19	0.23	0.07	
N	826	2074	2433	1818	

*p<0.05

Table D.11: Results for models of earnings by fields of study (42 months) (2006/07)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	10.073 (0.068)*	9.851 (0.076)*	9.996 (0.111)*	10.250 (0.156)*	9.841 (0.066)*	9.875 (0.058)*
Age (Base=18)	0.010 (0.014)	0.052 (0.013)*	-0.004 (0.022)	-0.012 (0.026)	0.042 (0.010)*	0.038 (0.011)*
Non-white ethnicity	-0.025 (0.032)	-0.012 (0.031)	-0.049 (0.055)	-0.065 (0.115)	0.000 (0.027)	-0.067 (0.030)*
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.014 (0.031)	-0.005 (0.031)	0.026 (0.052)	0.012 (0.073)	-0.032 (0.026)	-0.013 (0.030)
–Managerial or professional	0.013 (0.028)	0.055 (0.029)	0.022 (0.047)	-0.006 (0.068)	0.014 (0.024)	-0.013 (0.028)
Has a known disability	-0.028 (0.037)	-0.060 (0.040)	-0.056 (0.046)	0.063 (0.075)	-0.043 (0.031)	-0.107 (0.031)*
Male	0.072 (0.022)*	0.106 (0.020)*	0.057 (0.035)	0.032 (0.060)	0.142 (0.023)*	0.017 (0.018)
Domicile prior to HE						
(Ref: London)						
–North England	-0.166 (0.041)*	-0.135 (0.042)*	-0.085 (0.064)	-0.130 (0.126)	-0.065 (0.036)	-0.117 (0.030)*
–Northern Ireland	-0.324 (0.052)*	-0.305 (0.051)*	-0.192 (0.093)*	-0.009 (0.148)	-0.204 (0.043)*	-0.265 (0.043)*
–Scotland	-0.230 (0.049)*	-0.112 (0.048)*	-0.126 (0.088)	-0.011 (0.120)	0.012 (0.040)	-0.166 (0.040)*
–SE and East England	-0.126 (0.038)*	0.018 (0.040)	-0.079 (0.059)	-0.130 (0.118)	0.005 (0.035)	-0.030 (0.028)
–SW and Mid England	-0.157 (0.039)*	-0.062 (0.040)	-0.123 (0.061)*	-0.253 (0.114)*	-0.036 (0.035)	-0.107 (0.029)*
–Wales	-0.171 (0.050)*	-0.146 (0.055)*	-0.196 (0.085)*	-0.150 (0.120)	-0.156 (0.048)*	-0.152 (0.039)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	-0.007 (0.024)	0.059 (0.025)*	-0.012 (0.043)	0.045 (0.054)	0.031 (0.023)	0.044 (0.022)*
–3rd Quartile	-0.005 (0.033)	0.011 (0.037)	0.062 (0.057)	0.089 (0.095)	0.060 (0.028)*	0.093 (0.027)*
–4th Quartile	-0.008 (0.037)	0.016 (0.039)	-0.024 (0.041)	-0.054 (0.070)	0.014 (0.025)	0.155 (0.032)*
Privately educated	0.082 (0.033)*	0.007 (0.033)	0.202 (0.076)*	-0.049 (0.123)	0.020 (0.028)	0.118 (0.022)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.027 (0.029)	0.119 (0.029)*	0.007 (0.045)	0.127 (0.098)	0.076 (0.020)*	0.035 (0.024)
–Other degree class	-0.098 (0.023)*	-0.125 (0.023)*	-0.033 (0.037)	-0.166 (0.048)*	-0.120 (0.020)*	-0.014 (0.022)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.048 (0.026)	0.071 (0.026)*	0.122 (0.047)*	-0.063 (0.065)	0.121 (0.023)*	0.029 (0.025)
–Russell group university	0.067 (0.026)*	0.152 (0.032)*	0.084 (0.055)	-0.078 (0.067)	0.149 (0.024)*	0.043 (0.024)
Has postgraduate qualifications	-0.042 (0.021)*	0.013 (0.036)	-0.095 (0.046)*	0.036 (0.070)	0.024 (0.029)	-0.040 (0.018)*
Residual SD	0.284	0.322	0.372	0.251	0.293	0.298
R-square	0.12	0.20	0.08	0.22	0.21	0.15
N	913	1138	578	178	1324	1402

*p<0.05

Results for models of earnings by fields of study (42 months) (2006/07) cont.

	Law	Other STEM	Soc. Studies	Sub. Med.	Chi-sq. p value
Intercept	10.018 (0.126)*	9.800 (0.077)*	10.043 (0.088)*	9.944 (0.108)*	0.029
Age (Base=18)	-0.041 (0.026)	0.037 (0.015)*	-0.022 (0.017)	0.041 (0.018)*	0.001
Non-white ethnicity	-0.054 (0.052)	0.126 (0.039)*	0.022 (0.040)	0.077 (0.046)	0.013
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.049 (0.061)	0.057 (0.037)	-0.003 (0.046)	0.041 (0.048)	0.745
–Managerial or professional	0.061 (0.057)	0.035 (0.034)	-0.001 (0.042)	0.092 (0.045)*	0.689
Has a known disability	-0.083 (0.072)	-0.073 (0.037)*	-0.079 (0.041)	-0.007 (0.051)	0.594
Male	0.131 (0.036)*	0.093 (0.022)*	0.071 (0.025)*	-0.017 (0.038)	>0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.182 (0.069)*	-0.136 (0.046)*	-0.185 (0.047)*	-0.036 (0.065)	0.467
–Northern Ireland	-0.268 (0.081)*	-0.234 (0.059)*	-0.228 (0.067)*	-0.129 (0.070)	0.292
–Scotland	-0.092 (0.079)	-0.076 (0.054)	-0.080 (0.056)	0.006 (0.075)	0.016
–SE and East England	0.047 (0.067)	-0.066 (0.044)	-0.030 (0.040)	-0.055 (0.065)	0.205
–SW and Mid England	-0.129 (0.067)	-0.081 (0.045)	-0.085 (0.044)	-0.076 (0.062)	0.447
–Wales	-0.136 (0.080)	-0.148 (0.056)*	-0.092 (0.066)	-0.148 (0.083)	0.998
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	0.015 (0.052)	0.081 (0.030)*	0.035 (0.034)	0.028 (0.034)	0.574
–3rd Quartile	0.125 (0.060)*	0.134 (0.032)*	0.145 (0.041)*	0.062 (0.044)	0.049
–4th Quartile	0.115 (0.071)	0.135 (0.036)*	0.177 (0.046)*	0.044 (0.057)	>0.001
Privately educated	0.181 (0.056)*	0.044 (0.031)	0.098 (0.034)*	-0.015 (0.047)	0.005
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.266 (0.061)*	0.098 (0.028)*	0.106 (0.040)*	0.026 (0.042)	0.011
–Other degree class	-0.074 (0.039)	-0.092 (0.025)*	-0.062 (0.031)*	-0.057 (0.033)	0.002
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.062 (0.054)	0.065 (0.037)	0.031 (0.040)	0.032 (0.037)	0.066
–Russell group university	0.156 (0.056)*	0.076 (0.035)*	0.077 (0.042)	0.077 (0.037)*	0.011
Has postgraduate qualifications	0.047 (0.040)	0.085 (0.023)*	0.096 (0.028)*	-0.002 (0.042)	>0.001
Residual SD	0.343	0.302	0.332	0.296	
R-square	0.27	0.22	0.18	0.08	
N	464	863	765	479	

*p<0.05

Table D.12: Partial correlations with skills utilisation using graduates from all fields of study

Predictor	6 months		42 months	
	2006/07	2008/09	2006/07	2008/09
Age (Base=18)	0.082 (0.008)*	0.080 (0.009)*	0.026 (0.014)	0.054 (0.012)*
Non-white ethnicity	-0.013 (0.008)	0.001 (0.009)	-0.058 (0.013)*	-0.016 (0.011)
Socioeconomic background				
(Ref: Routine and semi-routine)				
–Intermediate	0.018 (0.008)*	0.021 (0.009)*	0.008 (0.013)	0.020 (0.011)
–Managerial or professional	0.028 (0.008)*	0.030 (0.009)*	0.020 (0.013)	0.038 (0.011)*
Has a known disability	-0.007 (0.008)	-0.014 (0.009)	-0.036 (0.013)*	-0.022 (0.011)
Male	0.055 (0.008)*	0.058 (0.008)*	0.023 (0.014)	0.038 (0.011)*
Domicile prior to HE				
(Ref: London)				
–North England	-0.025 (0.008)*	-0.005 (0.009)	-0.020 (0.014)	-0.011 (0.012)
–Northern Ireland	-0.004 (0.008)	-0.038 (0.009)*	-0.062 (0.014)*	-0.036 (0.011)*
–Scotland	0.009 (0.008)	0.003 (0.009)	-0.030 (0.014)*	-0.012 (0.012)
–SE and East England	0.005 (0.008)	0.010 (0.009)	-0.015 (0.014)	0.024 (0.012)*
–SW and Mid England	-0.008 (0.008)	-0.003 (0.009)	-0.030 (0.014)*	0.000 (0.012)
–Wales	-0.021 (0.008)*	-0.011 (0.009)	-0.045 (0.013)*	-0.009 (0.011)
UCAS tariff quartile				
(Ref: 1st Quartile)				
–2nd Quartile	0.031 (0.008)*	0.055 (0.009)*	0.021 (0.014)	0.039 (0.012)*
–3rd Quartile	0.046 (0.008)*	0.064 (0.009)*	0.027 (0.014)	0.036 (0.012)*
–4th Quartile	0.024 (0.008)*	0.026 (0.009)*	0.020 (0.014)	0.008 (0.011)
Privately educated	0.031 (0.008)*	0.052 (0.009)*	0.038 (0.015)*	0.034 (0.012)*
Degree classification				
(Ref: Upper second class honours)				
–First class honours	0.090 (0.009)*	0.118 (0.009)*	0.077 (0.015)*	0.080 (0.013)*
–Other degree class	-0.102 (0.008)*	-0.088 (0.009)*	-0.092 (0.013)*	-0.089 (0.011)*
Type of HEI				
(Ref: Post-1992 university)				
–Pre-1992 university	0.082 (0.008)*	0.063 (0.009)*	0.023 (0.013)	0.018 (0.011)
–Russell group university	0.086 (0.008)*	0.091 (0.009)*	0.067 (0.014)*	0.063 (0.012)*
Field of study [Ref: Biological sciences]				
–Business	0.141 (0.008)*	0.145 (0.008)*	0.012 (0.013)	0.020 (0.011)
–Creative arts	0.061 (0.007)*	0.043 (0.008)*	0.034 (0.013)*	0.020 (0.011)
–Education	0.189 (0.009)*	0.254 (0.010)*	0.080 (0.015)*	0.101 (0.013)*
–Engineering and computer science	0.198 (0.008)*	0.196 (0.009)*	0.103 (0.014)*	0.084 (0.012)*
–Humanities and languages	0.044 (0.007)*	0.026 (0.008)*	-0.011 (0.013)	-0.002 (0.011)
–Law	-0.008 (0.008)	-0.003 (0.008)	0.018 (0.013)	-0.016 (0.011)
–Other STEM	0.102 (0.008)*	0.087 (0.008)*	0.046 (0.014)*	0.020 (0.011)
–Social studies	0.072 (0.007)*	0.079 (0.008)*	0.003 (0.013)	-0.003 (0.011)
–Subjects allied to medicine	0.228 (0.009)*	0.314 (0.010)*	0.164 (0.016)*	0.200 (0.015)*
Has postgraduate qualifications			-0.158 (0.015)*	-0.205 (0.012)*
R-square	0.10	0.14	0.07	0.07
N	23889	20564	8104	11922

*p<0.05

Table D.13: Partial correlations with skills utilisation by fields of study (6 months) (2008/09)

Predictor	Bio. Sci.	Business	C. Arts	Fields of study Eng. Comp.	Human. Lang.	Other STEM	Soc. Studies	Chi-sq. p value
Age (Base=18)	0.081 (0.024)*	0.042 (0.020)*	0.064 (0.033)	0.163 (0.028)*	0.040 (0.020)*	0.113 (0.029)*	0.070 (0.026)*	0.007
Non-white ethnicity	0.053 (0.024)*	-0.032 (0.020)	-0.012 (0.034)	-0.072 (0.026)*	0.032 (0.020)	0.022 (0.029)	0.049 (0.027)	<0.001
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	0.037 (0.025)	0.009 (0.020)	0.117 (0.034)*	0.011 (0.026)	-0.005 (0.020)	0.001 (0.029)	0.039 (0.026)	0.057
–Managerial or professional	0.057 (0.025)*	0.025 (0.020)	0.113 (0.034)*	0.040 (0.027)	0.000 (0.020)	0.006 (0.029)	0.007 (0.026)	0.085
Has a known disability	-0.018 (0.025)	-0.008 (0.020)	-0.041 (0.033)	0.008 (0.029)	-0.026 (0.020)	0.013 (0.029)	0.001 (0.026)	0.824
Male	0.069 (0.024)*	0.079 (0.021)*	0.111 (0.032)*	0.058 (0.027)*	0.047 (0.020)*	0.072 (0.029)*	0.062 (0.026)*	0.748
Domicile prior to HE								
(Ref: London)								
–North England	-0.002 (0.024)	-0.011 (0.020)	0.113 (0.033)*	0.026 (0.028)	-0.020 (0.020)	0.002 (0.029)	-0.033 (0.026)	0.018
–Northern Ireland	-0.015 (0.025)	-0.054 (0.020)*	0.005 (0.033)	-0.043 (0.028)	-0.091 (0.024)*	-0.045 (0.027)	-0.011 (0.026)	0.160
–Scotland	0.014 (0.024)	0.014 (0.021)	-0.021 (0.035)	0.021 (0.028)	-0.018 (0.020)	-0.016 (0.028)	-0.015 (0.026)	0.788
–SE and East England	0.029 (0.024)	0.040 (0.020)*	0.040 (0.033)	0.012 (0.028)	-0.012 (0.020)	0.033 (0.029)	0.002 (0.026)	0.597
–SW and Mid England	-0.021 (0.024)	0.028 (0.020)	0.022 (0.033)	-0.002 (0.027)	-0.026 (0.020)	0.025 (0.029)	0.007 (0.026)	0.462
–Wales	-0.024 (0.025)	-0.013 (0.020)	0.029 (0.033)	0.017 (0.028)	-0.044 (0.021)*	0.038 (0.029)	-0.003 (0.026)	0.243
UCAS tariff quartile								
(Ref: 1st Quartile)								
–2nd Quartile	0.024 (0.024)	0.082 (0.021)*	0.039 (0.032)	0.030 (0.028)	0.067 (0.020)*	-0.009 (0.028)	0.049 (0.026)	0.178
–3rd Quartile	0.049 (0.024)*	0.075 (0.022)*	0.043 (0.033)	0.099 (0.033)*	0.052 (0.020)*	0.026 (0.028)	0.084 (0.026)*	0.579
–4th Quartile	0.018 (0.025)	-0.013 (0.020)	-0.002 (0.033)	0.034 (0.027)	0.050 (0.020)*	0.040 (0.029)	0.096 (0.026)*	0.055
Privately educated	0.030 (0.024)	0.026 (0.022)	0.066 (0.032)*	0.059 (0.034)	0.093 (0.020)*	0.090 (0.030)*	0.070 (0.027)*	0.228
Degree classification								
(Ref: Upper second class honours)								
–First class honours	0.106 (0.023)*	0.149 (0.023)*	0.190 (0.033)*	0.208 (0.033)*	0.068 (0.020)*	0.128 (0.030)*	0.064 (0.028)*	<0.001
–Other degree class	-0.079 (0.025)*	-0.118 (0.019)*	-0.082 (0.033)*	-0.121 (0.025)*	-0.037 (0.020)	-0.123 (0.027)*	-0.093 (0.026)*	0.075
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	0.024 (0.025)	0.077 (0.021)*	-0.014 (0.033)	0.200 (0.027)*	-0.007 (0.020)	0.176 (0.027)*	0.095 (0.026)*	<0.001
–Russell group university	0.078 (0.024)*	0.109 (0.022)*	-0.022 (0.032)	0.235 (0.027)*	0.031 (0.020)	0.224 (0.027)*	0.083 (0.026)*	<0.001
R-square (MacFadden)	0.05	0.07	0.07	0.14	0.04	0.10	0.06	
N	2295	3398	1279	2788	3123	1821	1949	

*p<0.05

Table D.14: Partial correlations with skills utilisation by fields of study (42 months) (2008/09)

Predictor	Fields of study							Chi-sq.
	Bio. Sci.	Business	C. Arts	Eng. Comp.	Human. Lang.	Other STEM	Soc. Studies	p value
Age (Base=18)	0.091 (0.036)*	0.096 (0.031)*	0.030 (0.043)	0.092 (0.034)*	0.003 (0.026)	0.027 (0.033)	0.035 (0.038)	0.153
Non-white ethnicity	-0.001 (0.035)	-0.027 (0.031)	-0.013 (0.041)	-0.032 (0.033)	0.003 (0.027)	0.043 (0.034)	-0.031 (0.037)	0.705
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	0.041 (0.033)	0.013 (0.030)	0.021 (0.041)	0.010 (0.033)	-0.013 (0.025)	0.045 (0.032)	-0.006 (0.037)	0.818
–Managerial or professional	0.063 (0.033)	0.063 (0.030)*	0.071 (0.042)	0.044 (0.033)	0.006 (0.025)	0.036 (0.032)	-0.001 (0.037)	0.613
Has a known disability	-0.006 (0.035)	0.012 (0.032)	0.023 (0.043)	0.020 (0.035)	-0.077 (0.025)*	-0.033 (0.032)	-0.056 (0.037)	0.134
Male	0.007 (0.034)	0.016 (0.031)	0.102 (0.043)*	0.052 (0.033)	0.043 (0.026)	0.085 (0.033)*	0.024 (0.038)	0.461
Domicile prior to HE								
(Ref: London)								
–North England	-0.016 (0.035)	0.043 (0.030)	-0.015 (0.043)	-0.065 (0.035)	-0.058 (0.027)*	-0.028 (0.033)	0.006 (0.038)	0.230
–Northern Ireland	-0.048 (0.034)	-0.029 (0.030)	-0.035 (0.042)	-0.085 (0.034)*	-0.090 (0.025)*	-0.057 (0.031)	-0.060 (0.036)	0.780
–Scotland	0.005 (0.035)	0.003 (0.030)	-0.029 (0.043)	-0.004 (0.037)	-0.099 (0.025)*	0.016 (0.033)	-0.002 (0.037)	0.052
–SE and East England	-0.006 (0.035)	0.065 (0.030)*	-0.005 (0.043)	-0.040 (0.036)	-0.040 (0.028)	0.084 (0.034)*	0.017 (0.038)	0.043
–SW and Mid England	0.009 (0.035)	0.050 (0.030)	-0.051 (0.043)	-0.041 (0.036)	-0.048 (0.028)	0.018 (0.033)	-0.006 (0.038)	0.187
–Wales	-0.009 (0.034)	0.033 (0.031)	-0.048 (0.042)	-0.015 (0.035)	-0.049 (0.026)	0.007 (0.032)	0.017 (0.038)	0.453
UCAS tariff quartile								
(Ref: 1st Quartile)								
–2nd Quartile	-0.004 (0.034)	0.069 (0.032)*	0.043 (0.043)	0.028 (0.034)	0.020 (0.025)	0.024 (0.032)	0.014 (0.037)	0.812
–3rd Quartile	0.021 (0.036)	-0.021 (0.031)	0.057 (0.046)	0.060 (0.038)	0.007 (0.026)	0.037 (0.032)	0.009 (0.038)	0.673
–4th Quartile	-0.057 (0.034)	-0.058 (0.030)	0.038 (0.042)	-0.001 (0.032)	0.023 (0.026)	0.054 (0.033)	0.038 (0.038)	0.071
Privately educated	0.020 (0.037)	0.093 (0.035)*	0.037 (0.045)	-0.027 (0.035)	0.049 (0.028)	-0.047 (0.033)	0.123 (0.041)*	0.008
Degree classification								
(Ref: Upper second class honours)								
–First class honours	0.049 (0.037)	0.055 (0.033)	0.116 (0.045)*	0.098 (0.039)*	0.015 (0.027)	0.131 (0.036)*	0.151 (0.043)*	0.048
–Other degree class	-0.103 (0.033)*	-0.142 (0.030)*	-0.027 (0.041)	-0.158 (0.031)*	-0.093 (0.024)*	-0.066 (0.032)*	-0.004 (0.036)	0.011
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	0.016 (0.034)	0.019 (0.031)	-0.046 (0.042)	0.059 (0.033)	0.009 (0.025)	0.023 (0.031)	0.060 (0.036)	0.472
–Russell group university	0.063 (0.035)	0.015 (0.032)	0.044 (0.048)	0.125 (0.034)*	0.058 (0.025)*	0.086 (0.031)*	0.067 (0.036)	0.412
Has postgraduate qualifications	-0.341 (0.036)*	-0.157 (0.036)*	-0.303 (0.051)*	-0.139 (0.040)*	-0.182 (0.027)*	-0.315 (0.036)*	-0.212 (0.040)*	<0.001
R-square (MacFadden)	0.10	0.07	0.08	0.07	0.06	0.09	0.06	
N	1273	1507	825	1672	2234	1579	1044	

*p<0.05

Table D.15: Differences in partial correlations by field of study between the 2006/07 and 2008/09 cohorts

Predictors	Fields of study							No. sig.
	Bio. Sci.	Business	C. Arts	Eng. Comp.	Human. Lang.	Other STEM	Soc. Studies	results*
6 months results								
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	-0.004 (0.033)	0 (0.028)	0.142 (0.043)*	-0.009 (0.035)	-0.039 (0.027)	-0.015 (0.039)	0.033 (0.035)	1
–Managerial or professional	0.024 (0.033)	-0.009 (0.028)	0.124 (0.043)*	0.015 (0.035)	-0.011 (0.027)	-0.032 (0.039)	-0.04 (0.035)	1
Male	0.044 (0.033)	0.042 (0.028)	-0.005 (0.042)	0.016 (0.036)	0.007 (0.027)	0.007 (0.04)	-0.04 (0.035)	0
Privately educated	-0.023 (0.032)	0.018 (0.03)	0.065 (0.042)	0.12 (0.043)*	0.024 (0.027)	0.098 (0.041)*	-0.018 (0.037)	1
Degree classification								
(Ref: Upper second class honours)								
–First class honours	0.03 (0.032)	0.075 (0.031)*	0.07 (0.043)	0.055 (0.045)	0.022 (0.027)	0.043 (0.042)	-0.029 (0.038)	0
–Other degree class	0.027 (0.033)	0.015 (0.027)	-0.006 (0.042)	0.044 (0.033)	0.031 (0.027)	-0.014 (0.038)	-0.017 (0.035)	0
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	-0.058 (0.033)	-0.002 (0.029)	-0.086 (0.043)*	0.003 (0.037)	-0.015 (0.027)	0.03 (0.037)	-0.018 (0.035)	0
–Russell group university	-0.037 (0.032)	-0.008 (0.03)	0.005 (0.042)	-0.011 (0.037)	0.014 (0.027)	0.064 (0.037)	-0.025 (0.035)	0
42 months results								
Socioeconomic background								
(Ref: Routine and semi-routine)								
–Intermediate	-0.002 (0.051)	0.004 (0.046)	-0.001 (0.065)	0.047 (0.049)	-0.019 (0.04)	0.046 (0.054)	0.012 (0.056)	0
–Managerial or professional	0.049 (0.051)	0.028 (0.046)	0.073 (0.064)	0.079 (0.05)	-0.006 (0.04)	0.018 (0.054)	-0.024 (0.057)	0
Male	0.004 (0.052)	-0.013 (0.047)	0.035 (0.066)	0.015 (0.049)	0.069 (0.041)	0.054 (0.055)	-0.053 (0.058)	0
Privately educated	-0.041 (0.056)	0.072 (0.05)	-0.003 (0.07)	-0.039 (0.055)	-0.014 (0.044)	-0.068 (0.057)	0.059 (0.062)	0
Degree classification								
(Ref: Upper second class honours)								
–First class honours	-0.001 (0.056)	-0.048 (0.049)	-0.005 (0.071)	0.052 (0.056)	-0.035 (0.044)	-0.018 (0.061)	0.179 (0.063)*	1
–Other degree class	-0.001 (0.051)	-0.006 (0.045)	0.077 (0.063)	-0.037 (0.047)	-0.017 (0.039)	-0.042 (0.053)	-0.008 (0.057)	0
Type of HEI								
(Ref: Post-1992 university)								
–Pre-1992 university	-0.021 (0.052)	0.072 (0.047)	-0.098 (0.066)	-0.042 (0.049)	0.034 (0.04)	-0.019 (0.052)	-0.021 (0.055)	0
–Russell group university	-0.029 (0.053)	0.054 (0.047)	0.01 (0.071)	-0.109 (0.052)*	0.078 (0.04)	-0.003 (0.052)	-0.063 (0.056)	0

*$p<0.05$ **Holm-Bonferroni

Table D.16: Results for models of earnings by fields of study (6 months) (2008/09)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	9.524 (0.037)*	9.658 (0.029)*	9.515 (0.047)*	9.877 (0.039)*	9.531 (0.034)*	9.492 (0.032)*
Age (Base=18)	0.037 (0.008)*	0.039 (0.006)*	0.030 (0.009)*	0.041 (0.008)*	0.063 (0.006)*	0.047 (0.006)*
Non-white ethnicity	0.047 (0.021)*	-0.014 (0.014)	-0.005 (0.035)	-0.076 (0.031)*	0.017 (0.017)	0.049 (0.023)*
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.018 (0.018)	0.030 (0.014)*	0.050 (0.023)*	0.011 (0.018)	0.001 (0.015)	-0.003 (0.018)
–Managerial or professional	0.028 (0.017)	0.046 (0.013)*	0.026 (0.021)	0.013 (0.017)	0.011 (0.014)	0.009 (0.016)
Has a known disability	-0.010 (0.020)	-0.024 (0.018)	-0.034 (0.022)	-0.060 (0.023)*	0.016 (0.017)	-0.003 (0.020)
Male	0.038 (0.012)*	0.079 (0.009)*	0.060 (0.015)*	-0.028 (0.021)	0.069 (0.013)*	0.060 (0.011)*
Domicile prior to HE						
(Ref: London)						
–North England	-0.112 (0.022)*	-0.197 (0.018)*	-0.114 (0.031)*	-0.155 (0.028)*	-0.071 (0.020)*	-0.136 (0.018)*
–Northern Ireland	-0.238 (0.041)*	-0.336 (0.026)*	-0.067 (0.066)	-0.123 (0.067)	-0.203 (0.029)*	-0.264 (0.035)*
–Scotland	-0.051 (0.033)	-0.165 (0.021)*	-0.216 (0.062)*	-0.064 (0.040)	-0.013 (0.023)	-0.137 (0.030)*
–SE and East England	-0.053 (0.021)*	-0.070 (0.017)*	-0.051 (0.028)	-0.108 (0.027)*	-0.026 (0.019)	-0.066 (0.016)*
–SW and Mid England	-0.110 (0.021)*	-0.128 (0.017)*	-0.118 (0.029)*	-0.164 (0.027)*	-0.036 (0.019)	-0.110 (0.017)*
–Wales	-0.114 (0.034)*	-0.187 (0.026)*	-0.047 (0.040)	-0.150 (0.036)*	-0.029 (0.029)	-0.133 (0.029)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.030 (0.014)*	0.045 (0.011)*	0.057 (0.019)*	0.026 (0.015)	0.035 (0.013)*	0.028 (0.013)*
–3rd Quartile	0.020 (0.019)	0.055 (0.016)*	0.085 (0.028)*	0.047 (0.026)	0.060 (0.015)*	0.034 (0.016)*
–4th Quartile	0.022 (0.018)	-0.005 (0.015)	-0.008 (0.018)	-0.070 (0.020)*	0.048 (0.014)*	0.036 (0.018)*
Privately educated	0.041 (0.019)*	0.052 (0.015)*	0.027 (0.030)	0.029 (0.031)	0.032 (0.016)*	0.085 (0.014)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.058 (0.016)*	0.106 (0.012)*	0.061 (0.020)*	0.027 (0.021)	0.070 (0.011)*	0.066 (0.015)*
–Other degree class	-0.042 (0.014)*	-0.074 (0.011)*	-0.054 (0.017)*	-0.037 (0.014)*	-0.095 (0.012)*	-0.013 (0.013)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.061 (0.015)*	0.073 (0.012)*	0.039 (0.019)*	0.014 (0.023)	0.153 (0.013)*	0.047 (0.015)*
–Russell group university	0.087 (0.015)*	0.109 (0.014)*	0.009 (0.025)	-0.040 (0.033)	0.191 (0.013)*	0.078 (0.014)*
Residual SD	0.262	0.248	0.248	0.194	0.251	0.271
R-square	0.10	0.21	0.11	0.11	0.25	0.13
N	2295	3398	1279	1038	2788	3123

*p<0.05

Results for models of earnings by fields of study (6 months) (2008/09) cont.

Predictor	Law	Other STEM	Soc. Studies	Sub. Med.	Chi-sq. p value
Intercept	9.602 (0.071)*	9.533 (0.049)*	9.593 (0.048)*	9.795 (0.030)*	<0.001
Age (Base=18)	0.026 (0.015)	0.035 (0.009)*	0.033 (0.010)*	0.041 (0.005)*	0.024
Non-white ethnicity	0.006 (0.035)	0.112 (0.029)*	0.122 (0.024)*	-0.079 (0.013)*	<0.001
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.057 (0.033)	0.031 (0.024)	0.030 (0.025)	0.000 (0.014)	0.421
–Managerial or professional	0.071 (0.030)*	0.019 (0.022)	0.008 (0.023)	0.002 (0.013)	0.286
Has a known disability	0.015 (0.049)	0.037 (0.027)	0.004 (0.027)	-0.001 (0.017)	0.155
Male	0.076 (0.023)*	0.066 (0.014)*	0.079 (0.015)*	-0.039 (0.012)*	<0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.188 (0.043)*	-0.113 (0.028)*	-0.106 (0.026)*	-0.020 (0.019)	<0.001
–Northern Ireland	-0.297 (0.075)*	-0.211 (0.064)*	-0.059 (0.048)	-0.123 (0.025)*	<0.001
–Scotland	-0.243 (0.059)*	-0.127 (0.038)*	-0.070 (0.039)	-0.087 (0.024)*	<0.001
–SE and East England	-0.102 (0.043)*	-0.024 (0.027)	0.004 (0.024)	0.018 (0.020)	0.002
–SW and Mid England	-0.150 (0.042)*	-0.063 (0.027)*	-0.062 (0.025)*	-0.018 (0.018)	<0.001
–Wales	-0.211 (0.063)*	-0.103 (0.042)*	-0.104 (0.045)*	0.002 (0.026)	<0.001
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	0.057 (0.030)	0.039 (0.021)	0.048 (0.020)*	-0.020 (0.011)	0.003
–3rd Quartile	0.106 (0.037)*	0.082 (0.023)*	0.098 (0.025)*	-0.028 (0.015)	<0.001
–4th Quartile	0.080 (0.043)	0.142 (0.024)*	0.122 (0.024)*	-0.048 (0.016)*	<0.001
Privately educated	0.108 (0.041)*	0.045 (0.021)*	0.121 (0.020)*	-0.051 (0.016)*	<0.001
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.022 (0.050)	0.095 (0.018)*	0.100 (0.022)*	0.014 (0.013)	<0.001
–Other degree class	0.010 (0.025)	-0.081 (0.018)*	-0.048 (0.018)*	-0.007 (0.011)	<0.001
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.003 (0.031)	0.133 (0.024)*	0.068 (0.022)*	-0.032 (0.012)*	<0.001
–Russell group university	0.041 (0.032)	0.137 (0.022)*	0.057 (0.022)*	-0.013 (0.011)	<0.001
Residual SD	0.267	0.299	0.314	0.212	
R-square	0.14	0.18	0.16	0.08	
N	637	1821	1949	2236	

*p<0.05

Table D.17: Results for models of earnings by fields of study (42 months) (2008/09)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	10.024 (0.066)*	9.888 (0.065)*	9.810 (0.103)*	9.919 (0.123)*	9.930 (0.060)*	9.968 (0.050)*
Age (Base=18)	0.009 (0.014)	0.033 (0.011)*	0.039 (0.020)*	0.070 (0.022)*	0.041 (0.010)*	0.020 (0.010)*
Non-white ethnicity	0.009 (0.033)	-0.015 (0.026)	-0.073 (0.053)	0.067 (0.084)	-0.038 (0.028)	0.002 (0.029)
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.025 (0.033)	0.048 (0.027)	0.083 (0.047)	-0.011 (0.048)	0.036 (0.025)	0.022 (0.026)
–Managerial or professional	0.060 (0.031)	0.086 (0.025)*	0.114 (0.043)*	-0.005 (0.044)	0.071 (0.023)*	0.011 (0.024)
Has a known disability	-0.010 (0.033)	0.002 (0.034)	0.020 (0.044)	-0.052 (0.056)	-0.009 (0.028)	-0.023 (0.027)
Male	0.052 (0.022)*	0.130 (0.017)*	0.060 (0.030)*	0.098 (0.054)	0.088 (0.023)*	0.011 (0.016)
Domicile prior to HE						
(Ref: London)						
–North England	-0.119 (0.039)*	-0.109 (0.036)*	-0.158 (0.061)*	-0.234 (0.093)*	-0.121 (0.033)*	-0.172 (0.028)*
–Northern Ireland	-0.250 (0.056)*	-0.318 (0.044)*	-0.059 (0.089)	-0.406 (0.134)*	-0.231 (0.043)*	-0.362 (0.042)*
–Scotland	-0.082 (0.050)	-0.041 (0.040)	-0.144 (0.080)	-0.157 (0.103)	-0.047 (0.038)	-0.277 (0.039)*
–SE and East England	-0.058 (0.038)	0.015 (0.034)	-0.041 (0.056)	-0.092 (0.093)	-0.058 (0.033)	-0.068 (0.026)*
–SW and Mid England	-0.090 (0.038)*	-0.051 (0.034)	-0.064 (0.057)	-0.166 (0.089)	-0.098 (0.033)*	-0.151 (0.027)*
–Wales	-0.151 (0.051)*	-0.065 (0.048)	-0.199 (0.076)*	-0.290 (0.099)*	-0.065 (0.048)	-0.186 (0.039)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	-0.008 (0.026)	0.054 (0.022)*	0.019 (0.037)	0.161 (0.045)*	0.001 (0.022)	0.035 (0.021)
–3rd Quartile	0.000 (0.033)	0.044 (0.031)	0.084 (0.054)	0.126 (0.084)	0.025 (0.026)	0.038 (0.024)
–4th Quartile	0.014 (0.034)	-0.040 (0.033)	-0.106 (0.037)*	0.026 (0.048)	-0.014 (0.024)	0.070 (0.028)*
Privately educated	0.008 (0.033)	0.073 (0.031)*	0.079 (0.060)	-0.031 (0.094)	0.033 (0.028)	0.072 (0.021)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.052 (0.030)	0.150 (0.023)*	0.011 (0.038)	-0.089 (0.061)	0.091 (0.020)*	0.016 (0.021)
–Other degree class	-0.089 (0.023)*	-0.158 (0.022)*	-0.087 (0.035)*	-0.081 (0.038)*	-0.121 (0.019)*	-0.089 (0.020)*
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	-0.018 (0.026)	0.030 (0.023)	-0.052 (0.036)	0.056 (0.054)	0.117 (0.022)*	0.034 (0.023)
–Russell group university	0.095 (0.027)*	0.097 (0.028)*	-0.007 (0.050)	0.083 (0.064)	0.146 (0.022)*	0.100 (0.022)*
Has postgraduate qualifications	-0.088 (0.021)*	0.032 (0.029)	-0.051 (0.037)	0.032 (0.049)	0.010 (0.026)	-0.007 (0.016)
Residual SD	0.347	0.332	0.396	0.312	0.329	0.343
R-square	0.09	0.21	0.09	0.16	0.15	0.13
N	1273	1507	825	373	1672	2234

*p<0.05

Results for models of earnings by fields of study (42 months) (2008/09) cont.

Predictor	Models				Chi-sq.
	Law	Other STEM	Soc. Studies	Sub. Med.	p value
Intercept	9.873 (0.098)*	10.020 (0.059)*	9.862 (0.076)*	9.918 (0.077)*	0.554
Age (Base=18)	0.033 (0.019)	0.005 (0.011)	0.054 (0.016)*	0.038 (0.013)*	0.058
Non-white ethnicity	-0.066 (0.041)	0.062 (0.030)*	0.053 (0.033)	0.104 (0.034)*	0.010
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.073 (0.048)	0.023 (0.028)	-0.002 (0.038)	-0.003 (0.033)	0.808
–Managerial or professional	0.051 (0.043)	0.016 (0.026)	0.004 (0.034)	0.037 (0.031)	0.149
Has a known disability	-0.017 (0.063)	-0.036 (0.028)	-0.028 (0.036)	-0.003 (0.038)	0.979
Male	0.093 (0.029)*	0.065 (0.017)*	0.121 (0.022)*	0.073 (0.029)*	<0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.324 (0.057)*	-0.186 (0.033)*	-0.159 (0.040)*	0.014 (0.048)	0.001
–Northern Ireland	-0.318 (0.070)*	-0.205 (0.053)*	-0.359 (0.061)*	-0.072 (0.054)	0.001
–Scotland	-0.173 (0.066)*	-0.156 (0.043)*	-0.103 (0.052)*	-0.065 (0.056)	0.001
–SE and East England	-0.126 (0.053)*	-0.030 (0.032)	-0.025 (0.037)	-0.003 (0.049)	0.550
–SW and Mid England	-0.222 (0.054)*	-0.110 (0.032)*	-0.074 (0.039)	-0.026 (0.049)	0.104
–Wales	-0.331 (0.068)*	-0.098 (0.046)*	-0.108 (0.062)	0.039 (0.059)	<0.001
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	0.014 (0.042)	0.047 (0.023)*	-0.008 (0.030)	0.065 (0.025)*	0.029
–3rd Quartile	0.171 (0.049)*	0.099 (0.025)*	0.047 (0.035)	0.053 (0.035)	0.111
–4th Quartile	0.128 (0.060)*	0.127 (0.029)*	0.071 (0.040)	-0.029 (0.040)	<0.001
Privately educated	0.160 (0.045)*	0.043 (0.023)	0.083 (0.031)*	-0.025 (0.038)	0.066
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.245 (0.046)*	0.094 (0.021)*	0.052 (0.032)	0.083 (0.032)*	<0.001
–Other degree class	-0.079 (0.036)*	-0.059 (0.019)*	-0.104 (0.027)*	0.015 (0.024)	<0.001
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.025 (0.042)	0.038 (0.029)	0.010 (0.033)	0.023 (0.028)	0.007
–Russell group university	0.185 (0.044)*	0.119 (0.028)*	0.133 (0.034)*	-0.007 (0.026)	<0.001
Has postgraduate qualifications	0.086 (0.030)*	0.006 (0.018)	0.021 (0.024)	0.047 (0.029)	<0.001
Residual SD	0.343	0.319	0.345	0.288	
R-square	0.31	0.15	0.18	0.08	
N	634	1579	1044	781	

*p<0.05

Table D.18: Differences in parameter estimates for models of earnings by field of study between the 2006/07 and 2008/09 cohorts

Predictors	Fields of study					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
6 months results						
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	-0.01 (0.02)	0.03 (0.02)	0.03 (0.03)	0.02 (0.03)	-0.01 (0.02)	-0.04 (0.02)
–Managerial or professional	0 (0.02)	0.02 (0.02)	0.01 (0.03)	0.02 (0.03)	0.01 (0.02)	-0.02 (0.02)
Male	-0.02 (0.02)	0.01 (0.01)	-0.01 (0.02)	0.02 (0.03)	-0.01 (0.02)	0.02 (0.01)
Privately educated	-0.03 (0.03)	-0.01 (0.02)	-0.04 (0.04)	0.05 (0.05)	0 (0.02)	0.01 (0.02)
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.01 (0.02)	0.04 (0.02)*	-0.02 (0.03)	-0.01 (0.04)	0 (0.02)	0.05 (0.02)*
–Other degree class	0.01 (0.02)	0 (0.01)	-0.04 (0.02)	0 (0.02)	-0.01 (0.02)	0 (0.02)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0 (0.02)	-0.03 (0.02)*	0.01 (0.03)	0.01 (0.03)	0.02 (0.02)	-0.01 (0.02)
–Russell group university	0.02 (0.02)	-0.01 (0.02)	0.03 (0.03)	0.01 (0.04)	0.01 (0.02)	0.01 (0.02)
42 months results						
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.01 (0.05)	0.05 (0.04)	0.06 (0.07)	-0.02 (0.09)	0.07 (0.04)	0.04 (0.04)
–Managerial or professional	0.05 (0.04)	0.03 (0.04)	0.09 (0.06)	0 (0.08)	0.06 (0.03)	0.02 (0.04)
Male	-0.02 (0.03)	0.02 (0.03)	0 (0.05)	0.07 (0.08)	-0.05 (0.03)	-0.01 (0.02)
Privately educated	-0.07 (0.05)	0.07 (0.05)	-0.12 (0.1)	0.02 (0.15)	0.01 (0.04)	-0.05 (0.03)
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.02 (0.04)	0.03 (0.04)	0 (0.06)	-0.22 (0.12)	0.01 (0.03)	-0.02 (0.03)
–Other degree class	0.01 (0.03)	-0.03 (0.03)	-0.05 (0.05)	0.08 (0.06)	0 (0.03)	-0.08 (0.03)*
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	-0.07 (0.04)	-0.04 (0.03)	-0.17 (0.06)*	0.12 (0.08)	0 (0.03)	0 (0.03)
–Russell group university	0.03 (0.04)	-0.05 (0.04)	-0.09 (0.07)	0.16 (0.09)	0 (0.03)	0.06 (0.03)

*p<0.05 **Holm-Bonferroni

Differences in parameter estimates for models of earnings by field of study between the 2006/07 and 2008/09 cohorts cont.

Predictors	Fields of study				No. sig.
	Law	Other STEM	Soc. Studies	Sub. Med.	results**
6 months results					
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.02 (0.05)	0 (0.03)	0.01 (0.03)	-0.01 (0.02)	0
–Managerial or professional	0.03 (0.04)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.02)	0
Male	0.02 (0.03)	0 (0.02)	-0.01 (0.02)	-0.02 (0.02)	0
Privately educated	-0.04 (0.05)	-0.02 (0.03)	0.01 (0.03)	-0.06 (0.02)*	0
Degree classification					
(Ref: Upper second class honours)					
–First class honours	-0.04 (0.08)	0.02 (0.02)	0 (0.03)	-0.02 (0.02)	0
–Other degree class	0.03 (0.03)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	0
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	-0.03 (0.04)	0.02 (0.03)	-0.03 (0.03)	-0.01 (0.02)	0
–Russell group university	-0.01 (0.04)	0.02 (0.03)	-0.06 (0.03)*	-0.02 (0.02)	0
42 months results					
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.02 (0.08)	-0.03 (0.05)	0 (0.06)	-0.04 (0.06)	0
–Managerial or professional	-0.01 (0.07)	-0.02 (0.04)	0 (0.05)	-0.05 (0.05)	0
Male	-0.04 (0.05)	-0.03 (0.03)	0.05 (0.03)	0.09 (0.05)	0
Privately educated	-0.02 (0.07)	0 (0.04)	-0.01 (0.05)	-0.01 (0.06)	0
Degree classification					
(Ref: Upper second class honours)					
–First class honours	-0.02 (0.08)	0 (0.04)	-0.05 (0.05)	0.06 (0.05)	0
–Other degree class	-0.01 (0.05)	0.03 (0.03)	-0.04 (0.04)	0.07 (0.04)	0
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	-0.04 (0.07)	-0.03 (0.05)	-0.02 (0.05)	-0.01 (0.05)	0
–Russell group university	0.03 (0.07)	0.04 (0.04)	0.06 (0.05)	-0.08 (0.05)	0

*p<0.05 **Holm-Bonferroni

Table D.19: Partial correlations between predictors and SOC(HE) skills (2006/07)

Predictors	6 months			42 months		
	Expertise	Orcherstration	Communication	Expertise	Orcherstration	Communication
Age (Base=18)	0.091 (0.006)*	0.047 (0.006)*	0.048 (0.006)*	0.041 (0.011)*	0.022 (0.011)*	0.008 (0.011)
Non-white ethnicity	0.004 (0.006)	0.013 (0.006)*	-0.01 (0.006)	-0.041 (0.011)*	-0.026 (0.011)*	-0.04 (0.011)*
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.004 (0.006)	0.012 (0.006)	0.005 (0.006)	-0.007 (0.011)	0.009 (0.011)	0.01 (0.011)
–Managerial or professional	0.015 (0.006)*	0.018 (0.006)*	0.023 (0.006)*	0.002 (0.011)	0.021 (0.011)	0.018 (0.011)
Has a known disability	0.002 (0.006)	0.003 (0.006)	0.001 (0.006)	-0.019 (0.011)	-0.041 (0.011)*	-0.028 (0.011)*
Male	0.075 (0.006)*	0.067 (0.007)*	-0.019 (0.006)*	0.052 (0.011)*	0.049 (0.011)*	-0.042 (0.011)*
Domicile prior to HE						
(Ref: London)						
–North England	0 (0.006)	0.005 (0.006)	-0.021 (0.006)*	0.007 (0.011)	-0.015 (0.011)	-0.015 (0.011)
–Northern Ireland	0.014 (0.006)*	0.007 (0.006)	-0.006 (0.006)	-0.031 (0.011)*	-0.043 (0.011)*	-0.035 (0.011)*
–Scotland	0.028 (0.006)*	0.007 (0.006)	-0.014 (0.006)*	0.002 (0.011)	-0.018 (0.011)	-0.028 (0.011)*
–SE and East England	0.009 (0.006)	0.008 (0.006)	-0.002 (0.006)	-0.005 (0.011)	-0.006 (0.011)	-0.024 (0.011)*
–SW and Mid England	0.007 (0.006)	0.004 (0.006)	-0.012 (0.006)	-0.008 (0.011)	-0.013 (0.011)	-0.026 (0.011)*
–Wales	0.001 (0.006)	0.001 (0.006)	-0.027 (0.006)*	-0.017 (0.011)	-0.008 (0.011)	-0.021 (0.011)
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.03 (0.006)*	0.005 (0.006)	0.015 (0.006)*	0.037 (0.011)*	0.028 (0.011)*	0.008 (0.011)
–3rd Quartile	0.041 (0.006)*	0.023 (0.006)*	0.009 (0.006)	0.036 (0.011)*	0.026 (0.011)*	0.006 (0.011)
–4th Quartile	0.019 (0.006)*	0.025 (0.006)*	0.016 (0.006)*	0.021 (0.011)	0.021 (0.011)	0.012 (0.011)
Privately educated	0.008 (0.006)	0.048 (0.006)*	0.029 (0.006)*	0.003 (0.011)	0.044 (0.011)*	0.018 (0.011)
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.084 (0.006)*	0.031 (0.006)*	0.012 (0.006)*	0.066 (0.011)*	0.025 (0.011)*	0.002 (0.011)
–Other degree class	-0.086 (0.006)*	-0.044 (0.006)*	-0.05 (0.006)*	-0.078 (0.011)*	-0.057 (0.011)*	-0.062 (0.011)*
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.096 (0.006)*	0.05 (0.006)*	0.008 (0.006)	0.043 (0.011)*	0.019 (0.011)	-0.004 (0.011)
–Russell group university	0.096 (0.006)*	0.068 (0.006)*	-0.006 (0.006)	0.066 (0.011)*	0.06 (0.011)*	-0.004 (0.011)
Field of study [Ref: Biological sciences]						
–Business	0.036 (0.006)*	0.097 (0.007)*	0.009 (0.006)	-0.087 (0.011)*	0.029 (0.011)*	-0.029 (0.011)*
–Creative arts	0.017 (0.007)*	-0.074 (0.007)*	0.023 (0.007)*	-0.003 (0.011)	-0.079 (0.011)*	0.061 (0.011)*
–Education	0.089 (0.006)*	0.042 (0.006)*	0.268 (0.006)*	0.018 (0.01)	-0.002 (0.01)	0.151 (0.011)*
–Engineering and computer science	0.274 (0.007)*	-0.004 (0.006)	-0.036 (0.006)*	0.146 (0.011)*	-0.038 (0.011)*	-0.072 (0.011)*
–Humanities and languages	-0.023 (0.006)*	0.007 (0.007)	0.042 (0.007)*	-0.063 (0.011)*	-0.001 (0.011)	0.052 (0.011)*
–Law	0.002 (0.006)	0.023 (0.006)*	0.004 (0.006)	0.111 (0.012)*	0.075 (0.01)*	0.046 (0.011)*
–Other STEM	0.094 (0.006)*	0.059 (0.006)*	-0.041 (0.006)*	0.034 (0.011)*	0.009 (0.011)	-0.065 (0.011)*
–Social studies	0.024 (0.006)*	0.093 (0.007)*	0.026 (0.006)*	-0.048 (0.011)*	0.064 (0.011)*	-0.008 (0.011)
–Subjects allied to medicine	0.245 (0.006)*	-0.048 (0.006)*	0.008 (0.006)	0.151 (0.011)*	-0.084 (0.011)*	-0.033 (0.01)*
Has postgraduate qualifications				-0.12 (0.011)*	0.024 (0.011)*	-0.225 (0.011)*
R-square	0.07	0.03	0.03	0.05	0.02	0.04
N	23889	23889	23889	8104	8104	8104

*p<0.05

Table D.20: Partial correlations between predictors and SOC(HE) skills (2008/09)

Predictors	6 months			42 months		
	Expertise	Orcherstration	Communication	Expertise	Orcherstration	Communication
Age (Base=18)	0.097 (0.007)*	0.042 (0.007)*	0.043 (0.007)*	0.054 (0.009)*	0.017 (0.009)	0.017 (0.009)
Non-white ethnicity	0.034 (0.007)*	0.01 (0.007)	-0.011 (0.007)	-0.014 (0.009)	0.004 (0.009)	-0.005 (0.009)
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.014 (0.007)*	0.01 (0.007)	0.009 (0.007)	0.018 (0.009)*	0.015 (0.009)	0.002 (0.009)
–Managerial or professional	0.016 (0.007)*	0.011 (0.007)	0.026 (0.007)*	0.018 (0.009)	0.02 (0.009)*	0.015 (0.009)
Has a known disability	-0.009 (0.007)	0 (0.007)	-0.005 (0.007)	-0.01 (0.009)	-0.007 (0.009)	-0.01 (0.009)
Male	0.065 (0.007)*	0.052 (0.007)*	-0.021 (0.007)*	0.067 (0.009)*	0.053 (0.009)*	-0.062 (0.009)*
Domicile prior to HE						
(Ref: London)						
–North England	0.014 (0.007)*	-0.003 (0.007)	-0.006 (0.007)	0 (0.009)	-0.015 (0.009)	-0.005 (0.009)
–Northern Ireland	-0.016 (0.007)*	-0.017 (0.007)*	-0.027 (0.007)*	-0.028 (0.009)*	-0.022 (0.009)*	-0.022 (0.009)*
–Scotland	0.027 (0.007)*	0.003 (0.007)	-0.027 (0.007)*	0.016 (0.009)	-0.008 (0.009)	-0.026 (0.009)*
–SE and East England	0.006 (0.007)	-0.006 (0.007)	-0.007 (0.007)	0.016 (0.009)	0.001 (0.009)	0.008 (0.009)
–SW and Mid England	0.007 (0.007)	-0.005 (0.007)	-0.011 (0.007)	0.006 (0.009)	-0.003 (0.009)	0.006 (0.009)
–Wales	-0.004 (0.007)	-0.005 (0.007)	-0.02 (0.007)*	0.002 (0.009)	0.005 (0.009)	-0.004 (0.009)
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.05 (0.007)*	0.019 (0.007)*	0.024 (0.007)*	0.032 (0.009)*	0.014 (0.009)	0.023 (0.009)*
–3rd Quartile	0.064 (0.007)*	0.033 (0.007)*	0.016 (0.007)*	0.052 (0.009)*	0.035 (0.009)*	0.014 (0.009)
–4th Quartile	0.029 (0.007)*	0.037 (0.007)*	0.015 (0.007)*	0.023 (0.009)*	0.024 (0.009)*	-0.001 (0.009)
Privately educated	0.019 (0.007)*	0.037 (0.007)*	0.035 (0.007)*	0.013 (0.009)	0.039 (0.009)*	0.015 (0.009)
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.107 (0.007)*	0.044 (0.007)*	0.03 (0.007)*	0.083 (0.009)*	0.038 (0.009)*	-0.012 (0.009)
–Other degree class	-0.072 (0.007)*	-0.027 (0.007)*	-0.028 (0.007)*	-0.087 (0.009)*	-0.045 (0.009)*	-0.028 (0.009)*
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.084 (0.007)*	0.052 (0.007)*	-0.008 (0.007)	0.038 (0.009)*	0.021 (0.009)*	-0.013 (0.009)
–Russell group university	0.096 (0.007)*	0.065 (0.007)*	-0.004 (0.007)	0.075 (0.009)*	0.054 (0.009)*	0.003 (0.009)
Field of study [Ref: Biological sciences]						
–Business	0.014 (0.007)*	0.069 (0.007)*	0.01 (0.007)	-0.078 (0.009)*	0.028 (0.009)*	0.001 (0.009)
–Creative arts	-0.019 (0.007)*	-0.088 (0.008)*	0.013 (0.007)	-0.008 (0.009)	-0.043 (0.009)*	0.069 (0.009)*
–Education	0.107 (0.006)*	0.04 (0.006)*	0.339 (0.007)*	0.014 (0.008)	0.009 (0.008)	0.179 (0.009)*
–Engineering and computer science	0.266 (0.007)*	-0.009 (0.007)	-0.044 (0.007)*	0.171 (0.009)*	-0.018 (0.009)*	-0.063 (0.009)*
–Humanities and languages	-0.06 (0.007)*	-0.022 (0.007)*	0.035 (0.007)*	-0.082 (0.009)*	0.01 (0.009)	0.078 (0.009)*
–Law	-0.01 (0.007)	0.009 (0.007)	-0.005 (0.007)	0.067 (0.01)*	0.071 (0.009)*	0.029 (0.009)*
–Other STEM	0.068 (0.007)*	0.043 (0.007)*	-0.054 (0.007)*	0.024 (0.009)*	-0.002 (0.009)	-0.071 (0.009)*
–Social studies	0.019 (0.007)*	0.083 (0.007)*	0.04 (0.007)*	-0.044 (0.009)*	0.063 (0.009)*	-0.004 (0.009)
–Subjects allied to medicine	0.287 (0.007)*	-0.038 (0.007)*	0.022 (0.007)*	0.167 (0.009)*	-0.085 (0.009)*	-0.034 (0.008)*
Has postgraduate qualifications				-0.172 (0.009)*	0.001 (0.009)	-0.231 (0.009)*
R-square	0.09	0.02	0.05	0.06	0.02	0.05
N	20564	20564	20564	11922	11922	11922

*p<0.05

Table D.21: Regression estimates for (log) earnings across models and fields of study (6 months, 2006/07)

		Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Model one	Male	0.058 (0.011)*	0.072 (0.008)*	0.071 (0.013)*	-0.044 (0.027)	0.076 (0.012)*	0.044 (0.009)*
(No employer predictors)	Privately educated	0.076 (0.016)*	0.071 (0.014)*	0.064 (0.027)	-0.045 (0.042)	0.024 (0.014)	0.074 (0.011)*
	Degree classification						
	–First class honours	0.049 (0.016)*	0.065 (0.013)*	0.08 (0.019)*	0.024 (0.04)	0.068 (0.011)*	0.013 (0.013)
	–Other degree class	-0.047 (0.012)*	-0.081 (0.01)*	-0.013 (0.014)	-0.031 (0.018)	-0.083 (0.01)*	-0.017 (0.011)
	Type of HEI						
	–Pre-1992 university	0.065 (0.013)*	0.098 (0.011)*	0.032 (0.019)	0.056 (0.026)	0.136 (0.012)*	0.05 (0.012)*
	–Russell group university	0.07 (0.014)*	0.11 (0.013)*	-0.016 (0.024)	0.051 (0.024)	0.183 (0.012)*	0.065 (0.012)*
Model two	Male	0.049 (0.009)*	0.049 (0.007)*	0.044 (0.012)*	-0.052 (0.023)	0.061 (0.01)*	0.027 (0.008)*
(Employer size and skills)	Privately educated	0.043 (0.014)*	0.044 (0.012)*	0.03 (0.024)	-0.076 (0.037)	0.03 (0.013)	0.027 (0.01)*
	Degree classification						
	–First class honours	0.014 (0.014)	0.042 (0.011)*	0.048 (0.017)*	0.042 (0.034)	0.035 (0.009)*	-0.009 (0.012)
	–Other degree class	-0.015 (0.01)	-0.043 (0.008)*	0.001 (0.012)	-0.028 (0.016)	-0.049 (0.009)*	0.007 (0.009)
	Type of HEI						
	–Pre-1992 university	0.028 (0.011)	0.052 (0.01)*	-0.003 (0.017)	0.012 (0.023)	0.073 (0.01)*	0.026 (0.011)
	–Russell group university	0.04 (0.012)*	0.049 (0.012)*	-0.034 (0.021)	0.006 (0.021)	0.098 (0.01)*	0.031 (0.01)*
Model three	Male	0.045 (0.01)*	0.05 (0.007)*	0.042 (0.012)*	-0.047 (0.023)	0.057 (0.01)*	0.032 (0.008)*
(Without skills)	Privately educated	0.041 (0.014)*	0.043 (0.012)*	0.03 (0.024)	-0.08 (0.037)	0.032 (0.013)	0.023 (0.01)
	Degree classification						
	–First class honours	0.017 (0.014)	0.041 (0.011)*	0.041 (0.017)	0.033 (0.035)	0.038 (0.01)*	-0.011 (0.012)
	–Other degree class	-0.017 (0.01)	-0.048 (0.008)*	0.007 (0.012)	-0.026 (0.016)	-0.051 (0.009)*	0.006 (0.009)
	Type of HEI						
	–Pre-1992 university	0.033 (0.011)*	0.057 (0.01)*	-0.003 (0.017)	0.015 (0.023)	0.083 (0.01)*	0.03 (0.011)*
	–Russell group university	0.047 (0.012)*	0.053 (0.012)*	-0.028 (0.021)	0.049 (0.021)	0.108 (0.01)*	0.035 (0.01)*
Model four	Male	0.057 (0.01)*	0.067 (0.008)*	0.071 (0.012)*	-0.052 (0.025)	0.086 (0.011)*	0.04 (0.008)*
(Without employer size)	Privately educated	0.055 (0.015)*	0.045 (0.013)*	0.032 (0.025)	-0.099 (0.039)	0.013 (0.013)	0.039 (0.011)*
	Degree classification						
	–First class honours	0.048 (0.015)*	0.061 (0.012)*	0.072 (0.018)*	0.039 (0.037)	0.055 (0.01)*	0.006 (0.012)
	–Other degree class	-0.039 (0.011)*	-0.065 (0.009)*	-0.011 (0.013)	-0.032 (0.017)	-0.074 (0.01)*	-0.008 (0.01)
	Type of HEI						
	–Pre-1992 university	0.043 (0.012)*	0.072 (0.01)*	0.015 (0.018)	0.022 (0.024)	0.116 (0.011)*	0.028 (0.011)
	–Russell group university	0.053 (0.013)*	0.088 (0.012)*	-0.035 (0.022)	0.004 (0.022)	0.149 (0.011)*	0.038 (0.011)*
Model five	Male	0.031 (0.009)*	0.036 (0.007)*	0.041 (0.011)*	-0.011 (0.021)	0.055 (0.009)*	0.021 (0.007)*
(Occupation and employer size)	Privately educated	0.035 (0.013)*	0.035 (0.011)*	0.015 (0.022)	-0.047 (0.033)	0.027 (0.011)	0.018 (0.009)
	Degree classification						
	–First class honours	0.026 (0.012)	0.034 (0.01)*	0.031 (0.015)	0.05 (0.031)	0.036 (0.009)*	0.008 (0.011)
	–Other degree class	-0.014 (0.009)	-0.03 (0.008)*	0.006 (0.011)	-0.002 (0.014)	-0.046 (0.008)*	0.003 (0.008)
	Type of HEI						
	–Pre-1992 university	0.005 (0.01)	0.035 (0.009)*	-0.005 (0.015)	0.018 (0.02)	0.059 (0.009)*	0.017 (0.01)
	–Russell group university	0.017 (0.011)	0.03 (0.011)*	-0.007 (0.019)	0.01 (0.019)	0.078 (0.009)*	0.025 (0.009)*

*p<0.05

Regression estimates for (log) earnings across models and fields of study (6 months, 2006/07) cont.

		Law	Other STEM	Soc. Studies	Sub. Med.	SD of param.
Model one	Male	0.067 (0.019)*	0.066 (0.012)*	0.091 (0.011)*	-0.014 (0.016)	0.048
(No employer predictors)	Privately educated	0.143 (0.031)*	0.061 (0.016)*	0.108 (0.014)*	-0.004 (0.019)	0.058
	Degree classification					
	–First class honours	0.055 (0.056)	0.07 (0.015)*	0.1 (0.017)*	0.035 (0.018)	0.033
	–Other degree class	-0.024 (0.02)	-0.087 (0.014)*	-0.077 (0.012)*	-0.026 (0.014)	0.036
	Type of HEI					
	–Pre-1992 university	0.038 (0.025)	0.113 (0.02)*	0.105 (0.016)*	-0.025 (0.016)	0.051
	–Russell group university	0.052 (0.027)	0.124 (0.018)*	0.123 (0.016)*	0.004 (0.015)	0.063
Model two	Male	0.041 (0.017)	0.048 (0.01)*	0.053 (0.009)*	-0.025 (0.014)	0.041
(Employer size and skills)	Privately educated	0.13 (0.027)*	0.058 (0.014)*	0.05 (0.012)*	-0.032 (0.017)	0.057
	Degree classification					
	–First class honours	-0.011 (0.048)	0.048 (0.013)*	0.05 (0.015)*	0.018 (0.016)	0.029
	–Other degree class	0.004 (0.017)	-0.047 (0.012)*	-0.045 (0.011)*	-0.021 (0.012)	0.028
	Type of HEI					
	–Pre-1992 university	0.024 (0.022)	0.061 (0.017)*	0.053 (0.014)*	-0.065 (0.014)*	0.043
	–Russell group university	0.008 (0.023)	0.066 (0.016)*	0.074 (0.014)*	-0.012 (0.013)	0.044
Model three	Male	0.044 (0.017)*	0.046 (0.01)*	0.056 (0.009)*	-0.027 (0.014)	0.04
(Without skills)	Privately educated	0.121 (0.027)*	0.055 (0.014)*	0.046 (0.012)*	-0.033 (0.017)	0.056
	Degree classification					
	–First class honours	-0.008 (0.049)	0.053 (0.013)*	0.053 (0.015)*	0.019 (0.016)	0.029
	–Other degree class	-0.001 (0.017)	-0.047 (0.012)*	-0.047 (0.011)*	-0.022 (0.012)	0.029
	Type of HEI					
	–Pre-1992 university	0.032 (0.022)	0.062 (0.017)*	0.048 (0.014)*	-0.061 (0.014)*	0.044
	–Russell group university	0.015 (0.024)	0.066 (0.016)*	0.07 (0.014)*	-0.015 (0.013)	0.044
Model four	Male	0.055 (0.018)*	0.06 (0.011)*	0.071 (0.01)*	-0.014 (0.015)	0.047
(Without employer size)	Privately educated	0.139 (0.029)*	0.044 (0.015)*	0.068 (0.013)*	-0.029 (0.018)	0.065
	Degree classification					
	–First class honours	0.022 (0.052)	0.064 (0.014)*	0.081 (0.016)*	0.034 (0.017)	0.029
	–Other degree class	-0.014 (0.018)	-0.075 (0.013)*	-0.068 (0.012)*	-0.029 (0.013)	0.032
	Type of HEI					
	–Pre-1992 university	0.024 (0.024)	0.106 (0.018)*	0.073 (0.015)*	-0.036 (0.015)	0.049
	–Russell group university	0.02 (0.025)	0.114 (0.017)*	0.093 (0.015)*	-0.012 (0.014)	0.062
Model five	Male	0.017 (0.015)	0.03 (0.009)*	0.029 (0.009)*	0.004 (0.013)	0.024
(Occupation and employer size)	Privately educated	0.108 (0.024)*	0.042 (0.013)*	0.049 (0.011)*	-0.021 (0.015)	0.044
	Degree classification					
	–First class honours	-0.006 (0.044)	0.051 (0.011)*	0.057 (0.013)*	0.023 (0.014)	0.025
	–Other degree class	0.006 (0.016)	-0.044 (0.011)*	-0.039 (0.01)*	-0.011 (0.011)	0.026
	Type of HEI					
	–Pre-1992 university	0.006 (0.02)	0.067 (0.016)*	0.035 (0.012)*	0.019 (0.013)	0.028
	–Russell group university	0 (0.021)	0.072 (0.015)*	0.056 (0.013)*	-0.004 (0.012)	0.035

*$p<0.05$

Table D.22: Regression estimates for (log) earnings across models and fields of study (42 months, 2006/07)

		Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Model one	Male	0.066 (0.023)*	0.113 (0.019)*	0.056 (0.029)	0.027 (0.069)	0.141 (0.025)*	0.018 (0.019)
(No employer predictors)	Privately educated	0.087 (0.036)	0.034 (0.031)	0.181 (0.062)*	-0.102 (0.136)	0.021 (0.029)	0.121 (0.023)*
	Degree classification						
	–First class honours	0.027 (0.032)	0.121 (0.028)*	-0.006 (0.037)	0.155 (0.109)	0.078 (0.022)*	0.033 (0.025)
	–Other degree class	-0.095 (0.025)*	-0.137 (0.022)*	-0.037 (0.031)	-0.139 (0.054)	-0.122 (0.021)*	-0.018 (0.022)
	Type of HEI						
	–Pre-1992 university	0.032 (0.028)	0.045 (0.023)	0.132 (0.036)*	0.043 (0.061)	0.119 (0.023)*	0.025 (0.026)
	–Russell group university	0.061 (0.028)	0.124 (0.03)*	0.102 (0.044)	0.037 (0.066)	0.138 (0.024)*	0.041 (0.025)
Model two	Male	0.068 (0.022)*	0.088 (0.018)*	0.043 (0.027)	-0.002 (0.065)	0.125 (0.024)*	0.003 (0.018)
(Employer size and skills)	Privately educated	0.075 (0.034)	0.027 (0.03)	0.16 (0.059)*	-0.062 (0.128)	0.019 (0.027)	0.102 (0.021)*
	Degree classification						
	–First class honours	0.01 (0.03)	0.102 (0.026)*	-0.003 (0.035)	0.102 (0.103)	0.078 (0.02)*	0.019 (0.024)
	–Other degree class	-0.082 (0.024)*	-0.108 (0.021)*	-0.025 (0.029)	-0.122 (0.051)	-0.093 (0.02)*	0 (0.021)
	Type of HEI						
	–Pre-1992 university	0.036 (0.026)	0.057 (0.022)*	0.135 (0.034)*	0.038 (0.057)	0.095 (0.022)*	0.033 (0.025)
	–Russell group university	0.061 (0.026)	0.116 (0.028)*	0.093 (0.042)	0.01 (0.063)	0.105 (0.023)*	0.04 (0.024)
Model three	Male	0.064 (0.022)*	0.091 (0.018)*	0.04 (0.027)	0.021 (0.066)	0.119 (0.024)*	0.005 (0.018)
(Without skills)	Privately educated	0.071 (0.035)	0.025 (0.03)	0.173 (0.06)*	-0.1 (0.13)	0.022 (0.028)	0.101 (0.022)*
	Degree classification						
	–First class honours	0.007 (0.031)	0.099 (0.027)*	-0.023 (0.035)	0.15 (0.105)	0.079 (0.021)*	0.021 (0.024)
	–Other degree class	-0.082 (0.024)*	-0.112 (0.021)*	-0.014 (0.03)	-0.105 (0.052)	-0.097 (0.02)*	-0.001 (0.022)
	Type of HEI						
	–Pre-1992 university	0.036 (0.026)	0.058 (0.022)*	0.129 (0.034)*	0.054 (0.058)	0.104 (0.022)*	0.039 (0.025)
	–Russell group university	0.06 (0.027)	0.121 (0.028)*	0.093 (0.043)	0.019 (0.063)	0.107 (0.023)*	0.043 (0.024)
Model four	Male	0.073 (0.023)*	0.103 (0.019)*	0.06 (0.028)	0.004 (0.067)	0.139 (0.024)*	0.014 (0.018)
(Without employer size)	Privately educated	0.087 (0.035)	0.032 (0.031)	0.166 (0.061)*	-0.073 (0.133)	0.018 (0.028)	0.117 (0.022)*
	Degree classification						
	–First class honours	0.028 (0.032)	0.12 (0.027)*	0.018 (0.036)	0.13 (0.107)	0.081 (0.021)*	0.03 (0.025)
	–Other degree class	-0.099 (0.025)*	-0.126 (0.021)*	-0.041 (0.03)	-0.139 (0.053)*	-0.111 (0.021)*	-0.016 (0.022)
	Type of HEI						
	–Pre-1992 university	0.041 (0.027)	0.055 (0.023)	0.135 (0.035)*	0.045 (0.059)	0.117 (0.023)*	0.029 (0.025)
	–Russell group university	0.068 (0.027)	0.118 (0.029)*	0.101 (0.044)	0.025 (0.065)	0.14 (0.024)*	0.042 (0.024)
Model five	Male	0.026 (0.021)	0.066 (0.017)*	0.02 (0.027)	0.031 (0.062)	0.114 (0.022)*	0 (0.017)
(Occupation and employer size)	Privately educated	0.021 (0.032)	0.026 (0.028)	0.172 (0.057)*	-0.135 (0.119)	0.013 (0.026)	0.086 (0.02)*
	Degree classification						
	–First class honours	-0.004 (0.029)	0.071 (0.025)*	0.008 (0.034)	0.139 (0.097)	0.08 (0.019)*	0.033 (0.022)
	–Other degree class	-0.068 (0.023)*	-0.088 (0.02)*	-0.05 (0.028)	-0.072 (0.048)	-0.081 (0.019)*	0.004 (0.02)
	Type of HEI						
	–Pre-1992 university	0.035 (0.025)	0.051 (0.021)	0.134 (0.032)*	0.01 (0.054)	0.095 (0.021)*	0.028 (0.023)
	–Russell group university	0.056 (0.025)	0.097 (0.026)*	0.106 (0.041)*	-0.018 (0.058)	0.09 (0.022)*	0.032 (0.022)

*p<0.05

Regression estimates for (log) earnings across models and fields of study (42 months, 2006/07) cont.

		Law	Other STEM	Soc. Studies	Sub. Med.	SD of param.
Model one	Male	0.126 (0.032)*	0.091 (0.022)*	0.065 (0.023)*	-0.009 (0.039)	0.065
(No employer predictors)	Privately educated	0.19 (0.048)*	0.037 (0.032)	0.097 (0.031)*	-0.026 (0.048)	0.100
	Degree classification					
	–First class honours	0.249 (0.055)*	0.093 (0.028)*	0.102 (0.037)*	0.026 (0.043)	0.087
	–Other degree class	-0.085 (0.034)	-0.088 (0.025)*	-0.06 (0.028)	-0.052 (0.033)	0.060
	Type of HEI					
	–Pre-1992 university	0.076 (0.046)	0.071 (0.037)	0.045 (0.037)	0.06 (0.037)	0.056
	–Russell group university	0.163 (0.048)*	0.08 (0.035)	0.101 (0.038)*	0.076 (0.037)	0.060
Model two	Male	0.115 (0.03)*	0.085 (0.021)*	0.043 (0.022)	-0.013 (0.037)	0.063
(Employer size and skills)	Privately educated	0.166 (0.046)*	0.04 (0.03)	0.103 (0.03)*	-0.016 (0.045)	0.084
	Degree classification					
	–First class honours	0.204 (0.052)*	0.07 (0.027)*	0.094 (0.035)*	0.03 (0.041)	0.073
	–Other degree class	-0.037 (0.032)	-0.074 (0.024)*	-0.044 (0.027)	-0.053 (0.031)	0.056
	Type of HEI					
	–Pre-1992 university	0.086 (0.043)	0.081 (0.035)	0.048 (0.035)	0.055 (0.035)	0.052
	–Russell group university	0.137 (0.045)*	0.086 (0.033)	0.084 (0.036)	0.063 (0.035)	0.055
Model three	Male	0.116 (0.03)*	0.085 (0.021)*	0.047 (0.022)	-0.011 (0.037)	0.061
(Without skills)	Privately educated	0.172 (0.046)*	0.04 (0.03)	0.095 (0.03)*	-0.026 (0.046)	0.094
	Degree classification					
	–First class honours	0.211 (0.052)*	0.077 (0.027)*	0.097 (0.035)*	0.035 (0.041)	0.081
	–Other degree class	-0.042 (0.033)	-0.078 (0.024)*	-0.046 (0.027)	-0.054 (0.032)	0.056
	Type of HEI					
	–Pre-1992 university	0.081 (0.044)	0.073 (0.036)	0.047 (0.035)	0.053 (0.035)	0.051
	–Russell group university	0.145 (0.046)*	0.077 (0.034)	0.084 (0.037)	0.058 (0.035)	0.056
Model four	Male	0.115 (0.031)*	0.087 (0.021)*	0.051 (0.023)	-0.009 (0.038)	0.065
(Without employer size)	Privately educated	0.188 (0.047)*	0.045 (0.031)	0.107 (0.031)*	-0.023 (0.047)	0.092
	Degree classification					
	–First class honours	0.236 (0.054)*	0.097 (0.028)*	0.099 (0.036)*	0.034 (0.042)	0.078
	–Other degree class	-0.084 (0.034)	-0.078 (0.025)*	-0.058 (0.028)	-0.056 (0.032)	0.057
	Type of HEI					
	–Pre-1992 university	0.091 (0.045)	0.085 (0.036)	0.053 (0.036)	0.071 (0.036)	0.054
	–Russell group university	0.15 (0.047)*	0.093 (0.035)*	0.105 (0.037)*	0.087 (0.036)	0.058
Model five	Male	0.107 (0.028)*	0.058 (0.02)*	-0.002 (0.021)	-0.028 (0.036)	0.060
(Occupation and employer size)	Privately educated	0.166 (0.043)*	0.012 (0.029)	0.076 (0.028)*	0 (0.043)	0.097
	Degree classification					
	–First class honours	0.206 (0.049)*	0.056 (0.026)	0.083 (0.034)	0.021 (0.038)	0.075
	–Other degree class	-0.048 (0.031)	-0.065 (0.023)*	-0.059 (0.025)	-0.044 (0.03)	0.046
	Type of HEI					
	–Pre-1992 university	0.103 (0.04)	0.077 (0.034)	0.004 (0.033)	-0.009 (0.033)	0.061
	–Russell group university	0.14 (0.042)*	0.074 (0.032)	0.039 (0.035)	0.022 (0.035)	0.060

*p<0.05

Table D.23: Regression estimates for (log) earnings across models and fields of study (6 months, 2008/09)

		Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Model one	Male	0.035 (0.012)*	0.082 (0.009)*	0.058 (0.016)*	-0.032 (0.028)	0.072 (0.014)*	0.061 (0.01)*
(No employer predictors)	Privately educated	0.039 (0.019)	0.062 (0.015)*	0.014 (0.031)	0.008 (0.041)	0.03 (0.016)	0.09 (0.013)*
	Degree classification						
	–First class honours	0.056 (0.016)*	0.105 (0.012)*	0.052 (0.02)	0.023 (0.028)	0.069 (0.012)*	0.066 (0.014)*
	–Other degree class	-0.04 (0.013)*	-0.077 (0.011)*	-0.054 (0.017)*	-0.034 (0.018)	-0.094 (0.013)*	-0.013 (0.012)
	Type of HEI						
	–Pre-1992 university	0.062 (0.014)*	0.064 (0.012)*	0.044 (0.02)	0.057 (0.027)	0.159 (0.014)*	0.046 (0.014)*
	–Russell group university	0.089 (0.015)*	0.103 (0.014)*	0.021 (0.026)	0.035 (0.031)	0.187 (0.013)*	0.078 (0.013)*
Model two	Male	0.026 (0.01)	0.063 (0.008)*	0.035 (0.014)*	-0.033 (0.025)	0.054 (0.012)*	0.045 (0.009)*
(Employer size and skills)	Privately educated	0.02 (0.016)	0.034 (0.013)	-0.003 (0.027)	0.02 (0.036)	0.021 (0.014)	0.039 (0.011)*
	Degree classification						
	–First class honours	0.011 (0.014)	0.063 (0.011)*	0.002 (0.018)	0.024 (0.025)	0.037 (0.01)*	0.034 (0.012)*
	–Other degree class	-0.01 (0.012)	-0.043 (0.01)*	-0.025 (0.015)	-0.02 (0.016)	-0.057 (0.011)*	0.008 (0.011)
	Type of HEI						
	–Pre-1992 university	0.045 (0.013)*	0.027 (0.01)*	0.03 (0.017)	0.02 (0.024)	0.086 (0.012)*	0.024 (0.012)
	–Russell group university	0.061 (0.013)*	0.044 (0.012)*	0.006 (0.022)	-0.01 (0.027)	0.103 (0.011)*	0.053 (0.011)*
Model three	Male	0.034 (0.021)	0.107 (0.017)*	0.047 (0.024)	0.081 (0.054)	0.068 (0.023)*	0 (0.015)
(Without skills)	Privately educated	-0.002 (0.03)	0.075 (0.03)	0.065 (0.048)	-0.031 (0.094)	0.034 (0.027)	0.054 (0.019)*
	Degree classification						
	–First class honours	0.03 (0.028)	0.134 (0.023)*	-0.008 (0.031)	-0.089 (0.062)	0.07 (0.02)*	0.005 (0.02)
	–Other degree class	-0.057 (0.022)*	-0.134 (0.021)*	-0.075 (0.028)*	-0.062 (0.038)	-0.092 (0.019)*	-0.069 (0.019)*
	Type of HEI						
	–Pre-1992 university	-0.018 (0.024)	0.017 (0.021)	-0.04 (0.029)	0.061 (0.048)	0.111 (0.022)*	0.02 (0.021)
	–Russell group university	0.089 (0.025)*	0.076 (0.026)*	0.004 (0.04)	0.088 (0.06)	0.123 (0.021)*	0.074 (0.02)*
Model four	Male	0.043 (0.021)	0.124 (0.017)*	0.071 (0.025)*	0.085 (0.055)	0.094 (0.023)*	0.01 (0.016)
(Without employer size)	Privately educated	0.006 (0.031)	0.09 (0.031)*	0.079 (0.049)	-0.023 (0.096)	0.025 (0.027)	0.07 (0.02)*
	Degree classification						
	–First class honours	0.04 (0.028)	0.144 (0.023)*	0.021 (0.032)	-0.098 (0.063)	0.087 (0.021)*	0.015 (0.021)
	–Other degree class	-0.077 (0.022)*	-0.143 (0.022)*	-0.089 (0.028)*	-0.084 (0.039)	-0.108 (0.02)*	-0.089 (0.019)*
	Type of HEI						
	–Pre-1992 university	-0.018 (0.024)	0.022 (0.022)	-0.041 (0.029)	0.039 (0.049)	0.126 (0.022)*	0.024 (0.022)
	–Russell group university	0.101 (0.025)*	0.078 (0.026)*	0.02 (0.041)	0.055 (0.061)	0.14 (0.022)*	0.088 (0.02)*
Model five	Male	0.019 (0.009)	0.04 (0.007)*	0.042 (0.013)*	-0.013 (0.022)	0.047 (0.011)*	0.036 (0.008)*
(Occupation and employer size)	Privately educated	0.001 (0.015)	0.028 (0.012)	0.001 (0.024)	0.024 (0.032)	0.015 (0.012)	0.027 (0.01)*
	Degree classification						
	–First class honours	0.019 (0.013)	0.048 (0.01)*	0.005 (0.016)	0.023 (0.022)	0.032 (0.009)*	0.034 (0.011)*
	–Other degree class	-0.01 (0.011)	-0.021 (0.009)	-0.028 (0.014)	-0.005 (0.014)	-0.06 (0.01)*	0.006 (0.01)
	Type of HEI						
	–Pre-1992 university	0.04 (0.011)*	0.021 (0.009)	0.028 (0.016)	0.012 (0.021)	0.061 (0.011)*	0.001 (0.011)
	–Russell group university	0.051 (0.012)*	0.031 (0.011)*	0.02 (0.02)	-0.022 (0.024)	0.077 (0.011)*	0.03 (0.01)*

*p<0.05

Regression estimates for (log) earnings across models and fields of study (6 months, 2008/09) cont.

		Law	Other STEM	Soc. Studies	Sub. Med.	SD of param.
Model one	Male	0.077 (0.022)*	0.065 (0.012)*	0.077 (0.012)*	-0.033 (0.015)	0.048
(No employer predictors)	Privately educated	0.112 (0.039)*	0.045 (0.018)	0.112 (0.016)*	-0.064 (0.02)*	0.057
	Degree classification					
	–First class honours	0.024 (0.048)	0.094 (0.015)*	0.099 (0.018)*	0.016 (0.016)	0.039
	–Other degree class	0.007 (0.023)	-0.08 (0.015)*	-0.047 (0.015)*	-0.003 (0.013)	0.040
	Type of HEI					
	–Pre-1992 university	-0.005 (0.029)	0.129 (0.021)*	0.073 (0.018)*	-0.02 (0.015)	0.057
	–Russell group university	0.043 (0.03)	0.135 (0.019)*	0.063 (0.018)*	-0.005 (0.014)	0.060
Model two	Male	0.041 (0.019)	0.047 (0.011)*	0.054 (0.011)*	-0.027 (0.013)	0.038
(Employer size and skills)	Privately educated	0.085 (0.034)	0.017 (0.015)	0.073 (0.014)*	-0.052 (0.017)*	0.042
	Degree classification					
	–First class honours	0.015 (0.041)	0.049 (0.013)*	0.055 (0.016)*	0.004 (0.014)	0.028
	–Other degree class	0.022 (0.02)	-0.034 (0.013)*	-0.019 (0.013)	0.006 (0.011)	0.030
	Type of HEI					
	–Pre-1992 university	-0.002 (0.025)	0.064 (0.018)*	0.038 (0.015)	-0.034 (0.013)*	0.038
	–Russell group university	0.031 (0.026)	0.063 (0.017)*	0.023 (0.015)	-0.008 (0.012)	0.039
Model three	Male	0.082 (0.027)*	0.045 (0.017)*	0.103 (0.021)*	0.062 (0.032)	0.047
(Without skills)	Privately educated	0.144 (0.042)*	0.036 (0.024)	0.068 (0.028)	-0.053 (0.043)	0.066
	Degree classification					
	–First class honours	0.211 (0.043)*	0.059 (0.022)*	0.03 (0.03)	0.059 (0.036)	0.088
	–Other degree class	-0.042 (0.033)	-0.049 (0.019)	-0.086 (0.025)*	0.016 (0.026)	0.052
	Type of HEI					
	–Pre-1992 university	0.055 (0.038)	0.039 (0.03)	0.008 (0.031)	0.053 (0.03)	0.055
	–Russell group university	0.16 (0.04)*	0.104 (0.029)*	0.111 (0.031)*	0.008 (0.029)	0.059
Model four	Male	0.075 (0.028)*	0.06 (0.017)*	0.112 (0.021)*	0.076 (0.033)	0.048
(Without employer size)	Privately educated	0.16 (0.043)*	0.036 (0.024)	0.089 (0.029)*	-0.04 (0.043)	0.069
	Degree classification					
	–First class honours	0.233 (0.043)*	0.079 (0.022)*	0.062 (0.031)	0.086 (0.036)	0.093
	–Other degree class	-0.071 (0.034)	-0.061 (0.02)*	-0.093 (0.026)*	0.03 (0.027)	0.056
	Type of HEI					
	–Pre-1992 university	0.06 (0.038)	0.038 (0.03)	0.02 (0.032)	0.079 (0.031)	0.059
	–Russell group university	0.19 (0.041)*	0.116 (0.029)*	0.123 (0.032)*	0.02 (0.03)	0.064
Model five	Male	0.04 (0.017)	0.031 (0.01)*	0.041 (0.01)*	0.008 (0.012)	0.025
(Occupation and employer size)	Privately educated	0.081 (0.031)*	0.002 (0.014)	0.054 (0.013)*	-0.022 (0.015)	0.034
	Degree classification					
	–First class honours	0.037 (0.037)	0.043 (0.012)*	0.044 (0.014)*	0.023 (0.012)	0.021
	–Other degree class	0.027 (0.018)	-0.037 (0.012)*	-0.013 (0.011)	0.015 (0.01)	0.030
	Type of HEI					
	–Pre-1992 university	-0.012 (0.022)	0.053 (0.016)*	0.037 (0.014)*	0.03 (0.012)*	0.028
	–Russell group university	0.015 (0.024)	0.058 (0.015)*	0.033 (0.014)	0.004 (0.011)	0.032

*p<0.05

Table D.24: Regression estimates for (log) earnings across models and fields of study (42 months, 2008/09)

		Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Model one	Male	0.048 (0.022)	0.131 (0.018)*	0.059 (0.025)	0.087 (0.056)	0.091 (0.024)*	0.009 (0.016)
(No employer predictors)	Privately educated	0.007 (0.031)	0.091 (0.031)*	0.075 (0.05)	-0.034 (0.098)	0.029 (0.028)	0.073 (0.02)*
	Degree classification						
	–First class honours	0.048 (0.029)	0.151 (0.024)*	0.008 (0.032)	-0.088 (0.064)	0.087 (0.021)*	0.015 (0.021)
	–Other degree class	-0.086 (0.023)*	-0.159 (0.022)*	-0.087 (0.029)*	-0.085 (0.04)	-0.12 (0.02)*	-0.095 (0.02)*
	Type of HEI						
	–Pre-1992 university	-0.023 (0.025)	0.005 (0.022)	-0.051 (0.03)	0.051 (0.05)	0.125 (0.022)*	0.017 (0.022)
	–Russell group university	0.096 (0.026)*	0.073 (0.027)*	0.018 (0.042)	0.095 (0.062)	0.151 (0.022)*	0.085 (0.021)*
Model two	Male	0.034 (0.021)	0.106 (0.017)*	0.057 (0.024)	0.074 (0.053)	0.078 (0.023)*	0.001 (0.015)
(Employer size and skills)	Privately educated	0.003 (0.03)	0.078 (0.03)*	0.074 (0.047)	-0.021 (0.093)	0.029 (0.027)	0.052 (0.019)*
	Degree classification						
	–First class honours	0.029 (0.027)	0.127 (0.022)*	0.006 (0.03)	-0.093 (0.061)	0.071 (0.02)*	0.006 (0.02)
	–Other degree class	-0.054 (0.021)	-0.124 (0.021)*	-0.078 (0.027)*	-0.065 (0.038)	-0.086 (0.019)*	-0.067 (0.019)*
	Type of HEI						
	–Pre-1992 university	-0.019 (0.023)	0.015 (0.021)	-0.038 (0.028)	0.047 (0.047)	0.102 (0.021)*	0.019 (0.021)
	–Russell group university	0.09 (0.024)*	0.072 (0.025)*	-0.002 (0.04)	0.051 (0.059)	0.11 (0.021)*	0.07 (0.02)*
Model three	Male	0.034 (0.021)	0.107 (0.017)*	0.047 (0.024)	0.081 (0.054)	0.068 (0.023)*	0 (0.015)
(Without skills)	Privately educated	-0.002 (0.03)	0.075 (0.03)	0.065 (0.048)	-0.031 (0.094)	0.034 (0.027)	0.054 (0.019)*
	Degree classification						
	–First class honours	0.03 (0.028)	0.134 (0.023)*	-0.008 (0.031)	-0.089 (0.062)	0.07 (0.02)*	0.005 (0.02)
	–Other degree class	-0.057 (0.022)*	-0.134 (0.021)*	-0.075 (0.028)*	-0.062 (0.038)	-0.092 (0.019)*	-0.069 (0.019)*
	Type of HEI						
	–Pre-1992 university	-0.018 (0.024)	0.017 (0.021)	-0.04 (0.029)	0.061 (0.048)	0.111 (0.022)*	0.02 (0.021)
	–Russell group university	0.089 (0.025)*	0.076 (0.026)*	0.004 (0.04)	0.088 (0.06)	0.123 (0.021)*	0.074 (0.02)*
Model four	Male	0.043 (0.021)	0.124 (0.017)*	0.071 (0.025)*	0.085 (0.055)	0.094 (0.023)*	0.01 (0.016)
(Without employer size)	Privately educated	0.006 (0.031)	0.09 (0.031)*	0.079 (0.049)	-0.023 (0.096)	0.025 (0.027)	0.07 (0.02)*
	Degree classification						
	–First class honours	0.04 (0.028)	0.144 (0.023)*	0.021 (0.032)	-0.098 (0.063)	0.087 (0.021)*	0.015 (0.021)
	–Other degree class	-0.077 (0.022)*	-0.143 (0.022)*	-0.089 (0.028)*	-0.084 (0.039)	-0.108 (0.02)*	-0.089 (0.019)*
	Type of HEI						
	–Pre-1992 university	-0.018 (0.024)	0.022 (0.022)	-0.041 (0.029)	0.039 (0.049)	0.126 (0.022)*	0.024 (0.022)
	–Russell group university	0.101 (0.025)*	0.078 (0.026)*	0.02 (0.041)	0.055 (0.061)	0.14 (0.022)*	0.088 (0.02)*
Model five	Male	0.025 (0.02)	0.084 (0.016)*	0.057 (0.023)	0.044 (0.051)	0.074 (0.022)*	0.007 (0.014)
(Occupation and employer size)	Privately educated	-0.015 (0.028)	0.088 (0.028)*	0.017 (0.046)	-0.066 (0.087)	0.018 (0.025)	0.04 (0.018)
	Degree classification						
	–First class honours	0.04 (0.026)	0.104 (0.021)*	0.028 (0.029)	-0.067 (0.057)	0.065 (0.019)*	0.013 (0.019)
	–Other degree class	-0.041 (0.021)	-0.081 (0.02)*	-0.072 (0.026)*	-0.044 (0.035)	-0.072 (0.018)*	-0.042 (0.018)
	Type of HEI						
	–Pre-1992 university	-0.016 (0.022)	0.021 (0.02)	-0.035 (0.027)	0.047 (0.045)	0.095 (0.021)*	0.01 (0.02)
	–Russell group university	0.083 (0.024)*	0.053 (0.024)	0.015 (0.038)	0.06 (0.056)	0.091 (0.02)*	0.055 (0.019)*

*$p<0.05$

Regression estimates for (log) earnings across models and fields of study (42 months, 2008/09) cont.

		Law	Other STEM	Soc. Studies	Sub. Med.	SD of param.
Model one	Male	0.085 (0.028)*	0.06 (0.018)*	0.124 (0.022)*	0.079 (0.034)	0.050
(No employer predictors)	Privately educated	0.16 (0.044)*	0.033 (0.025)	0.09 (0.029)*	-0.051 (0.044)	0.073
	Degree classification					
	–First class honours	0.241 (0.044)*	0.09 (0.023)*	0.057 (0.031)	0.077 (0.037)	0.095
	–Other degree class	-0.075 (0.035)	-0.064 (0.02)*	-0.102 (0.026)*	0.023 (0.027)	0.058
	Type of HEI					
	–Pre-1992 university	0.052 (0.039)	0.038 (0.031)	0.008 (0.032)	0.058 (0.032)	0.060
	–Russell group university	0.202 (0.042)*	0.115 (0.03)*	0.12 (0.033)*	0.001 (0.03)	0.068
Model two	Male	0.068 (0.027)	0.047 (0.017)*	0.098 (0.021)*	0.076 (0.032)	0.046
(Employer size and skills)	Privately educated	0.141 (0.041)*	0.042 (0.023)	0.067 (0.028)	-0.042 (0.042)	0.063
	Degree classification					
	–First class honours	0.198 (0.042)*	0.053 (0.021)	0.033 (0.03)	0.066 (0.035)	0.084
	–Other degree class	-0.044 (0.033)	-0.046 (0.019)	-0.079 (0.025)*	0.018 (0.026)	0.050
	Type of HEI					
	–Pre-1992 university	0.052 (0.037)	0.038 (0.029)	0.017 (0.03)	0.057 (0.03)	0.052
	–Russell group university	0.15 (0.04)*	0.103 (0.028)*	0.11 (0.031)*	0.016 (0.029)	0.057
Model three	Male	0.082 (0.027)*	0.045 (0.017)*	0.103 (0.021)*	0.062 (0.032)	0.047
(Without skills)	Privately educated	0.144 (0.042)*	0.036 (0.024)	0.068 (0.028)	-0.053 (0.043)	0.066
	Degree classification					
	–First class honours	0.211 (0.043)*	0.059 (0.022)*	0.03 (0.03)	0.059 (0.036)	0.088
	–Other degree class	-0.042 (0.033)	-0.049 (0.019)	-0.086 (0.025)*	0.016 (0.026)	0.052
	Type of HEI					
	–Pre-1992 university	0.055 (0.038)	0.039 (0.03)	0.008 (0.031)	0.053 (0.03)	0.055
	–Russell group university	0.16 (0.04)*	0.104 (0.029)*	0.111 (0.031)*	0.008 (0.029)	0.059
Model four	Male	0.075 (0.028)*	0.06 (0.017)*	0.112 (0.021)*	0.076 (0.033)	0.048
(Without employer size)	Privately educated	0.16 (0.043)*	0.036 (0.024)	0.089 (0.029)*	-0.04 (0.043)	0.069
	Degree classification					
	–First class honours	0.233 (0.043)*	0.079 (0.022)*	0.062 (0.031)	0.086 (0.036)	0.093
	–Other degree class	-0.071 (0.034)	-0.061 (0.02)*	-0.093 (0.026)*	0.03 (0.027)	0.056
	Type of HEI					
	–Pre-1992 university	0.06 (0.038)	0.038 (0.03)	0.02 (0.032)	0.079 (0.031)	0.059
	–Russell group university	0.19 (0.041)*	0.116 (0.029)*	0.123 (0.032)*	0.02 (0.03)	0.064
Model five	Male	0.067 (0.025)*	0.023 (0.016)	0.086 (0.02)*	0.065 (0.031)	0.042
(Occupation and employer size)	Privately educated	0.142 (0.039)*	0.022 (0.022)	0.036 (0.026)	-0.056 (0.04)	0.070
	Degree classification					
	–First class honours	0.196 (0.04)*	0.042 (0.021)	0.031 (0.028)	0.039 (0.034)	0.074
	–Other degree class	-0.046 (0.031)	-0.026 (0.018)	-0.087 (0.024)*	0.001 (0.025)	0.042
	Type of HEI					
	–Pre-1992 university	0.053 (0.035)	0.039 (0.028)	-0.007 (0.029)	0.025 (0.029)	0.049
	–Russell group university	0.161 (0.038)*	0.075 (0.027)*	0.082 (0.03)*	0.005 (0.028)	0.054

*$p<0.05$

Table D.25: Results for models of earnings by fields of study adjusted for sample selection (6 months) (2006/07)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	9.328 (0.191)*	9.595 (0.11)*	9.673 (0.159)*	9.959 (0.065)*	9.606 (0.197)*	9.456 (0.087)*
Age (Base=18)	0.049 (0.011)*	0.058 (0.009)*	0.034 (0.008)*	0.024 (0.009)*	0.047 (0.019)*	0.032 (0.006)*
Non-white ethnicity	-0.035 (0.047)	-0.023 (0.038)	0.054 (0.046)	-0.074 (0.059)	-0.016 (0.05)	-0.029 (0.026)
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.029 (0.017)	-0.004 (0.013)	0.018 (0.021)	0 (0.02)	0.005 (0.014)	0.025 (0.015)
–Managerial or professional	0.016 (0.016)	0.023 (0.012)	0.023 (0.017)	0.001 (0.02)	0.004 (0.012)	0.026 (0.014)
Has a known disability	-0.013 (0.027)	-0.019 (0.027)	0.019 (0.028)	0.019 (0.031)	0.003 (0.031)	-0.039 (0.026)
Male	0.026 (0.021)	0.058 (0.018)*	0.094 (0.021)*	-0.036 (0.023)	0.071 (0.014)*	0.034 (0.011)*
Domicile prior to HE						
(Ref: London)						
–North England	-0.2 (0.014)*	-0.222 (0.01)*	-0.148 (0.014)*	-0.157 (0.025)*	-0.133 (0.009)*	-0.178 (0.009)*
–Northern Ireland	-0.271 (0.036)*	-0.374 (0.023)*	-0.23 (0.057)*	-0.104 (0.028)*	-0.205 (0.021)*	-0.346 (0.032)*
–Scotland	-0.196 (0.032)*	-0.25 (0.015)*	-0.157 (0.031)*	-0.103 (0.04)*	-0.078 (0.013)*	-0.223 (0.02)*
–SE and East England	-0.09 (0.009)*	-0.097 (0.007)*	-0.076 (0.01)*	-0.103 (0.017)*	-0.047 (0.006)*	-0.086 (0.006)*
–SW and Mid England	-0.185 (0.012)*	-0.178 (0.009)*	-0.129 (0.012)*	-0.128 (0.022)*	-0.1 (0.007)*	-0.159 (0.008)*
–Wales	-0.207 (0.018)*	-0.234 (0.017)*	-0.136 (0.022)*	-0.173 (0.036)*	-0.118 (0.012)*	-0.216 (0.018)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.008 (0.013)	0.038 (0.012)*	0.034 (0.016)*	0.028 (0.015)	0.005 (0.013)	0.037 (0.011)*
–3rd Quartile	0.027 (0.018)	0.065 (0.021)*	0.06 (0.026)*	0.035 (0.024)	0.023 (0.015)	0.053 (0.014)*
–4th Quartile	0.03 (0.023)	0.018 (0.019)	0.011 (0.017)	-0.002 (0.021)	-0.007 (0.021)	0.065 (0.02)*
Privately educated	0.054 (0.026)*	0.061 (0.021)*	0.094 (0.032)*	-0.027 (0.044)	0.02 (0.021)	0.06 (0.016)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.004 (0.034)	0.078 (0.019)*	0.093 (0.026)*	0.031 (0.021)	0.076 (0.013)*	-0.019 (0.027)
–Other degree class	-0.021 (0.02)	-0.08 (0.015)*	-0.021 (0.014)	-0.035 (0.014)*	-0.103 (0.025)*	0.008 (0.015)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.055 (0.015)*	0.103 (0.012)*	0.043 (0.019)*	0.005 (0.022)	0.129 (0.013)*	0.034 (0.02)
–Russell group university	0.028 (0.028)	0.11 (0.015)*	0.022 (0.043)	-0.015 (0.031)	0.177 (0.014)*	0.036 (0.025)

*p<0.05

Results for models of earnings by fields of study adjusted for sample selection (6 months) (2006/07) cont.

Predictor	Models				Chi-sq.
	Law	Other STEM	Soc. Studies	Sub. Med.	p value
Intercept	9.743 (0.17)*	9.586 (0.099)*	9.778 (0.196)*	9.808 (0.12)*	>0.001
Age (Base=18)	0.019 (0.015)	0.023 (0.008)*	0.018 (0.009)*	0.038 (0.014)*	0.064
Non-white ethnicity	-0.033 (0.057)	0.09 (0.027)*	0.095 (0.045)*	-0.079 (0.02)*	>0.001
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.019 (0.029)	0.026 (0.022)	0.013 (0.021)	-0.006 (0.016)	0.771
–Managerial or professional	0.032 (0.031)	0.036 (0.019)	0.015 (0.024)	0.004 (0.015)	0.881
Has a known disability	-0.001 (0.055)	-0.011 (0.037)	0.001 (0.052)	0.011 (0.021)	0.902
Male	0.06 (0.023)*	0.048 (0.019)*	0.08 (0.016)*	-0.019 (0.023)	>0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.278 (0.024)*	-0.221 (0.014)*	-0.217 (0.014)*	-0.095 (0.012)*	>0.001
–Northern Ireland	-0.38 (0.054)*	-0.249 (0.049)*	-0.198 (0.041)*	-0.19 (0.022)*	>0.001
–Scotland	-0.292 (0.059)*	-0.173 (0.024)*	-0.24 (0.035)*	-0.102 (0.017)*	>0.001
–SE and East England	-0.133 (0.018)*	-0.094 (0.011)*	-0.099 (0.009)*	-0.049 (0.009)*	>0.001
–SW and Mid England	-0.232 (0.026)*	-0.171 (0.013)*	-0.161 (0.011)*	-0.086 (0.013)*	>0.001
–Wales	-0.283 (0.039)*	-0.174 (0.019)*	-0.192 (0.025)*	-0.097 (0.017)*	>0.001
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	-0.009 (0.026)	0.045 (0.018)*	0.014 (0.017)	-0.022 (0.016)	0.039
–3rd Quartile	0.013 (0.032)	0.096 (0.022)*	0.058 (0.021)*	-0.052 (0.018)*	>0.001
–4th Quartile	0.078 (0.036)*	0.122 (0.024)*	0.146 (0.031)*	-0.003 (0.018)	>0.001
Privately educated	0.13 (0.047)*	0.052 (0.018)*	0.125 (0.024)*	0.001 (0.023)	0.004
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.079 (0.074)	0.056 (0.024)*	0.107 (0.032)*	0.03 (0.017)	0.009
–Other degree class	-0.015 (0.041)	-0.075 (0.017)*	-0.066 (0.024)*	-0.022 (0.012)	>0.001
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.044 (0.026)	0.088 (0.021)*	0.09 (0.02)*	-0.035 (0.015)*	>0.001
–Russell group university	0.032 (0.034)	0.078 (0.032)*	0.108 (0.032)*	0.013 (0.031)	>0.001

*p<0.05

Table D.26: Results for models of earnings by fields of study adjusted for sample selection (6 months) (2008/09)

Predictor	Models					
	Bio. Sci.	Business	C. Arts	Education	Eng. Comp.	Human. Lang.
Intercept	9.53 (0.217)*	9.708 (0.11)*	9.486 (0.198)*	9.885 (0.08)*	9.647 (0.137)*	9.249 (0.124)*
Age (Base=18)	0.04 (0.01)*	0.037 (0.01)*	0.033 (0.01)*	0.038 (0.011)*	0.055 (0.012)*	0.053 (0.008)*
Non-white ethnicity	0.02 (0.066)	0 (0.048)	-0.014 (0.059)	-0.072 (0.038)	0.032 (0.034)	-0.002 (0.031)
Socioeconomic background						
(Ref: Routine and semi-routine)						
–Intermediate	0.018 (0.017)	0.025 (0.014)	0.057 (0.02)*	0.009 (0.017)	-0.001 (0.015)	0 (0.015)
–Managerial or professional	0.03 (0.015)*	0.045 (0.013)*	0.029 (0.02)	0.005 (0.016)	0.013 (0.014)	0.006 (0.014)
Has a known disability	-0.004 (0.033)	-0.015 (0.02)	-0.049 (0.028)	-0.055 (0.027)*	0.018 (0.017)	-0.024 (0.022)
Male	0.036 (0.023)	0.081 (0.014)*	0.05 (0.028)	-0.03 (0.025)	0.083 (0.014)*	0.035 (0.016)*
Domicile prior to HE						
(Ref: London)						
–North England	-0.157 (0.017)*	-0.213 (0.012)*	-0.117 (0.016)*	-0.135 (0.019)*	-0.104 (0.01)*	-0.159 (0.011)*
–Northern Ireland	-0.268 (0.046)*	-0.343 (0.031)*	-0.085 (0.112)	-0.135 (0.046)*	-0.202 (0.019)*	-0.305 (0.037)*
–Scotland	-0.121 (0.038)*	-0.177 (0.015)*	-0.181 (0.048)*	-0.069 (0.034)*	-0.059 (0.015)*	-0.178 (0.027)*
–SE and East England	-0.098 (0.011)*	-0.082 (0.008)*	-0.053 (0.011)*	-0.077 (0.016)*	-0.04 (0.007)*	-0.078 (0.007)*
–SW and Mid England	-0.154 (0.012)*	-0.144 (0.009)*	-0.097 (0.013)*	-0.137 (0.02)*	-0.069 (0.008)*	-0.137 (0.009)*
–Wales	-0.189 (0.022)*	-0.227 (0.017)*	-0.066 (0.02)*	-0.162 (0.033)*	-0.095 (0.013)*	-0.174 (0.019)*
UCAS tariff quartile						
(Ref: 1st Quartile)						
–2nd Quartile	0.025 (0.015)	0.042 (0.013)*	0.046 (0.018)*	0.017 (0.017)	0.036 (0.014)*	0.029 (0.013)*
–3rd Quartile	0.023 (0.02)	0.044 (0.02)*	0.077 (0.031)*	0.037 (0.02)	0.057 (0.015)*	0.041 (0.017)*
–4th Quartile	0.021 (0.019)	-0.005 (0.015)	-0.017 (0.018)	-0.064 (0.024)*	0.051 (0.014)*	0.034 (0.018)
Privately educated	0.034 (0.024)	0.06 (0.018)*	0.029 (0.031)	0.03 (0.036)	0.046 (0.019)*	0.054 (0.019)*
Degree classification						
(Ref: Upper second class honours)						
–First class honours	0.054 (0.029)	0.098 (0.02)*	0.063 (0.021)*	0.01 (0.019)	0.057 (0.018)*	0.029 (0.021)
–Other degree class	-0.04 (0.013)*	-0.07 (0.017)*	-0.051 (0.017)*	-0.043 (0.014)*	-0.082 (0.02)*	-0.006 (0.014)
Type of HEI						
(Ref: Post-1992 university)						
–Pre-1992 university	0.047 (0.017)*	0.075 (0.012)*	0.05 (0.019)*	0.026 (0.02)	0.136 (0.014)*	0.008 (0.021)
–Russell group university	0.068 (0.024)*	0.111 (0.014)*	0.007 (0.038)	-0.018 (0.03)	0.182 (0.013)*	0.031 (0.024)

*p<0.05

Results for models of earnings by fields of study adjusted for sample selection (6 months) (2008/09) cont.

Predictor	Models				Chi-sq.
	Law	Other STEM	Soc. Studies	Sub. Med.	p value
Intercept	9.601 (0.395)*	9.41 (0.205)*	9.377 (0.299)*	10.037 (0.071)*	>0.001
Age (Base=18)	0.031 (0.027)	0.039 (0.01)*	0.04 (0.012)*	0.013 (0.011)	0.278
Non-white ethnicity	-0.017 (0.117)	0.058 (0.048)	-0.02 (0.08)	-0.066 (0.017)*	0.119
Socioeconomic background					
(Ref: Routine and semi-routine)					
–Intermediate	0.055 (0.03)	0.013 (0.024)	0.016 (0.028)	0.007 (0.014)	0.458
–Managerial or professional	0.066 (0.029)*	0.008 (0.022)	-0.019 (0.027)	0.017 (0.013)	0.218
Has a known disability	0.006 (0.063)	0.007 (0.036)	-0.07 (0.069)	0.009 (0.017)	0.306
Male	0.074 (0.027)*	0.04 (0.031)	0.039 (0.032)	0.004 (0.02)	>0.001
Domicile prior to HE					
(Ref: London)					
–North England	-0.184 (0.031)*	-0.16 (0.016)*	-0.219 (0.019)*	-0.09 (0.012)*	>0.001
–Northern Ireland	-0.311 (0.085)*	-0.256 (0.054)*	-0.213 (0.037)*	-0.144 (0.017)*	>0.001
–Scotland	-0.261 (0.114)*	-0.173 (0.03)*	-0.219 (0.056)*	-0.122 (0.017)*	>0.001
–SE and East England	-0.148 (0.026)*	-0.061 (0.012)*	-0.106 (0.011)*	-0.06 (0.009)*	>0.001
–SW and Mid England	-0.177 (0.028)*	-0.134 (0.013)*	-0.164 (0.014)*	-0.087 (0.011)*	>0.001
–Wales	-0.27 (0.042)*	-0.143 (0.024)*	-0.201 (0.032)*	-0.085 (0.015)*	>0.001
UCAS tariff quartile					
(Ref: 1st Quartile)					
–2nd Quartile	0.057 (0.033)	0.044 (0.023)	0.038 (0.021)	-0.032 (0.011)*	0.001
–3rd Quartile	0.083 (0.034)*	0.107 (0.041)*	0.088 (0.03)*	-0.027 (0.015)	>0.001
–4th Quartile	0.067 (0.045)	0.165 (0.038)*	0.126 (0.029)*	-0.02 (0.017)	>0.001
Privately educated	0.095 (0.065)	0.048 (0.022)*	0.095 (0.034)*	-0.019 (0.021)	0.166
Degree classification					
(Ref: Upper second class honours)					
–First class honours	0.023 (0.073)	0.074 (0.027)*	0.098 (0.026)*	0.019 (0.011)	0.004
–Other degree class	0.017 (0.039)	-0.08 (0.018)*	-0.032 (0.02)	-0.006 (0.011)	0.001
Type of HEI					
(Ref: Post-1992 university)					
–Pre-1992 university	0.005 (0.04)	0.092 (0.038)*	0.038 (0.037)	-0.037 (0.012)*	>0.001
–Russell group university	0.041 (0.052)	0.103 (0.041)*	0.029 (0.038)	0.018 (0.017)	>0.001

*p<0.05

Bibliography

Acemoglu, D., S. Johnson, and J. a. Robinson (2001). The Colonial Origins of Comparative Development : An Empirical Investigation. *The American Economic Review 91*(5), 1369–1401.

Ahn, H. and J. Powell (1993). Semiparametric estimation of censored selection models with a nonparametric selection mechanism. *Journal of Econometrics 58*(1), 3–29.

Allison, P. (2001). *Missing data*. Thousand Oaks, CA: Sage.

Allison, P. D. (1999). Comparing Logit and Probit Coefficients Across Groups. *Sociological Methods & Research 28*(2), 186–208.

Angrist, J. D. and A. B. Krueger (1990). Does compulsory school attendance affect schooling and earnings? *Quarterly Journal of Economics 106*(4), 979–1014.

Arrow, K. J. (1973). Higher education as a filter. *Journal of Public Economics 2*(3), 193–216.

Arrow, K. J. (1998). What Has Economics to Say About Racial Discrimination? *Journal of Economic Perspectives 12*(2), 91–100.

Atfield, G. and K. Purcell (2010). *Job search strategies and employment preferences of higher education students*. Futuretrack working paper. Warwick: Institute for Employment Research.

Babyak, M. A. (2004). What You See May Not Be What You Get: A Brief, Nontechnical Introduction to Overfitting in Regression-Type Models. *Psychosomatic Medicine 66*(3), 411–421.

Ball, C. (2015). *Loyals, Stayers, Returners and Incomers: Graduate migration patterns*. Manchester: Higher Education Careers Services Unit.

Barber, A. E., M. J. Wesson, Q. M. Roberson, and M. S. Taylor (1999). A tale of two job markets: organizational size and its effects on hiring practices and job search behavior. *Personnel Psychology 52*(4), 841–868.

Bartram, D., P. a. Lindley, L. Marshall, and J. Foster (1995). The recruitment and selection of young people by small businesses. *Journal of Occupational and Organizational Psychology 68*(4), 339–358.

Bartram, R., M. Wesson, Q. Robertson, and M. S. Taylor (1992). *The Selection of Young People by Medium-sized and Large Organisations*. Sheffield: Employment Department, Careers Service Branch.

Bathmaker, A.-M. (2003). The Expansion of Higher Education: A Consideration of Control, Funding and Quality. *Education Studies: Essential Issues*, 169–189.

Bathmaker, A.-M., N. Ingram, and R. Waller (2013). Higher education, social class and the mobilisation of capitals: recognising and playing the game. *British Journal of Sociology of Education 34*(5-6), 723–743.

Becker, G. (1975). *Human capital* (2 ed.). New York: Columbia University Press.

Becker, G. (2006). The age of human capital. In H. Lauder, P. Brown, J. Dillabough, and A. Halsey (Eds.), *Education, Globalisation and Social Change*, pp. 292–295. Oxford: Oxford University Press.

Beloff, M. (1970). *The Plateglass Universities*. Madison, New Jersey: Fairleigh Dickinson University Press.

Biglan, A. (1973). The characteristics of subject matter in different academic areas. *Journal of Applied Psychology 57*(3), 195–203.

Billig, M. (2006). A Psychoanalytic Discursive Psychology: from consciousness to unconsciousness. *Discourse Studies 8*(1), 17–24.

Bills, D. B. (2003). Credentials, Signals, and Screens: Explaining the Relationship Between Schooling and Job Assignment. *Review of Educational Research 73*(4), 441–449.

Blackaby, D. H., D. G. Leslie, P. D. Murphy, and N. C. O'Leary (2005). Born in Britain: How are native ethnic minorities faring in the British labour market? *Economics Letters 88*(3), 370–375.

Blasko, Z. (2002). *Access to what: analysis of factors determining graduate employability*. Milton Keynes: Centre for Higher Education Research and Information.

Blau, P. M. and O. D. Duncan (1967). *The American Occupational Structure*. New York: Free Press.

Blaug, M. (1976). The Empirical Status of Human Capital Theory : A Slightly Jaundiced Survey. *Journal of Economic Literature 14*(3), 827–855.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources 8*, 436–455.

Bolton, P. (2012). *Education: Historical statistics*. London: House of Commons Library.

Bourdieu, P. and J. Passeron (1977). *Reproduction in Education, Society and Culture*. London: Sage.

Bourguignon, F., M. Fournier, and M. Gurgand (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys 21*(1), 174–205.

Breen, R., A. Holm, and K. B. Karlson (2014). Correlations and Nonlinear Probability Models. *Sociological Methods & Research 43*(4), 571–605.

British Psychological Society (2014). What is Accreditation? http://www.bps.org.uk/careers-education-training/accredited-courses-training-programmes/what-accreditation/what-accreditat. Accessed: 28 May 2015.

Broughton, N. (2013). *In the Balance: The STEM Human Capital Crunch*. London: The Social Market Foundation.

Brown, P. (2013). Education, opportunity and the prospects for social mobility. *British Journal of Sociology of Education 34*(5-06), 678–700.

Brown, P. and A. Hesketh (2004). *The Mismanagement of Talent: Employability and Jobs in the Knowledge Economy.*

Brown, P., H. Lauder, and D. Ashton (2011). *The global auction: the broken promises of education, jobs, and incomes.* Oxford: Oxford University Press.

Browne Review of Higher Education and Student Finance in England (2010). *Securing a sustainable future for higher education.* London: Department for Business Innovations and Skills.

Buckley-Irvine, N. and J. Burn-Murdoch (2012). Guardian university tuition fees league table. http://www.theguardian.com/education/datablog/2012/aug/15/students-tuition-fees-2012-league-table-data. Accessed: 28 May 2015.

Bushway, S., B. D. Johnson, and L. A. Slocum (2007). Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology. *Journal of Quantitative Criminology 23*(2), 151–178.

Campaign for Science and Engineering (CaSE) (2014). *Improving Diversity in STEM.* London: Campaign for Science and Engineering.

Campbell, E., C. Lockyer, and D. Scholarios (1997). *Selection Practices in Scottish Private Sector Companies: Linkages to Organisation Size and Industrial Sector.* Glasgow: University of Strathclyde, Department of Human Resource Management.

Carroll, M., M. Marchington, J. Earnshaw, and S. Taylor (1999). Recruitment in small firms: Processes, methods and problems. *Employee Relations 21*(3), 236–250.

Chevalier, A. (2006). *Education, Occupation and Career Expectation: Determinants of the Gender Pay Gap for UK Graduates.* London: Centre for the Economics of Education, LSE.

Chevalier, A. (2011). Subject choice and earnings of UK graduates. *Economics of Education Review 30*(6), 1187–1201.

Chevalier, A. (2012). *To be or not to be ... a Scientist?* Bonn, Germany: Institute for the Study of Labour.

Chevalier, A. and G. Conlon (2003). *Does it pay to attend a prestigious university?* London: Centre for the Economics of Education.

Chevalier, A. and J. Lindley (2009). Overeducation and the skills of UK graduates. *Journal of the Royal Statistical Society. Series A: Statistics in Society 172*(2), 307–337.

Coffield, F. and B. Williamson (1997). The challenges facing higher education. In F. Coffield and B. Williamson (Eds.), *Repositioning Higher Education*, pp. 1–26. Buckingham: Open University Press.

Committee on Higher Education (1963). *Report of the committee appointed by the Prime Minister under the chairmanship of Lord Robbins.* London: HMSO.

Conlon, G. and P. Patrignani (2011). *The Returns to Higher Education Qualifications.* Department for Business Innovation and Skills Research Paper. London: Department for Business Innovation and Skills.

Cribb, J., R. Disney, and L. Sibieta (2014). *The public sector workforce: past , present and future*. IFS Briefing note. London: Institute for Fiscal Studies.

Cribb, J., C. Emmerson, and L. Sibieta (2014). *Public sector pay in the UK*. IFS report. London: Institute of Fiscal Studies.

Department for Education and Skills (2003). *The Future of Higher Education*. London: Department for Education and Skills.

Department for Innovation Universities and Skills (2008). *Higher Education at Work*. London: Department for Innovation Universities and Skills.

Department for Innovation Universities and Skills (2011). *Higher Education: Students at the Heart of the System*. London: Department for Innovation Universities and Skills.

Department for Innovation Universities and Skills (2014). *Participation Rates in Higher Education: Academic Years 2006 and 2007 to 2012 and 2013 (Provisional)*. London: Department for Innovation Universities and Skills.

Derrida, J. (1977). *Limited Inc*.

Di Stasio, V., T. Bol, and H. G. Van de Werfhorst (2015). What makes education positional? Institutions, overeducation and the competition for jobs. *Research in Social Stratification and Mobility (In press)*.

Drucker, P. F. (1993). *Post-Capitalist Society*. New York: Harper Business.

Dunn, O. J. (1961). Multiple Comparisons Among Means. *Journal of the American Statistical Association 56*(293), 52–64.

Edwards, D., M. Ashmore, and J. Potter (1995). Death and Furniture: the rhetoric, politics and theology of bottom line arguments against relativism. *History of the Human Sciences 8*(2), 25–49.

Elias, P. and M. Birch (2010). SOC2010: revision of the Standard Occupational Classification. *Economic & Labour Market Review 4*(7), 48–55.

Elias, P., P. Jones, and S. McWhinnie (2006). *Representation of Ethnic Groups in Chemistry and Physics*. London: The Royal Society of Chemistry and the Institute of Physics.

Elias, P. and K. Purcell (2004). *SOC (HE): a classification of occupations for studying the graduate labour market*. Researching Graduate Careers Seven Years On. Warwick: Institute for Employment Research.

Elias, P. and K. Purcell (2012). Higher Education and Social Background. In S. McFall (Ed.), *Understanding Society Findings 2012*, pp. 23–24. Colchester: Institute for Social and Economic Research.

Elias, P. and K. Purcell (2013). *Classifying graduate occupation for the knowledge society*. Futuretrack Working Paper. Warwick: Institute for Employment Research.

Engineering Council (2014). Standard Routes to Registration as a Professional Engineer or Technician. http://www.engc.org.uk/engcdocuments/internet/Website/Flowchartshowingstandardroutestoregistration.pdf. Accessed: 18 Nov 2015.

Farrall, S. (2006). *What is Qualitative Longitudinal Research?* Papers in Social Research Methods Qualitative Series. London: London School of Economics and Political science Methodology Institute.

Felstead, A., D. Gailie, and F. Green (2012). *Skills and Employment Survey 2012*. Cardiff: Cardiff University.

Feng, A. and G. Graetz (2015). *A Question of Degree: The Effects of Degree Class on Labour Market Outcomes*. Centre for Economic Performance Discussion Paper. London: Centre for Economic Performance.

Fevre, R. (1989). Informal Practices, Flexible Firms and Private Labour Markets. *Sociology 23*(1), 91–109.

Franzen, A. and D. Hangartner (2006). Social Networks and Labour Market Outcomes: The Non-Monetary Benefits of Social Capital. *European Sociological Review 22*(4), 353–368.

Freedman, D. A. and J. S. Sekhon (2010). Endogeneity in Probit Response Models. *Political Analysis 18*(2), 138–150.

Gelman, A. and J. Hill (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press.

Gerber, T. P. and S. Y. Cheung (2008). Horizontal stratification in postsecondary education: Forms, explanations and implications. *Annual Review of Sociology 34*(1), 299–318.

Gittins, P. and S. Luke (2012). *Impact of the Recession on Household Spending*. Office for National Statistics paper. Newport, UK: Office for National Statistics.

Goldstein, H. and M. Healy (1995). The graphical presentation of a collection of means. *Journal of the Royal Statistical Society. Series A: Statistics in Society 158*(1), 175–177.

Goldthorpe, J. and M. Jackson (2008). Education-based meritocracy: The barriers to its realisation. In A. Lareau and D. Conley (Eds.), *Social Class: How does it Work?*, pp. 93–117. London: Sage.

Goldthorpe, J. H. (2014). The role of education in intergenerational social mobility: Problems from empirical research in sociology and some theoretical pointers from economics. *Rationality and Society 26*(3), 265–289.

Government Statistical Service (2015). Fast Stream. https://gss.civilservice.gov.uk/people-and-careers-2/fast-stream-recruitment/. Accessed: 28 May 2015.

Graduate Jobs (2015). When to Apply: The Recruitment Calendar. http://www.graduate-jobs.com/gco/Booklet/graduate-recruitment-calendar.jsp. Accessed: 18 Nov 2015.

Grannovetter, M. (1974). *Getting A Job: A Study of Contacts and Careers*. Cambridge, MA: Harvard University Press.

Greenaway, D. and M. Haynes (2000). *Funding universities to meet national and international challenges*. Nottingham: University of Nottingham.

Greenberg, J. and M. Fernandez (2016). The Strength of Weak Ties in MBA Job Search : A Within – Person Test. *3*, 296–316.

Grusky, D. (2014). *Social Stratification: Class, Race, and Gender in Sociological Perspective* (4th ed.). Boulder, CO: Westview Press.

Guadalupe, M. (2007). Product Market Competition, Returns to Skill, and Wage Inequality. *Journal of Labor Economics 25*(3), 439–474.

Hällsten, M. (2013). The class-origin wage gap: heterogeneity in education and variations across market segments. *The British journal of sociology 64*(4), 662–90.

Hansen, M. N. (1996). Earnings in Elite Groups: The Impact of Social Class Origin. *Acta Sociologica 39*(4), 385–408.

Hansen, M. N. (2001). Education and economic rewards. Variations by social-class origin and income measures. *European Sociological Review 17*(3), 209–231.

Hansen, M. N. and A. Mastekaasa (2006). Social origins and academic performance at university. *European Sociological Review 22*(3), 277–291.

Health and Care Professions Council (2009). Standards of Education and Training. http://www.hcpc-uk.org/assets/documents/1000295EStandardsofeducationandtraining-fromSeptember2009.pdf. Accessed: 28 May 2015.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica 47*(1), 153–161.

Heckman, J. J. (2005). The scientific model of causality. *Sociological Methodology 35*, 1–97.

Heckman, J. J. and S. Polachek (1974). Empirical evidence on the functional form of the earnings-schooling relationship. *Journal of the American Statistical Association 69*(346), 350– 354.

Heckman, J. J. and E. J. Vytlacil (2007). Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation. In *Handbook of econometrics*, pp. 4779–4874.

Henry, J. and C. Fleet (2011). Recruitment and Selection Policy for Queen Elizabeth Hospital King's Lynn. http://www.qehkl.nhs.uk/Documents/eq-policies/5RecruitmentandSelectionPolicy.pdf. Accessed: 18 Nov 2015.

Hesketh, A. and P. Brown (2006). I say Tomato, you say tamato: Putting critical realism to work in the knowledge worker recruitment process. In S. Fleetwood and S. Ackroyd (Eds.), *Critical Realist Applications in Organisational and Management Studies*, pp. 337–356. London: Routledge.

High Fliers Research (2015). *The Graduate Market in 2015*. London: High Fliers Research.

Higher Education Funding Council for England (2001). Partnerships for Progression. ww.hefce.ac.uk/pubs/hefce/2001/01{_}73.htm. Accessed: 29 June 2015.

Higher Education Funding Council for England (2002). *Supply and demand in higher education*. London: Higher Education Funding Council for England.

Higher Education Funding Council for England (2011). Approaches to measuring employment circumstances of recent graduates. http://www.hefce.ac.uk/pubs/year/2011/201102/name,63892,en.html. Accessed: 11 July 2015.

Higher Education Funding Council for England (2013). *Higher Education and Beyond: Outcomes from Full-time First Degree Study*. London: Higher Education Funding Council for England.

Higher Education Funding Council for Wales (2014). Participation Rates for Welsh Students in Higher Education within the UK during 2009/10. http://www.hefcw.ac.uk/documents/about{_}he{_}in{_}wales/statistics/Participationrates0910.pdf. Accessed: 29 June 2015.

Higher Education Statistics Agency (2008). Destinations of Leavers from Higher Education Institutions 2006/07 - Introduction. https://hesa.ac.uk/component/content/article/246-statistics/publications-archive/3078-?limit=1{&}start=1. Accessed: 28 May 2015.

Higher Education Statistics Agency (2010). Destinations of Leavers from Higher Education Institutions 2008/09 - Introduction. https://www.hesa.ac.uk/component/content/article/246-statistics/publications-archive/3433-destinations-of-leavers-from-higher-education-institutions-2008-09?limit=1{&}start=1. Accessed: 28 May 2015.

Higher Education Statistics Agency (2014a). Statistical First Release 205. https://www.hesa.ac.uk/sfr205. Accessed: 28 May 2015.

Higher Education Statistics Agency (2014b). Student, Qualifiers and Staff data tables. https://www.hesa.ac.uk/content/view/1973/239/. Accessed: 21 Sep 2014.

Higher Education Statistics Agency (2015). Statistical First Release 210. https://www.hesa.ac.uk/sfr210. Accessed: 28 Oct 2015.

Hillage, J. and E. Pollard (1998). *Employability: Developing a Framework for Policy Analysis—Summary*. London: Department for Education and Employment.

Hinchliffe, G. W. and A. Jolly (2011). Graduate identity and employability. *British Educational Research Journal 37*(4), 563–584.

Hirsch, F. (1977). *The Social Limits to Growth*. London: Routledge & Kegan Paul.

Hochschild, A. R. (2003). *The managed heart. Commercialization of Human Feeling*. Oakland, CA: University of California Press.

Hodkinson, P., A. Sparkes, and H. Hodkinson (1996). *Triumphs and tears : young people, markets and the transition from school to work*. London: Routledge.

Holland, J., R. Thomson, and S. Henderson (2006). *Qualitative Longitudinal Research: A Discussion Paper*. London: London South Bank University.

Holland, P. W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association 81*(396), 945–960.

Hollway, W. and T. Jefferson (2005a). But why did Vince get sick? A reply to Spears and Wetherell. *The British Journal of Social Psychology 44*(Pt 2), 175–180.

Hollway, W. and T. Jefferson (2005b). Panic and perjury: a psychosocial exploration of agency. *The British Journal of Social Psychology 44*(Pt 2), 147–163.

Holm, S. (1979). A Simple Sequentially Rejective Multiple Test Procedure. *Scandinavian Journal of Statistics 6*(2), 65–70.

Holzer, H. J. and K. R. Ihlanfeldt (1998). Customer Discrimination and Employment Outcomes for Minority Workers. *Quarterly Journal of Economics 113*(3), 835–867.

Hughes, T., A. Porter, S. Jones, and J. Sheen (2013). *Privately Funded Providers of Higher Education in the UK*. London: Department for Business, Innovation and Skills.

IFF Research (2011). *DLHE Longitudinal Survey 2006/07: Technical Report*. London: IFF Research.

IFF Research (2013). *DLHE Longitudinal Survey 2008/09*. London: IFF Research.

Jackson, M. (2007). How far merit selection? Social stratification and the labour market. *British Journal of Sociology 58*(3), 367–390.

Jackson, M., J. H. Goldthorpe, and C. Mills (2005). Education, Employers and Class Mobility. *Research in Social Stratification and Mobility 23*(05), 3–33.

Jackson, M., R. Luijkx, R. Pollak, L.-a. Vallet, and H. G. van de Werfhorst (2008). Educational Fields of Study and the Intergenerational Mobility Process in Comparative Perspective. *International Journal of Comparative Sociology 49*(4-5), 369–388.

James, S., C. Warhurst, J. Commander, L. Kimberley, and G. Tholen (2011). *The Five Obstacles that Hamper Better Understanding of Graduate Labour and Skills*. SKOPE Issues Paper. Cardiff: Centre on Skills, Knowledge and Organisational Performance.

Jenkins, A. and A. Wolf (2002). *Why do employers use selection tests? Evidence from British workplaces*. Centre for the Economics of Education paper. London: Centre for the Economics of Education.

Jenkins, J. (2010). The labour market in the 1980s, 1990s and 2008/09 recessions. *Economic & Labour Market Review 4*(8), 29–36.

Jones, M. P. (1996). Indicator and Stratification Methods for Missing Explanatory Variables in Multiple Linear Regression. *Journal of the American Statistical Association 91*(433), 222–230.

Keele, L. and D. K. Park (2006). *Difficult Choices: An Evaluation of Heterogeneous Choice Models*. Oxford: Oxford University.

Keep, E. and S. James (2010). *Recruitment and Selection—The Great Neglected Topic*. SKOPE Research Paper. Cardiff: Centre on Skills, Knowledge and Organisational Performance.

Koenker, R. (2009). *Quantreg: quantile regression*. R package version 4.

Kohler, U., K. B. Karlson, and A. Holm (2011). Comparing coefficients of nested nonlinear probability models. *The Stata Journal 11*(3), 420–438.

Lauder, H., P. Brown, and A. Halsey (2009). Sociology of education: a critical history and prospects for the future. *Oxford Review of Education 35*(5), 569–585.

Learning and Skills Council (2008). *Recruitment and Training among Large Employers—Final report*. Coventry: Learning and Skills Council.

Lee, D. (2011). Networks, cultural capital and creative labour in the British independent television industry. *Media, Culture & Society 33*(4), 549–565.

Lucas, S. R. (2001). Effectively Maintained Inequality: Education Transitions, Track Mobility, and Social Background Effects. *American Journal of Sociology 106*(6), 1642–1690.

Machin, S. and P. Puhani (2002). *Subject of Degree and the Gender Wage Differential: Evidence from the UK and Germany.* IZA Discussion Paper. Bonn, Germany: Institute for the Study of Labour.

Macmillan, L., C. Tyler, and A. Vignoles (2015). Who Gets the Top Jobs? The Role of Family Background and Networks in Recent Graduates' Access to High-status Professions. *Journal of Social Policy 44*(03), 487–515.

Marsden, P. V. and E. H. Gorman (2001). Social Networks, Job Changes and Recruitment. In *Sourcebook of Labor Markets Evolving Structures and Processes*, pp. 467–502.

Mason, M. (2010). Sample Size and Saturation in PhD Studies Using Qualitative Interviews. *Forum: Qualitative Research 11*(3).

Mastekaasa, A. (2004). Social Origins and Recruitment to Norwegian Business and Public Sector Elites. *European Sociological Review 20*(3), 221–235.

Mayhew, K., C. Deer, and M. Dua (2004). The move to mass higher education in the UK: many questions and some answers. *Oxford Review of Education 30*(1), 65–82.

McCullagh, P. (1980). Regression models for ordinal data. *Journal of the Royal Statistical Society. Series B (Methodological) 42*(2), 109–142.

McQuaid, R. W. and C. D. Lindsay (2005). The concept of employability. *Urban Studies 42*(2), 197–219.

Mincer, J. (1958). Investment in human capital and personal income distribution. *The Journal of Political Economy 66*(4), 281–302.

Molloy, D., K. Woodfield, and J. Bacon (2002). *Longitudinal Qualitative Research Approaches in Evaluation Studies.* London: Department for Work and Pensions.

Moreau, M.-P. and C. Leathwood (2006). Graduates' employment and the discourse of employability: a critical analysis. *Journal of Education & Work 19*(4), 305–324.

Mouw, T. (2006). Estimating the causal effect of social capital : A review of recent research. *Annual review of sociology 32*, 79–102.

National Committee of Inquiry into Higher Education (1997). *Higher Education in the Learning Society: Report of the National Committee.* London: HMSO.

Naylor, R., J. Smith, and A. McKnight (2002). *Sheer Class? The Extent and Sources of Variation in the UK Graduate Earnings Premium.* Centre for Analysis of Social Exclusion paper. Centre for Analysis of Social Exclusion, LSE.

Nickson, D., C. Warhurst, J. Commander, S. A. Hurrell, and A. M. Cullen (2011). Soft Skills and Employability: Evidence from UK Retail. *Economic and Industrial Democracy 33*(1), 65–84.

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review 14*(3), 693–709.

Office for National Statistics (2012a). *Graduates in the labour market 2012.* Newport, UK: Office for National Statistics.

Office for National Statistics (2012b). Relationship between SOC2010 and SOC2000. http://www.ons.gov.uk/ons/guide-method/classifications/current-standard-classifications/soc2010/index.html. Accessed: 25 Feb 2015.

Office for National Statistics (2013). *Graduates in the labour marker 2013*. Newport, UK: Office for National Statistics.

Office of Science and Technology Policy (2014). Women in STEM. https://www.whitehouse.gov/administration/eop/ostp/women. Accessed: 20 June 2016.

O'Leary, N. C. and P. J. Sloane (2005). The return to a university education in Great Britain. *National Institute Economic Review 193*(1), 75–89.

O'Regan, M. (2010). *Graduate Transitions to Employment: Career Motivation, Identity and Employability*. Reading: Centre for Career Management Skills.

Parry, G. (2009). Higher Education, Further Education and the English Experiment. *Higher Education Quarterly 63*(4), 322–342.

Parry, G., C. C, P. Scott, and P. Temple (2012). *Understanding Higher Education in Further Education Colleges*. London: Department for Innovation, Universities and Skills.

Perkin, H. (1991). Dream, Myth and Reality: New Universities in England, 1960-1990. *Higher Education Quarterly 45*(4), 294–310.

Potter, J., M. Wetherell, R. Gill, and D. Edwards (1990). Discourse: noun, verb or social practice? *Philosophical Psychology 3*(2), 205–217.

Price Waterhouse Coopers (2007). *The Economic Benefits of a Degree*. Universities UK Research Report. London: Price Waterhouse Coopers.

Psacharopoulos, G. (1979). On the weak versus the strong version of the screening hypothesis. *Economics Letters 4*(2), 181–185.

Puhani, P. A. (2000). The Heckman Correction for Sample Selection and Its Critique. *Journal of Economic Surveys 14*(1), 53–68.

Purcell, K., G. Atfield, C. Ball, and P. Elias (2008). *An investigation of the factors affecting the post-university employment of chemical science graduates in the UK*. Warwick: Institute for Employment Research.

Purcell, K. and P. Elias (2004). *Researching Graduate Careers Seven Years on: Higher Education and Gendered Career Development*. Warwick: Institute for Employment Research.

Purcell, K. and P. Elias (2008). Achieving equality in the knowledge economy. In J. Scott, S. Dex, and H. Joshi (Eds.), *Women and Employment: Changing Lives and New Challenges*, pp. 19–53. Cheltenham: Edward Elgar.

Purcell, K., P. Elias, G. Atfield, H. Behle, R. Ellison, D. Luchinskaya, J. Snape, L. Conaghan, and C. Tzanakou (2013). *Transitions into employment , further study and other outcomes: The Futuretrack Stage 4 Report*. Warwick: Institute for Employment Research.

Purcell, K., P. Elias, R. Davies, and N. Wilton (2005). *The Class of 99: A study of the early labour market experience of recent graduates*. London: Department for Education and Skills.

Purcell, K., P. Elias, and N. Wilton (2006). *Looking through the Glass Ceiling: A Detailed Investigation of the Factors that contribute to Gendered Career Inequalities.* Liverpool: European Social Fund.

R Core Team (2015). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. Version 3.2.0.

Ramsey, A. (2008). *Graduate Earnings: An Econometric Analysis of Returns, Inequality and Deprivation across the UK.* London: Department for Employment and Learning.

Reich, R. (1991). *The Work of Nations.* New York: Vintage.

Roksa, J. (2005). Double Disadvantage or Blessing in Disguise? Understanding the Relationship Between College Major and Employment Sector. *Sociology of Education 78*(3), 207–232.

Rubin, D. B. (1976). Inference and Missing Data. *Biometrika 63*(3), 581–592.

Rubin, D. B. and Rubin (1996). Multiple Imputation After 18+ Years. *Journal of the American Statistical Association 91*(434), 473–489.

Rumberger, R. W. and S. L. Thomas (1993). The economic returns to college major, quality and performance: A multilevel analysis of recent graduates. *Economics of Education Review 12*(1), 1–19.

Sage, J., M. Evandrou, and J. Falkingham (2012). *The Complex Migration Pathways of UK Graduates.* CPC Briefing paper. Southampton: ESRC Centre for Population Change.

Sainsbury Review Team (2007). *The Race to the Top: A Review of Government's Science and Innovation Policies.* London: HMSO.

Schmidt, F. L. and J. E. Hunter (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin 124*(2), 262–274.

Schultz, T. (1971). *Investment in Human Capital: The Role of Education and of Research.* New York: Free Press.

Scottish Funding Council (2013). *Participation Rates for Entrants to Scottish Higher Education.* Edinburgh: Scottish Funding Council.

Searle, J. R. (1969). *Speech Acts.*

Smetherham, C. (2005). *The Employability of First Class Graduates.* Ph. D. thesis, Cardiff University.

Smetherham, C. (2006). Firsts among equals? Evidence on the contemporary relationship between educational credentials and the occupational structure. *Journal of Education and Work 19*(1), 29–45.

Smith, J. and R. Naylor (2001). Determinants of degree performance in UK universities: a statistical analysis of the 1993 student cohort. *Oxford Bulletin of Economics and Statistics 63*(1), 29–59.

Smith, J. and R. Naylor (2005). Schooling effects on subsequent university performance: Evidence for the UK university population. *Economics of Education Review 24*, 549–562.

Smyth, R. and R. Strathdee (2010). The effects of type of institution attended on graduate earnings in New Zealand: a cross-field comparison. *British Journal of Sociology of Education 31*(4), 489–508.

Spence, M. (1973). Job Market Signalling. *The Quarterly Journal of Economics 87*(3), 355–374.

Steele, F. (2008). Multilevel models for longitudinal data. *Journal of the Royal Statistical Society. Series A: Statistics in Society 171*(1), 5–19.

Stiglitz, J. E. (1975). The Theory of "Screening," Education, and the Distribution of Income. *American Economic Review 65*(3), 283–300.

Stoecker, J. L. (1993). The Biglan classification revisited. *Research in Higher Education 34*(4), 451–464.

Strathdee, R. (2009). Reputation in the sociology of education. *British Journal of Sociology of Education 30*(1), 83–96.

Strobl, C., J. Malley, and G. Tutz (2009). An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological methods 14*(4), 323–48.

Teichler, U. (1988). *Changing patterns of the higher education system. The experience of three decades.* London: Jessica Kingsley.

The Complete University Guide (2014). Foundation and Undergraduate Tuition Fees UK/EU Students. http://www.thecompleteuniversityguide.co.uk/university-tuition-fees/reddin-survey-of-university-tuition-fees/foundation-undergraduate-tuition-fees-2014\T1\textendash15-ukeu/. Accessed: 11 Nov 2015.

Thomas, K. (1990). *Gender and Subject in Higher Education.* Milton Keynes: Open University Press.

Thurow, L. (1972). Education and economics equality. *Public Interest 28*, 66–81.

Thurow, L. (1975). *Generating Inequality: Mechanisms of Distribution in the U.S. Economy.* New York: Basic Books.

Tomlinson, M. (2005). *Higher education and graduate employability : student and academic attitudes to graduate work, careers and employability.* Ph. D. thesis, Cardiff University.

Tomlinson, M. (2008). 'The degree is not enough': students' perceptions of the role of higher education credentials for graduate work and employability. *British Journal of Sociology of Education 29*(1), 49–61.

trust, S. (2010). *The mobility manifesto.* London: Sutton trust.

trust, S. (2016). Pathways to Law. http://www.suttontrust.com/programmes/pathways-to-law. Accessed: 20 June 2016.

Tucker, A. (2013). *Staying put or moving on? The migration decisions of students and graduates in Brighton & Hove.* Phd, University of Brighton.

Tymon, A. (2013). The student perspective on employability. *Studies in Higher Education 38*(6), 841–856.

UK Commission for Employment and Skills (2010). *Ambition 2020: World Class Skills and Jobs for the UK.* London: UK Commission for Employment and Skills.

van de Ven, W. and B. van Praag (1981). The demand for deductibles in private health insurance : A probit model with sample selection. *Journal of Econometrics 17*(2), 229–252.

van de Werfhorst, H. G. (2002a). A Detailed Examination of the Role of Education in Intergenerational Social-class Mobility. *Social Science Information 41*(3), 407–438.

van de Werfhorst, H. G. (2002b). Fields of Study, Acquired Skills and the Wage Benefit from a Matching Job. *Acta Sociologica 45*, 287–303.

van de Werfhorst, H. G. (2011a). Skill and education effects on earnings in 18 Countries: The role of national educational institutions. *Social Science Research 40*(4), 1078–1090.

van de Werfhorst, H. G. (2011b). Skills, positional good or social closure? The role of education across structural–institutional labour market settings. *Journal of Education and Work 24*(5), 521–548.

van de Werfhorst, H. G. and G. Kraaykamp (2001). Four Field-Related Educational Resources and Their Impact on Labor, Consumption, and Sociopolitical Orientation. *Sociology of Education 74*(4), 296–317.

Vygotsky, L. S. (1962). *Thought and language.*

Wakefield, P. (2009). *Social Class and Access to Postgraduate Education in the UK: A Sociological Analysis*. Phd, University of Manchester.

Walford, G. (1991). Changing relationship between government and higher education in Britain. In G. Neave and F. van Vught (Eds.), *The Changing Relationship Between Government and Higher Education in Western Europe*, pp. 165–183. Oxford: Pergamon Press.

Walker, I. and Y. Zhu (2003). Education, Earnings and Productivity: Recent UK Evidence. *Labour Market Trends 111*(3), 145–152.

Walker, I. and Y. Zhu (2008). The college wage premium and the expansion of higher education in the UK. *Scandinavian Journal of Economics 110*(4), 695–709.

Walker, I. and Y. Zhu (2011). Differences by degree: Evidence of the net financial rates of return to undergraduate study for England and Wales. *Economics of Education Review 30*(6), 1177–1186.

Warren, C. (2002). Qualitative Interviewing. In J. Gubrium and J. Holstein (Eds.), *Handbook of Interview Research*, pp. 83–101. London: Sage.

Weber, M. (1956). *Economy and society.* Los Angeles: University of California Press.

Wellman, N. (2010). The employability attributes required of new marketing graduates. *Marketing Intelligence & Planning 28*(7), 908 – 930.

Wengraf, T. (2001). *Qualitative Research Interviewing: Biographic Narratives and Semi- structured Methods.* London: Sage.

Williams, R. (2009). Using Heterogeneous Choice Models to Compare Logit and Probit Coefficients Across Groups. *Sociological Methods & Research 37*(4), 531–559.

Williams, R. D. (2004). The demand for labour in the UK. *Labour Market Trends 112*(8), 321–330.

Wilton, N. (2011). Do employability skills really matter in the UK graduate labour market? The case of business and management graduates. *Work, Employment & Society 25*(1), 85–100.

Winship, C. and R. D. Mare (1983). Structural Equations and Path Analysis for Discrete Data. *American Journal of Sociology 89*(1), 54–110.

Wooldridge, J. (2010). *Econometric analysis of cross section and panel data.* Cambridge, MA: MIT press.

Yitzhaki, S. and R. Lerman (1991). Income stratification and income inequality. *Review of Income and Wealth 37*(3), 113–139.

Zhang, M.-L. (2011). *An Investigation in the Prospective Plans of Final Year Students after Graduation.* Master dissertation, Cardiff University.