GRADUATES WAGE-PREMIUM: A CASE FOR SUBJECT CHOICE, GENDER, ETHNICITY, BACKGROUND, AND SKILLS

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ABSTRACT

This thesis presents three chapters, each addressing the key variables affecting the wage premium of graduates. The first chapter gives the heterogeneity analysis of differences in gender wage premium. The second chapter explores the impact of the financial crisis on the evolution of new graduates' wage premiums. Lastly, the third chapter answers how the graduate wage premium varies with individuals' skill level and family background and how individual achievement score at school level and family background influence degree subject choices.

The first chapter starts with the understanding that there has been a gender wage premium difference in the UK labour market and men are likely to earn a higher wage premium compared to women. We analyse this difference in-depth and differentiate among subject choices, part-time and full-time workers, white and non-white ethnicity individuals, and London based and non-London based individuals. The results show that graduates in medicine, maths and engineering earn the highest premium compared to other subjects for both part-time and full-time workers. Further heterogeneity analysis shows that being employed in London and coming from ethnic minority backgrounds also significantly affect the wage premium.

The second chapter is based on the understanding that there has been a significant impact of the financial crisis, 2008/09 on the labour market of the UK. We in this chapter explore how the financial crisis of 2008/09 had an impact on the wage premium of new graduates and on the probability of individuals securing a professional job. We cannot categorically say that the financial crisis had an impact on the wage premium or on the likelihood of new graduates securing a professional job.

Lastly, literature has shown that there has been a significant effect of cognitive/non-cognitive skills and family background on the subject choices made at degree level and (the individuals') wage premium. This chapter presents significant evidence that in the UK, the graduate wage premium is impacted by (the individuals') numeracy and literacy scores at Key stage 3 and family background. We have also depicted that the Key Stage 3 achievement score and family background has a significant impact on the subject choices made by individuals at degree level.

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1. INTRODUCTION

The UK has experienced substantial transformation in its educational and labour market since the mid-1990s (Blundell et al., 2016). Clegg (2017) in a report published by Office of National Statistics shows that from July to September 2017 there were 14 million (42%) graduates in the UK Labour Market, 7 million (21%) had an A-level equivalent qualification, 7 million (20%) had GCSEs or an equivalent qualification, 3 million (9%) had other qualification and 3 million (8%) had no qualification[1]. Non-graduates between ages 21-30 years have much higher inactivity rates than recent graduates. Approximately 40% of graduates worked in public administration, educational and health industries. It is particularly common for those who graduated in medicine, dentistry, education, and subjects related to medicine to take these jobs. The inactivity rate for graduates was 15% in September 2017. This inactivity percentage is lower than for students with A-levels (19%), GCSEs (24%), other qualifications (29%) and no qualification (53%).

Labour Force Survey by Office of National Statistics indicate that graduates are more likely to be employed, less likely to be searching for new jobs, and much less likely to be completely out of the labour force than people with lower or no educational qualification at all. When looking at recent graduates and non-graduates aged 21 to 30 years, the recent graduates have shown consistently lower unemployment rates. Since the 2008 to 2009 economic downturn, unemployment rates have risen for all types of qualification groups but the sharpest rise in unemployment was experienced by non-graduates aged 21 to 30 years. However, from 2013, the unemployment rates for all groups have been falling.

According to the Clegg (2017), on average, graduates aged 21 earn a lower gross annual wage than those aged 21 years who left education with an apprenticeship. Graduates aged 21 earn similar to 21-year-olds who left education with a GSCE standard qualification (Clegg, 2017). This could be explained by the fact that graduates at the age of 21 will have just entered the labour market, therefore working at an entry level role or (lower skilled) compared to their non-graduate but employed counterparts.

Historically, since early 1970s it has been found that there is strong correlation between higher education and labour market success (Walker & Zhu et, 2008, 2017; Walker et al., 2010; Belfield et

[1] For the purpose of this thesis, we use the term "graduate" to refer to people who left education with qualifications higher than the A-level standard, with a university degree qualification.

al., 2014, 2018). However, the extent to which higher education improves the productivity and efficiency of individuals, and a causal relationship between wage and education, has been an ambitious question for empirical researchers.

The main objective of this study is to conduct a heterogeneity analysis of the wage premium for graduates in different subjects. In addition, this study estimates how the financial crisis influenced the subject-wage-premium and the job market for new graduates in the UK. Lastly, we will also consider whether the underlying factors are cognitive skills, non-cognitive skills or a result of family background, without ruling out the possibility that high ability individuals, and individuals from strong educational and financial backgrounds, choose more lucrative subjects.

Understanding the returns to subject choices by gender, ethnicity and region is essential from both the educational policy and students' perspective, as it will enhance students' ability to make rational decisions on what future higher education degree subjects to study. The gender, ethnicity and regional analysis of wage premiums associated with different subjects will assist policy makers in better understanding the labour market.

Previously it has been established that the Financial Crisis of 2008 had a large impact on unemployment and earnings of individuals (O'Farrell, 2010; Pissarides, 2009). However, there has been little research on the impact of the crisis on the new graduate wages as the graduate group saw a lower rise in unemployment compared to non-graduates. This will be a useful (part of literature) as it will give an insight into the impact of the financial crisis of 2008 on the evolution of the graduate wage premium.

Furthermore, this study aims to investigate the impact of cognitive and non-cognitive skills on the wages of individuals. In the process, we will also pick up on the impact of family background and social status. This will be useful in looking at how early education has an influence on the wages of individuals. Further, learning about the family background and wage premium will provide insights on social mobility.

1.1 Human Capital Theory

Human Capital is defined as the totality of investments made in humans so that those humans are better at producing goods and services. These investments might include education, skills, talents, and experiences that make the individual more productive and skilled. Ultimately, higher worker productivity leads to higher worker value and more lucrative labour markets. Classical human capital theory assumes that education is a form of human capital, meaning that those who invest in their education are strategically optimising to increase their capital, which will in turn lead to higher income and productivity.

The increase in human capital can be classified into multiple categories, including economic capital, cultural capital and social capital. Economic capital is measured typically by skills and the ability to perform, which results in value to the economy. Marketable talents, education and job training are a few ways through which individuals acquire the ability to gain knowledge and help to generate higher wages. Cultural capital and social capital refer to the relationships and impact that individuals contribute to society. It is difficult to measure social and cultural capital, but it is important to understand their existence and value on the lives of individuals and on society. Although economic capital can be measured by wages and the income generated by individuals, it is difficult to measure the full intrinsic value of human capital.

Human capital theory, formalized by Becker (1962), resulted in the Mincer (1974) Human Capital Earnings Function. This forms the basis of much of our analysis in this thesis and we will consider it in more detail below.

1.2 Mincer Human Capital Earning Function

Schooling, Experience and Earnings is a classic study published by Jacob Mincer, in 1974. Following the human capital theory, Mincer (1974) considers schooling as an investment for future earnings, the investment decision being influenced also by education's cost and foregone earnings during the time-period of studying. In his discussion of investment in human capital, he assumes that full-time investment in education, which is basically obtained in schools, goes before on the job training. His model also takes into consideration the concavity of the experience profile, i.e., an individuals earning profile starts to decrease as they age.

Education is considered as an investment in human capital; investment of current resources in exchange for future benefits[2]. Education or years of schooling 's' is completed to maximise the present value of the future wage 'w', from when work starts 's+1' up until the retirement at time 'T'.

[2] Current resources include both the direct costs of education and the time involved.

Therefore, at the optimum 's', the present value of the s^th year of schooling will just be equal to cost of the s^th year of education. So, in equilibrium:

$$\sum_{t=1}^{T-s} \frac{w_s - w_{s-1}}{(1+r_s)^t} = w_{s-1} + c_s$$

Here the r_s is called the individual rate of return; for simplicity the assumption is that s is infinitely divisible, so the year should not be interpreted literally. The optimal investment decision on number of years in education will depend on how high the value of r_s is compared to the market rate of interest 'i'; that is, one would invest in s^th year if '$r_s > i$'. If 'T' is larger and 'c_s' is comparatively small then we can just write in terms of log, as follows:

$$\frac{w_s - w_{s-1}}{r_s} \approx w_{s-1}$$

$$r_s \approx \frac{w_s - w_{s-1}}{w_{s-1}} \approx \log w_s - \log w_{s-1}$$

This says that the return for the s^th year of schooling is approximately the difference in log wages between leaving at s and at s-1. Using the above we could estimate the returns to 'S' by seeing how log wages varies with 'S'.

$$r_s \approx \log w_s - \log w_{s-1}$$

The empirical model was redefined intuitively by Mincer (1974) as the human capital framework in the following form:

$$w_i = \alpha . w_0 + rs_i + \beta_1 . x_i + \beta_2 . x_i^2 + u_i$$

Where w_i is the earning measure that is hourly or weekly for individuals, s_i represent the years of completed education, x_i is the age and x_i^2 is the age squared to capture the concavity of the experience earning profile. The Mincer (1974)[3] derivation of the empirical model considers r as the financial return to education, or the proportionate effect on the wages of an increment to s_i.

According to Mincer, the explanatory power of the schooling-earnings function is only 7 percent, the explanatory power of the function with the quadratic experience profile is 29 percent, which is increased to 53 percent when dummy variables are used for schooling and the log weeks worked variable is added to the equation.

[3] This Mincer model specification has been extended and used to address the wage differences such as discrimination, effectiveness of training programs (Blundell et al., 1996), school and education quality (Card et al., 1996), and change in returns because of language skills (Borjas, 1999).

This model treats education and schooling as exogenous, though education has since been seen as an endogenous human choice variable with earnings[4]. In understanding the wage and education relationship, Card (1994) pointed to three types of bias that might affect the estimators. First is ability and skills, which might differ for each individual in terms of their cognitive, interpersonal and other skills. Higher ability individuals may earn a higher income even if they have a lower educational qualification and this would normally cause an upward bias in the estimates.

Similarly, an individual with a higher physical or mental ability may have a lower education level but work, an exceptional number of hours or choose a steep career path. In this case, a low educated worker might receive a higher income than the individuals with similar or higher qualification and background, and this factor tends to cause an upward bias in the estimates. One can also think that high ability parents would typically earn high income and are able to give better quality education to their children, and their children may inherit this ability to help them earn a higher income.

Measurement error can also affect the estimates. This can happen while selecting a sample, data accumulation, or just human error likely to bias in the estimates downwards.

In the Mincer (1974) equation mentioned earlier, years of schooling is an investment decision based on the future earnings and costs for any individual, the investment of time and resources in education continues until the difference between the marginal cost and marginal return to education is zero.

Since training and education are investment decisions, the internal rate of return is the discount rate that equates the present value of benefits to the present value of costs. If the internal rate of return is greater than the market rate of interest, more education is worthwhile. In making this investment decision, individuals who place more value on current income than future income will have a higher internal discount rate. Therefore, individuals with higher discount rates are less likely to invest in higher education.

A higher education cost has a direct effect on the net benefits of education. If the probability of employment increases with education achievement, then it is more likely for individuals to achieve

[4] This problem arises because people with high marginal returns will normally choose a high level of qualification. Also, higher educated workers will earn higher wages, whereas on the contrary higher earnings are earned by higher educated workers. So, there is a problem of reverse causality. In addition to this, the schooling variable is unable to capture all the wage differential and, due to the missing variables, becomes related to the error term. In strict econometric language, we can say that the independent variables are co-related to the error term, that is $E(X_i u_i) \neq 0$, thus, giving us inconsistent and biased estimators.

higher education (Harmon et al., 2003). Also, if the earnings gap between the educated and the non-educated individuals widens, or if the opportunity cost of education is decreased (through maintenance grants and tuition subsidy), the net effect on the decision to invest in education should be positive. There are also non-pecuniary benefits associated with higher education, such as status, which cannot be measured by wages but is part of human capital, as discussed before (Chevalier et al., 2001).

In the Mincer specification, the error term captures unobservable individual characteristics, and these characteristics also influence the education decision, hence this induces a correlation between education and the error term. This problem of endogeneity has always been there in the returns to education literature. There have been a few approaches to tackle this problem. For example, one is to have measures of ability (generally cognitive skills) incorporated in the model for unobserved effects. This inclusion of a measure of skills should reduce the estimated education coefficient, so that the education coefficient is capturing the effect of education alone as ability is controlled for. Also, attempts have been made to exploit within-twins or within-siblings differences (Harmon et al., 2003), on the assumption that unobserved differences between twins or among siblings will be almost similar. Another approach to deal with this problem is the use of a two-equation system, identified using instrumental variable which affects education but not wages (Dickson, 2013).

There has also been a developing spotlight in the past decade on non-subjective aptitudes and capacities (Heckman & Rubinstein, 2001). Non-cognitive abilities comprise of the practices, awareness, mental capacity, learning systems and social aptitudes that can profoundly affect the manner in which humans learn. For instance, a worker might be subjectively very productive. However, on the off chance that they don't have the determination to go into higher education, a worker will never arrive at their maximum capacity. For example, self-viability, coarseness, inspiration, discretion, versatility, positive thinking, trust, and the capacity to work with others are critical to the achievement of workers (Heckman & Rubinstein, 2001).

We will also focus on discussing the literature, particularly on the degree subject choice and its impact on the wage premium, and will learn how the wage premium estimates for graduates differ by gender, region, and ethnicity.

2 Returns to Graduate Subjects from 2005 to 2018: Understanding the Gender Difference

2.1 Introduction

Much of the existing analyses of returns to education have concentrated on the years of education undertaken by individuals or the levels of education completed. In recent years, attention has turned to the subject studied by individuals. This is what we concentrate on in this chapter. We are interested in the returns to subjects studied at university by men and women. Evidence to date (Britton et al., 2020; Belfield et al., 2018a, b; Walker & Zhu 2017; Britton et al., 2016) indicates that returns to education are higher for women than for men. Are these returns different by subject? Is there a different premium for some subjects than for others? Do these returns differ by employment type, region and ethnicity, as well as gender? This heterogeneity analysis will enable us to understand what might be influencing the gender differences. We analyse this issue using the Labour Force Survey for the UK between 2005 and 2018. Our results provide the overall context for further analysis that we undertake in Chapters 3 and 4. Chapter 3 assesses the changes over time in these returns and Chapter 4 considers the impact that ability might have on them.

Previous studies have evidenced that degree level qualification contributes to a significant rise in the wage premium. Individuals graduated in different degree subjects earn different subject premia. There is also evidence of a significant difference in subject wage premia among men and women (Walker & Zhu, 2011; Belfield et al., 2018; Britton et al. 2020). This chapter will add to the literature by presenting an in-depth study of the gender wage premium associated with different subject choices and the extent to which it varies based on the type of employment, region, and ethnicity.

To our knowledge, none of the previous literature has done an in-depth heterogeneity analysis of differences in the gender wage-premium covering the time period of 2005-2018 using the Labour Force survey (LFS).

2.2 Related Literature

Human capital theory suggests that higher education is positively associated with productivity and skills, and this is then reflected in the wage premium received by graduates compared to those with A-level qualifications (Becker, 1964).

In this section, we present a survey of recent literature on returns to subject choice. We have reported the most relevant studies in two Tables: Table 2-1 summarises 15 major studies on returns to subject choice at degree level in the UK, for the period 2001 to 2020, listed in chronological order, and Table 2-2 does the same for non-UK based studies. Both tables report the dataset used, cohort and time frame, the modelling approach and whether the analysis considered gender, ethnicity, and regional inequalities.

Table 2-1 Relevant literature from UK on returns to subject choice

Author	**Data Set**	**Cohort and time frame**	**Estimation approach**	**Analysis**	**Key Findings**
Britton et al. (2020)	Longitudinal Educational Outcomes (LEO)	Men and women. Birth Cohorts: from 1975-1985	Probit modelling for employment, Ordinary least squares (OLS)	-Subject choice analysis. -Gender analysis.	- Average earnings for graduate men grow from 5% at the age of 29 to 40% at the age of 60. - For women, the returns increase from 25% at the age of 29, then to 40% at the age of 40 but then drop back down to 35% at the age of 60. - Non-graduate women earnings grow faster in their 40s compared to graduates. - Subjects as medicine, law and economics offers lucrative careers. - Computing, education, and pharmacology are the safe choices. – Life-time earnings remain low or negative for subjects as creative arts and English.
a. Belfield et al. (2018)	Longitudinal Educational Outcomes (LEO)[5]	Men and women. Individual with at least 5 A*-C GCSE from 2002-2007 and age of 29 in both full time and part time work	Non-parametric analysis, OLS with Inverse, probability weighted regression adjustment	-Subject choice analysis. -Gender analysis.	- Impact of degree qualification on the wage premium for the individuals at the age of 29 is 6% for men and 26% for women. - Studying English or philosophy reduces the average earnings by 4%, whereas studying medicine and economics increases the average earnings by 20%.
b. Belfield et al. (2018)	Longitudinal Educational Outcomes (LEO)	Men and women. Earning sample: 2007-2012 Employment Sample: 2007-2010	OLS, Inverse probability weighted regression adjustment	-Subject choice analysis. -Gender analysis. -Ethnicity analysis	- Earning differences can be explained by characteristics of students taking different degrees. - Higher earning subjects and institutions typically take students with prior higher attainment. - Individuals from higher socio-economic backgrounds normally earn higher earnings. - Medicine and economics graduates earn almost 20% more. - Individuals in top institutions earn at least 30% more.

[5] Longitudinal Educational Outcomes (LEO) dataset created by the Department for Education. The dataset links administrative school, higher education and tax and benefit records from the following four component datasets:

- The National Pupil Database (NPD);
- Higher Education Statistics Agency (HESA);
- Her Majesty’s Revenue and Customs (HMRC) earnings and employment data;
- Work and Pensions Longitudinal Study (WPLS) benefits data.

Table 2-1 Relevant literature from UK on returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Walker and Zhu (2017)	Quarterly Labour Force Survey and HESA data	Men and women. Data Exclude Scottish HEI, Post-1992 universities and subjects allied to medicine. 2012 Q1-2015 Q2	OLS	-Subject choice analysis. -Gender analysis.	- Positive wage premium for medicine & dentistry, law and maths relative to the languages, arts and business administrative studies.
Britton et al. (2016)	Database of official earnings data for English domiciled (at the time they first borrow) borrowers from the Student Loan Company linked to HMRC and HESA data.	Men and women working full-time in work. 2002-2013 tax years for the cohort of 1999 and 2002	Quantile (10, 20, 30, 40, 50, 60, 70, 80, 90 and 95) regression analysis	-Subject choice analysis. -Gender analysis.	- There is a substantial earning difference between the graduates and non-graduates. - Subjects such as Medicine have higher earnings irrespective of the institutions. - Subjects as Creative arts are associated with lower earnings. - During the period of 2002-2011 there is a growth in number of students who got enrolled in business and administrative studies.
Vries (2014)	Destinations of Leavers of Higher Education (DLHE).	Estimation does not differentiate between men and women. For individuals in full-time work. Cohort graduated in 2012/13 Cohort graduated in 2008/09	Non-parametric analysis	-Gender analysis.	- After accounting for the university type and graduate characteristics there were no substantial differences in returns to degree subject choice. - Although individuals from the private schools had an advantage. - Economics and business graduates, whose parents had a high paid professional job can secure better paid jobs. - Private school attendees have an advantage in securing professional jobs.
Walker and Zhu (2013)	Labour Force Survey	Men and women in Full time work from 1993-2010	OLS, and probit modelling for employment	-Subject choice analysis. -Gender analysis.	- There is a substantial effect of degree on the net present value of the life cycle of incomes. - The wage premium is higher for good degrees than for the lower degrees. - There are no large differences in returns across the different types of Higher education institutions.

Table 2-1 Relevant literature from UK on returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Abreu et al. (2012)	Higher Education Statistical Agency (HESA)[6].	Estimation does not differentiate between men and women. Controlled for the full-time and part-time work for 2002/03	OLS	-Subject choice analysis -Regional Analysis. -Ethnicity analysis	- The results show that individuals in creative subjects earn lower salaries, and the employment status is rather precarious compared to non-creative subjects. - Non-creative (social sciences, business, law economics, medicine, education, languages) graduate females start with salary gap of about 5.5% after the graduation, whereas creative subjects (arts, communication, design, engineering, technology, architecture, and land scape design) graduates starts with a salary gap of 4.5% compared to males. This gap does not close and increases to 8.5% in 3 years. - Non-creative graduates working in London start with an average salary of 21.4% higher compared to their other counterparts, this gap is increased to 24.5%. Creative graduates in London start with a salary of 18.7% but this decreases to 14%.
Chevalier (2011)	Longitudinal Destination of Leavers of Higher Education. (DLHE)	Men and women in full-time workers for 2002/03	OLS	-Subject choice analysis. -Gender analysis.	- Male graduates have significantly higher earnings than females: economics (17%), Law (12%), IT (9%), subjects allied to medicine (8%). - Female graduates earn significantly more than males in the subjects of education (22%), combined science (21%), linguistics (14%), history and philosophy (9%) and mixed subjects with science (9%).

[6] Analysis is built on three different data streams:

1. The students in higher education institutions
2. The destination of leavers from higher education DLHE

The more recent 'Longitudinal Destination of leavers from higher education' LDHLE

Table 2-1 Relevant literature from UK on returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Walker and Zhu (2011)	Labour Force Surveys (LFS)	Men and women in full time workers from 2005-2009	OLS, estimated a differenced Mincer equation to remove the age and experience effect and quantile regression.	-Subject choice analysis. -Gender analysis.	- Wage premium for men is 10% across different quantiles for the STEM[7] subjects, and for women these results are similar. - Wage premium for men graduated in LEM[8] is 25%, for women it is over 30%. - Wage premium for men for the subject of OSSAH[9] was in-significant, for women graduated in OSSAH is earning like 13% more wage premium for the bottom quantile and 9% for the median.
Walker et al. (2010)	Labour Force Surveys (LFS)	Men and women both full time and part time workers from 1993-2005	OLS	-Subject choice analysis. -Occupational Analysis -Gender analysis.	- Higher education teaching professionals earn higher-than-average hourly earnings, compared to all other workers, although they also work longer hours than most. - If the higher education teaching professionals' earnings are compared to the graduates in the legal profession, consultants, engineers, physicians, and pharmacists the comparison is very poor. - The individuals in the school teaching did worse as compared to the higher education teachers.
Bratti et al. (2008)	British Cohort Study (BCS)	Men and women. Following the cohort of 1970	OLS	-Subject choice analysis. -Gender analysis.	- Undergraduate degree for men gives a premium of 15% and for women its 18% compared to individuals with two or more A-levels. - There is existence of positive wage return for a good degree class over the lower degree class. HE wages return to women is only little greater than that for the male graduates.

7 STEM: Science, technology, engineering, and mathematics.
8 LEM: Law, Economics and Management.
9 OSSAH: other social sciences, arts and humanities, including languages.

Table 2-1 Relevant literature from UK on returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Chevalier (2007)	10,384 graduates from 33 UK higher education institutions	Men and women. (Elias *et al.*, 1999). 1995 (analysis exclude students of over age 28)	Oaxaca-Blinder decomposition	-Subject choice analysis. -Gender analysis.	- Controls for subjects of graduation increases the gap to 50%, with the contribution of subject to the explained component reaching 77%. - The wage gap for graduates does not originate from differences in educational attainment but mostly from subject segregation. - Women graduated in different subjects that have lower financial returns. Women expecting to spend less time on the job market anticipate lower returns. - Women in UK are still paid 20% less than men.
Machin and Puhani (2003)	UK LFS German LFS	Men and women for the year of 1996	Oaxaca-blinder decomposition, OLS	-Subject choice analysis. -Gender analysis.	Subject Degree matters in explaining gender-related wage difference among the degree graduates. For both UK and Germany, the results show that the degree subject explains 2-4% higher wage for male over females.
Ashworth and Evans (2001)	941 students in their second and final year of A-level education at 33 institutions.	Estimation is done on full sample and does not differentiate between men and women for 1989	Multinomial Logit modelling for the decision to choose subjects	-Subject choice analysis.	- Several factors that make a difference in the decision to study economics like maths ability, achievement level of economics, previous studies in economics, classroom features.

Table 2-1 shows that the main datasets used in UK-based studies have been the LFS, LEO, HESA, DLHE and BCS. These studies vary, as some follow cohorts on a yearly basis, while others are cross-sectional over the years. Overall, LFS was the most frequently used dataset for less recent studies. However, more recent studies, particularly published by the Institute of Fiscal Studies, have made more use of the LEO dataset. This is because the LEO is linked to the HESA, HMRC earnings and employment data and WPLS so that analysis using LEO is able to use in-depth information on individuals' characteristics and yearly earnings at the age of 29. Another dataset, the BCS, follows the cohort of individuals born in England, Scotland, and Wales in the first week of 1970. It provides individual characteristic variables such as degree class, wage, and other individual background variables (Bratti et al., 2008). Chevalier (2007) and Ashworth (2001) used data from 33 higher education institutions. Finally, HESA data has been used by Abreu et al. (2012). They concentrated only on the graduate cohort from 2002/03 but were able to conduct various heterogeneity analyses. In this chapter, we will be using the LFS because it is a comprehensive dataset representing almost 0.1% of the UK population. It includes individuals of different ages from 2005-2018, provides information on hourly wages and is readily available to use from the UK Data Service. It therefore allows us to provide broad results, which we will build on in later chapters.

Looking at cohort and time frame, we can see that the most recent time frame uses quarterly LFS data for 2012-2015 (Walker & Zhu, 2017). Britton et al. (2016) and Belfield et al. (2018a; 2018b) used LEO, which is a cohort data with the latest information given up to 2012. The longest time frame has been used by Walker and Zhu (2013) from 1993-2010. In this chapter, we will be using data from 2005-2018 and therefore updating existing estimates.

Discussing the modelling and estimation approach used by the literature, Table 2-1 shows that the most common approach towards estimation of wage premia has been the OLS estimator. However, some recent studies like Britton et al. (2020; 2016) and Belfield et al. (2018a; 2018b) have estimated causal models, using an inverse probability weighted (IPW) function, by calculating the weighted probability of individuals choosing different subjects at degree level using the multinomial logit estimator. These estimated weighted probabilities were then included in a Mincer equation to calculate the subject premium estimates. IPW requires a set of characteristic variables to determine the values for the subject choice and is normally used in longitudinal cohort studies. In addition, the instrumental variable technique can also be used to obtain causal estimates. But finding an instrument that has an impact on the individual's subject choice and not the wage is especially difficult. Dearden (1999) gives a comparison of different empirical techniques and concluded that the Mincer (1974) education-wage-equation estimated using OLS gives reliable wage premium estimates.

Almost all the studies provide the wage premium estimates for male and female sub-groups, though only Chevalier (2011) gives the difference between females compared to males. Abreu et al. (2012) consider ethnic and regional differences for a single cohort of students who graduated in 2002/3. In this chapter, we will be exploring gender differences further, analysing in particular whether male and female returns differ by the type of employment (full-time/part-time), ethnicity and region.

Table 2-1 also shows that returns are higher for men and women with a degree qualification (Britton et al. 2020) than for those without. Women have higher returns to education at age 29 compared to men, although men's returns increase as they grow older, but women's returns to different degree subject choices decrease with age. The table also suggests that there is significant variation among the different subject choices for both men and women. For example, subjects such as economics, medicine and law offer higher returns, whereas subjects such as computing, education and pharmacy are the safe mid-return choices. However, subjects such as creative arts and English have lower, even negative, returns compared to individuals who are A-level qualified (Belfield et al., 2018a). Medicine seems to be an excellent option for women as the returns are more than 100%, that is earnings are twice as high as compared to women who did not attend university by the age of 40. Studies also show that the degree qualification in Medicine and Economics leads to higher earnings for individuals, irrespective of the institution attended and the personal characteristics of the individuals (Britton et al. 2016).

Belfield et al. (2018a, b) also show that, on average, the impact of degree qualification on the wage premium for individuals at the age of 29 is 6% for men and 26% for women. Walker and Zhu (2011) also confirm that wage premia vary with not only subject classification but also with degree class, experience, and cohort. A comparison of the UK subject-premia with those of other countries suggests similar results.

Table 2-2 Selected International literature on Returns to subject choice

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Ashworth and Ransom (2018)	Five major household surveys 1 American Community Survey (ACS) 2 Current Population Survey outgoing rotation groups (CPS) 3 National Longitudinal Surveys of youth (NLSY 79 and NLSY 97) 4 Panel Study of Income Dynamics (PISD) 5 Survey of Income and Program Participation (SIPP)	Birth cohorts 1950–1985: the 1980, 1990, and 2000. Census 5% Public Use Micro Samples and the 2001-2016 American Community Survey. For individuals working full time	OLS	Gender analysis	- All birth cohorts from 1950-1965 saw an increase in their wages, whereas there is a flattening of wages for the cohorts born in 1970 and there was decline in wages of those born after 1977 and continue for the birth cohorts of 1980s and after. - Demand for skill-based subjects is flattening and may even be falling in some cases. - The decline in wages is more pronounced for men than for women.
Lili et al. (2018)	China Family Panel Studies (CFPS)	Men and women aged 20-60 whose highest qualification is senior high school. 2010	OLS, Random Effect estimates and Inverse probability weighted regression adjustment	subject choice analysis, gender analysis	- Returns to Higher education have declined due to higher education expansion, except for Law, Economics and Management subjects from Key (Top rated) universities.
Kirkeboen et al. (2015)	Norwegian administrative data, Norwegian Population Registry.	Estimation done on full sample and does not differentiate between men and women for 1998 to 2004.	OLS and 2SLS instrumental variable technique	subject choice analysis, gender analysis	- For many subjects, the payoff rivals the University wage premium, suggesting that the subject choice is potentially as important as the decision to enrol in college. - The payoffs are largest for medicine, followed by engineering, science, business, laws and technology. - In comparison subjects as social science, education and humanities have substantially lower payoffs.

Table 2-2 Selected International literature on Returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Kamhofer and Schmitz (2015)	German Socio-Economic Panel, (SOEP)	2006 wave as it included information on cognitive skills and include birth cohorts from 1940-1970	OLS and Instrumental variable	subject choice analysis	- The increase in 1 year of higher education have a positive impact of 6.9% higher wages on average.
Kelly et al. (2010)	Graduates follow up survey from Ireland institution, 2001	Individual entered in labour market in 2002	OLS, quantile regressions	subject choice analysis	- Relative to Arts and humanities returns are higher for medicine and veterinary by 38%, for education 36.3%, social science by 14.7%, engineering and architecture by 13.4 percent, science by 12.7% and computer and IT by 7.5 percent, while there is no premium for business and law.
Arcidiacono et al. (2010)	Survey of male undergraduate students at Duke University.	Estimation done on full sample and does not differentiate between men and women for 2009	multinomial logit model	subject choice analysis, gender analysis	- Students sort out the subjects based on the expected earnings and perceptions of their relative ability to perform in a particular subject. - If the abilities are equalised more students like to take Economics and lower number of students take Humanities and social science.
Ammermüller (2005)	German Socio-Economic Panel study.	Men and women for 1985-2002	OLS	subject choice analysis, gender analysis, Regional Analysis	- The yearly returns are highest for the fields of law and medicine. - The lowest returns are observed for the theology, agriculture science and arts and music. - For men subjects as business, economics, natural sciences, and some engineering degrees yield high returns of over 90% compared to no-degree and lower or intermediate secondary education. - For women instead returns to engineering degrees are rather low, while the returns for studies to become a teacher are highest.

Table 2-2 Selected International literature on Returns to subject choice (Cont.)

Author	Data Set	Cohort and time frame	Estimation approach	Analysis	Key Findings
Staniec (2004)	National Education Longitudinal Study of 1998.	Followed the cohort of male and female eighth graders in 1988 up until 1994	Multinomial Logit model	subject choice analysis, gender analysis	- Asian Students have a higher probability of choosing SEM majors. - Females are less likely to choose SEM majors, irrespective of ability, income, parental variables, and expected returns. - Black ethnicities are more likely to choose SEM majors compared to their white ethnicity counterparts.
Trostel et al. (2002)	International Social Survey Program	Males and Females from 1985-1999	OLS and IV regress	subject choice analysis, gender analysis, Cross countries Analysis	- Average rate of schooling is 5% for men and approximately 6% for women. There is a variation across countries
Finnie and Frenette (2001)	National Graduates Surveys.	Males and females for three Cohorts 1982, 1986, 1990	OLS	subject choice analysis, gender analysis	- There is a significant gender differences in the distribution of graduates by discipline. - The highest earning fields are health, engineering, maths, physics, and computer science. The lower earning fields are arts and humanities, agriculture and biological sciences and other social sciences. Education and Economics are in the middle of earning distribution.

Table 2-2 summarises, in a similar fashion to Table 2-1, international studies in relation to returns to subject choice. Most of these papers relate to studies in Western Europe and North America, though we also consider one study from China, which provides a contrast in terms of the results.

The main data sets used in the international studies are panel or cross-sectional, for example, the German Panel Data Analysis, the China Family Panel Studies, and the International Social Survey Program. Some studies, like Staniec (2004), Kamhofer and Schmitz (2015) and Kirkeboen et al. (2015), use longitudinal data for different countries. In this chapter, we employ the cross-sectional data set to lay the foundation for subsequent longitudinal analysis in chapter 6.

Similar to the UK based studies, most of the wage premium heterogeneity analysis conducted in the international literature is also based on gender (Lili et al., 2018; Kirkeboen et al., 2015; Kamhofer & Schmitz, 2015; Kelly et al., 2010). A large study in terms of coverage is that of Trostel et al. (2002), which looks at 28 countries. It finds a positive return of 4-7% on average for each extra year of education received by individuals across the 28 countries. For men, this average is 5% and for women it is 6%. For the US labour market, Ashworth and Ransom (2018) show that there has been a flattening of demand and wages for the skills-based subjects for the birth cohorts of 1978, and it is even negative for the birth cohorts of 1980-1985. Kamhofer and Schmitz (2015) studying Germany, find that the difference in return is significant at 6.9% for 1 year of higher education, but there is no difference in returns for compulsory education. Ammermuller (2005) shows that in Germany men who graduated in business, economics, science, and engineering degrees are likely to earn 90% more income compared to non-degree and lower education individuals. Kirkeboen et al. (2015) study in Norway shows that subject choices are important decisions for future returns. The largest payoffs are for medicine, law, economics and engineering and the lowest payoffs are for education, social science, and humanities. In common, it seems that in the Western European countries and in the United States, the highest payoff is for individuals graduating in the subjects of medicine, engineering, economics and law, and lower payoffs are for the subjects of humanities and arts. However, in China due to the education expansion projects, there is a decline in the wage premium for graduates except for those from the top-rated institutions in the subjects of law, economics, and management (Lili et al., 2018).

In summary, the previous literature from the UK and other countries' labour markets show that undergraduate degrees are associated with higher earnings, and this is particularly the case for subjects like medicine, law, and economics, and slightly less so for subjects such as maths, engineering, pharmacology, and education (Britton et al, 2020). Instead, there appear to be low and negative returns for subjects such as creative arts and literature.

2.3 Research Question

Our core research question is to look at the gender gaps in returns to subject choice. While many studies in Table 2-1 and Table 2-2 have considered gender either as a control or separately, few have considered the extent to which the impact of gender varies across other factors, including full and part time work, ethnicity and region of employment.

The focus on the intersection of gender and employment patterns, ethnicity and region is important for the following reasons:

- It is often argued that women earn less across all subjects because they are more likely than men to work part time, often also because of the impact of career breaks. By considering whether returns to subject vary by full and part time employment, we can consider whether this is the case.
- Studies have found major wage differences between individuals employed in London and those employed in other regions of the UK (Francis-Devine, 2020).[10] London has a dominant presence of the financial services sector, which is associated with substantial wage inequality and is also a relatively high gender segregated sector. Both the so-called "very, very rich" and the "very rich" are disproportionately likely to be male, live in London and work in finance, law, or property (Brewer et al., 2008).

Research shows that the ethnicity-wage-gap is larger for men than for women (Belfield et al., 2018; Abreu et al., 2012; Evans, 2020).[11] In this chapter, we will explore this further and estimate the differences between white and non-white individuals working full/part time in different subjects.

[10] An illustration of the median weekly pay by region of residence is given in Appendix 2-1, Figure 2-2 Median Weekly pay by region of Residence.
[11] There is large literature on ethnicity wage gaps but it is beyond the scope of this study as we are more focused on the subject-wage premium associated with white and ethnic minority ethnicity.

2.4 Data and Methodology

Our analysis is based on the Mincer (1974) wage model and shares similar limitations to the previous literature. The main limitation is that the estimates provide correlations and not the causal effects of subject-groups on wages. In addition to this, we cannot control for individuals' skills, which would require data on individual characteristics, for example numeracy and literacy skills, which the LFS does not have. LFS also does not allow us to control for institutional differences because it lacks institutional variables and is also short on instruments to estimate the causal effects. However, the LFS is the most comprehensive data set on the UK labour force, with a sample of almost 1% of the UK population and information on around 33,000 households. Therefore, it will give reasonable estimates of the average earnings of graduates of different ages and ethnicities (Dearden, 1999). We will address the issue of causality and endogeneity in Chapter 6 by using the Next Steps dataset, which allows us to control for ability and skills.

The LFS is a quarterly survey, which includes a representative sample of households in the UK.[12] Data from the four quarters for each year are appended into annual data sets and these are pooled into one cross-sectional data set. Respondents in the LFS are surveyed for five successive quarters. For all years, observations with reported wages are kept and this is collected in wave 1. Therefore, in any annual data set constructed from the data for four quarters, no individual can be repeated in the constructed data set twice as the respondents in wave 1 cannot re-appear in the same calendar year.

Our sample includes individuals who are employed and have a minimum of two A-levels. We have dropped all the observations for individuals who did not achieve a minimum of two A-level qualifications, as this is the minimum requirement to enter the university. We have also dropped all individuals who are recent immigrants[13] (this is determined by dropping all the individuals listed in the variable 'first move to UK' in the LFS). This gives a pooled sample of 168,271 individuals from 2005 to 2018. The sample includes 75,462 males and 98,533 females, of whom 59,271 are with 2 or more A-levels and 114,724 are graduates.[14] The group of A-level qualified individuals will be our control group and will be used as a base category to compare the wage premium.

[12] An intended representative sample, whereas in reality there are always issues such as individual not responding, missing information or wrong information.

[13] According to Blundell et al. (2016), the proportion of UK workers born outside of the UK has doubled over the past two decades. It is debatable whether one should count immigrants with the university education or not. Immigrants are more likely to have university degrees than natives, but Dustmann et al. (2013), for instance, shows that immigrants usually work in places that do not match their observed skills and qualifications. This implies that adding immigrants with university education will understate the returns to education.

[14] Number of female graduates in the sample are 64,884 and number of male graduates are 49,840.

We are interested in investigating how differences in degree subjects influence the wage premium and how this varies by gender. To do so we estimate the effects of each subject at degree level on the wage premium of men and women using the Mincer framework of the human capital earning functions. We estimate a model similar to that of Dearden (1999, 2010), Card (1994, 1999, 2001) and Walker and Zhu (2008, 2011, 2013) to estimate the subject premium.

$$\log \boldsymbol{w}_i = \alpha X_i + \ rS_i + \delta \boldsymbol{x}_i + \gamma \boldsymbol{x}_i^2 + \vartheta \boldsymbol{t} + \varepsilon_i \qquad \text{Equation 2.1}$$

Here $\boldsymbol{w}_i$ shows the log of hourly wages for each year. The logarithm of hourly wage will be used as the dependent variable, derived from usual hours worked and usual hourly pay. To reduce measurement error, we have dropped any values below the hourly wage of £5 and above £99 as suggested by the Labour Force Survey guide 2018. This is because the minimum wage for individuals aged 21 and above increased to £ 5.05 in 2005 and more thereafter. S_i represents choice of degree subject from 2005-2018. The base category is of A-level qualification. $\boldsymbol{x}_i$ represents the number of years an individual has worked since completing their education and, therefore, represents a measure of experience in the labour market, $\boldsymbol{x}_i^2$ captures the concavity of experience earning profile and ε_i represents the error term. X_i represent characteristics of individuals such as gender, employment type, region of employment,[15] marital status and ethnicity. $\boldsymbol{t}$ represents the yearly time dummies from 2005-2018 to control for cyclicality of wages over the years. As proposed by Verdugo (2016), cyclical changes matter because at times of unemployment, demand is lower and so wages fall.

In addition to this we also want to estimate the gender difference in wage premium of graduates in different subjects compared to A-levels by including an interaction of gender with subjects chosen.

$$log\, \boldsymbol{w}_i = \alpha X_i + \ rS_i + \beta S_i * \ \boldsymbol{g}_{\eta i} + \ \lambda \boldsymbol{g}_{\eta i} + \delta \boldsymbol{x}_i + \gamma \boldsymbol{x}_i^2 + \varepsilon_i \qquad \text{Equation 2.2}$$

Here S_i is interacted with female gender dummy $\boldsymbol{g}_{\eta i}$, thus β will give the interaction coefficient of the difference by gender as we expect wage and subject choice relationship differs by gender. X_i here will control for ethnicity, region of employment and marital status. We will estimate this model for both full-time and part-time workers.

[15] We have used is for dummy variable for the individuals employed in London. The reason for this is because we particularly wanted to see the difference in wages for individuals working in London compared to other parts of UK.

To estimate the gender difference in wage premium by region of employment, we will be using the interaction between subject choice S_i and individuals employed in $\boldsymbol{London}_i$.

$$log\, \boldsymbol{w}_i = \alpha X_i + rS_i + \beta_1 S_i * \boldsymbol{London}_i + \omega \boldsymbol{London}_i + \delta \boldsymbol{x}_i + \gamma \boldsymbol{x}_i^2 + \varepsilon_i \ \ (for\ men\ and\ women) \qquad \text{Equation 2.3}$$

Equation 2.3 will give the estimates of the wage premium earned by male and female graduates employed in London, in different subject categories, compared to male and female graduates employed in other regions of the UK. In Equation 2.3 X_i will control for ethnicity and marital status. We will also split the sample by full-time and part-time to observe the differences in more dept (in Appendix 2-2).

Next, we investigate the wage premium for white male and female groups when we control for ethnicity.

$$log\, \boldsymbol{w}_i = \alpha X_i + rS_i + \beta_2 S_i * \boldsymbol{white}_i + \partial \boldsymbol{white}_i + \delta \boldsymbol{x}_i + \gamma \boldsymbol{x}_i^2 + \varepsilon_i \ (for\ men\ and\ women) \qquad \text{Equation 2.4}$$

In Equation 2.4, $\boldsymbol{white}_i$ is a binary variable which separates the white from the other ethnic minority individuals. Its interaction with the subject choice will help to determine the gender differences in subject-wage-premium by ethnicity. Here we will also split the sample by full-time and part-time work (given in Appendix 2-2). For Equation 2.4 X_i will control for region of employment and marital status.[16]

In summary Equation 2.1 is a general Mincer-type model that we follow to estimate the degree subject-premium. Equation 2.2 addresses gender more specifically and then addresses the Part-Time/Full-Time question by splitting the sample. Equation 2.3 addresses region and splits sample by gender. Equation 2.4 addresses ethnicity and splits sample by gender.

[16] Lastly, we will also consider white ethnicity individuals employed in London, a small sub-group within our data. This will certainly reduce the sample size but will be interesting as we will be able to find the gender difference between White ethnicity men and women employed in London:

$$log\boldsymbol{w}_i^{E,L} = \alpha X_i^{E,L} + rS_i^{E,L} + \varphi S_i^{E,L} * \boldsymbol{g}_\eta^{E,L} + \lambda \boldsymbol{g}_\eta + \delta \boldsymbol{x}_i^{E,L} + \gamma \boldsymbol{x}_i^{2\,E,L} + \vartheta \boldsymbol{t} + \varepsilon_i$$

Here $\boldsymbol{w}_i^{E,L}$ represent the wages for all the White ethnicity individuals employed in London. φ will estimate the difference in gender wage premium for different subject categories for the individuals living in London for the sample of White ethnicity. These results will be presented in Appendix 2-2.

2.5 Classification of Subject Categories

Undergraduate degrees in the LFS data are categorised into 19 subjects. Since some of the subjects have small cell sizes and some are clearly related to others, we have re-classified these 19 subjects into 7 categories using the JACS[17] code (as followed by Herman G. W. et al 2002):

Table 2-3 Classification of subject categories

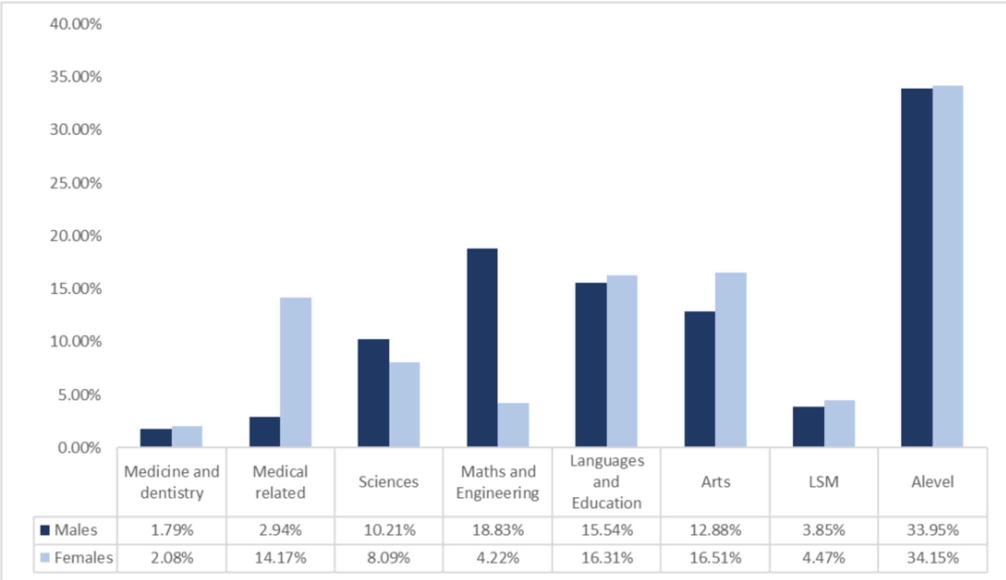
Categorisation	Degree Subject Choice	Males	Females
Medicine and dentistry *(medicine)*	**Medicine**	1,353	2,047
Medical related and nursing *(medical related)*	**Medical-related**	2,219	13,965
Sciences *(science)*	**Biology and related sciences** **Agriculture** **Physical Sciences**	7,706	7,967
Mathematics, computing, and Engineering *(maths and engineering)*	**Mathematics** **Engineering** **Technology** **Architecture** **Computing**	14,207	4,159
Languages, education and humanities *(languages)*	**Education** **Linguistics** **European Languages** **Other languages** **Humanities**	11,730	16,075
Fine arts, creative arts and performing arts *(arts)*	**Arts**	9,723	16,269
Law, social sciences and management *(LSM)*	**Business related** **Social Sciences** **Economics** **Law**	2,902	4,402
	A-level	25,622	33,649

(Source: data extraction using LFS 2005-2018)

Table 2-3 gives the percentage of men and women who have graduated in different subjects. There is a higher percentage of men with a degree in Mathematics, engineering and science subjects and a higher percentage of women with a degree in arts, medicine, medical related, languages and education subjects.

[17] Joint Academic Coding System.

Figure 2-1 Percentage of men and women graduated in different subjects



(Author's calculations using LFS 2005-2018)

Our sample data contain individuals who reported whether they are working full-time (97,739) or part-time (36,919). The top panel of Table 2-4 shows the break-down of males and females working full-time and part-time. The table illustrates that overall, there is a higher proportion of women (21.34%) than men (6.07%) who are in part-time work. There are a smaller percentage of women with A levels who work part-time; smaller percentage of women graduated in science, maths, LSM and Arts are in part-time than men.

Table 2-4 Number of males and females in full-time and part-time work and mean hourly wages

Subjects	**Full-time**		**Part-time**	
	FEMALES	**MALES**	**FEMALES**	**MALES**
A-levels	12,552 (27.3%)	15,587 (30.1%)	10,185 (35.4%)	3,043 (37.2%)
Medicine	1,063 (2.3%)	1,010 (1.9%)	674 (2.3%)	147 (1.8%)
Medical related	6,390 (13.9%)	1,610 (3.1%)	4,664 (16.2%)	244 (3.0%)
Science	4,286 (9.3%)	5,445 (10.5%)	2,103 (7.3%)	799 (9.8%)
Maths and engineering	2,260 (4.9%)	10,714 (20.7%)	1,080 (3.8%)	1,105 (13.5%)
LSM	8,838 (19.2%)	8,562 (16.5%)	4,178 (14.5%)	1,254 (15.3%)
Languages and humanities	8,432 (18.4%)	6,889 (13.3%)	4,458 (15.5%)	1,158 (14.2%)
Arts	2,109 (4.6%)	1,992 (3.8%)	1,400 (4.9%)	427 (5.2%)
Total	45,930	51,809	28,742	8,177
	(34.11%) +	(38.47%) +	(21.34%) +	(6.07%) +

(Author's calculations using LFS 2005-2018)

+ Percentage calculated using the full sample population.

*Table 2-4 Mean Gross hourly pay for full and part time workers with degree subjects (**Cont**.)*

Mean of Gross hourly pay for full/part time workers with different degree subjects (£s)				
	Full-time		**Part-time**	
Subjects	**FEMALE**	**MALE**	**FEMALE**	**MALE**
A-level	13.29	16.48	11.34	12.21
Medicine	20.62	28.00	23.36	41.02
Medical-Related	14.95	17.99	14.75	17.80
Science	16.52	19.76	15.99	18.65
Maths and engineering	18.55	21.70	17.67	19.25
LSM	17.51	21.66	15.69	18.66
Languages and humanities	16.63	19.50	15.58	16.95
Creative and Fine Arts	14.97	16.94	14.41	14.07

(Author's calculations using LFS 2005-2018)

+ Percentage calculated using the full sample population.

The bottom panel of Table 2-4 shows the mean of the hourly pay for males and females in full-time and part-time work. As expected, medicine graduates earn the highest hourly pay, but the part-time medicine graduates earn a higher mean hourly pay than full-time workers. Next, in decreasing order, is maths and engineering, then law, social science and management graduates followed by science and languages, lastly it is arts. In addition, we can also observe that men's hourly wages are higher than women's for all subjects, apart from medicine, for all other subjects, individuals in part-time employment earn lower wage than individuals in full-time employment. This higher premium for part-time medical specialists than full-time is interesting. British Medical Association reports suggest that, generally, junior medical doctors work full-time, whereas senior medical specialists and consultants are shifting towards part-time work.

2.6 Empirical Analysis

We present the results from the empirical analysis through two sets of tables. For each type of analysis, the first table (for example, Table 2-5 in this subsection) reports the coefficient values of each variable; the second table (for example, Table 2-6 in this subsection) focuses on the total interaction effects, when these are significant. The latter will allow us to estimate the overall impact of the interaction between gender and subject choice. We start with the overall results on the full sample and by gender and then, in each subsection, delve into the heterogeneity analysis by assessing the gender differences by full time and part-time employment, region of employment and ethnicity.

2.6.1 Wage Premium analysis by gender

Table 2-5 gives the wage premium earned by individuals with different subject degrees in comparison to individuals with A-level qualification. Column 1, estimated for the full sample, illustrates the average wage premium earned by graduates for the 2005-2018 period.

Table 2-5 Wage premium estimated for full-sample and gender interactions

	(1)	(2)
	All	Gender Interactions
VARIABLES	lhrpay	lhrpay
Base category: A-level qualified		
Medicine	0.5911***	0.6498***
	(0.0132)	(0.0215)
Medical Related	0.1970***	0.1670***
	(0.0055)	(0.0145)
Science	0.2663***	0.2345***
	(0.0061)	(0.0091)
Maths and Engineering	0.3546***	0.3278***
	(0.0060)	(0.0075)
LSM	0.2812***	0.2713***
	(0.0053)	(0.0085)
Languages and humanities	0.2388***	0.1877***
	(0.0053)	(0.0090)
Arts	0.1160***	0.0445***
	(0.0087)	(0.0142)
Females (male=0)	-0.1806***	-0.2159***
	(0.0036)	(0.0063)
Medicine#Female		-0.0865***
		(0.0270)
Medical Related# Female		0.0467***
		(0.0157)
Science# Female		0.0577***
		(0.0122)
Maths# Female		0.0649***
		(0.0133)
LSM # Female		0.0185*
		(0.0107)
Language# Female		0.0837***
		(0.0111)
Arts# Female		0.1204***
		(0.0179)
Employment type (FT=1/PT=0)	0.1963***	0.1954***
	(0.0044)	(0.0044)
Constant	0.6438***	0.6650***
	(0.0248)	(0.0250)
Observations	93,227	93,227
R-squared	0.2440	0.2450
Controlled for age, age-squared, region of employment, ethnicity, employment type, relationship status, yearly dummy variables		
Robust standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		
Note: Confidence intervals with the coefficients are given in (Author's calculations)		

Appendix 2-3 Figure *2-5* & Figure *2-5*

The hourly wage premium associated with different subject choices is listed as follows in decreasing order: Medicine (59%), Maths and Engineering (35%), LSM (28%), Science (27%), Languages, education, and humanities (24%), Medical Related (20%) and Arts (12%). Thus, medical graduates earn the highest premium followed by mathematicians and engineers.

Column (2) in Table 2-5 reports the interaction variable estimates between undergraduate subject-choice and gender. The results suggest that graduate women earn a higher wage premium for all different subject categories, apart from medicine, than men. One possible reason can be that women who graduated with maths and engineering have a higher chance of employment and observed a boost in engineering job market opportunities (Botcherby & Buckner, 2014). Another possible explanation for the men and women differences graduated in languages, education, arts, medical related is due to occupational differences, as women are more likely to take nursing, medical related and teaching occupations (Joy, 2006). A third and most important possibility, given that you are comparing with A level students is that women have less good employment opportunities than men if they are not educated.

Table 2-6 reports the total interaction effects of gender and subject from Table 2-5. It calculates the overall impact from the interaction of being a female choosing a particular subject compared to men with A-level qualification. Women who graduated in medicine earned the highest premium. Women get a higher premium for graduating in subject categories of medicine, maths, and engineering, followed by Science, LSM and Languages, education, and humanities. The estimates show that women earn less than the A-level qualified males if they are graduated in medical related subjects and arts. We believe the main reason can be that women who only have A-levels have very few options for employment, whereas men with only A-levels have an option to go into multiple employment. Therefore, the differential between A-levels and degree for men will be smaller than for women.

Table 2-6 Interaction term calculations from Table 2-5 (significant interaction coefficients only)

Subject	Interaction term calculation from Column 2 in Table 2-5
Medicine	0.347
Medical Related	-0.002
Science	0.076
Maths and Engineering	0.177
LSM	0.074
Languages and humanities	0.055
Arts	-0.051

(Author's calculations)

The average wage premium estimates from the Table 2-5 and Table 2-6 for different subjects and the gender differences shows that overall medicine is the highest paying subject on average and arts and creative arts is the lowest paying subject. Further to this Table 2-5 also shows that individuals working full-time earn higher than the part-time workers, following is the further discussion and analysis on the full-time and part-time workers based on their gender and degree subject choice.

2.6.2 Wage Premium analysis by gender and Full-time and Part-time Employment

Our results above clearly demonstrate that there is a significant gender difference in returns to subject choice. What is not clear is why this might arise? It is sometimes suggested that women have lower returns to certain subjects because they are more likely to work part-time. In this section, we will consider whether there is systematic evidence for this.

Table 2-7 Wage premium for full-time and part-time employed workers graduated in different subjects.

VARIABLES	Without Gender Interactions		With Gender Interactions	
	(1)	(2)	(3)	(4)
	Full-time lhrpay	Part-time lhrpay	Full-time lhrpay	Part-time lhrpay
Base category: A-level qualified				
Medicine	0.5310***	0.7111***	0.5947***	1.0674***
	(0.0139)	(0.0325)	(0.0205)	(0.1270)
Medical Related	0.1528***	0.2759***	0.1474***	0.2445***
	(0.0062)	(0.0108)	(0.0138)	(0.0703)
Science	0.2374***	0.2911***	0.2114***	0.3064***
	(0.0064)	(0.0158)	(0.0089)	(0.0443)
Maths and Engineering	0.3269***	0.3519***	0.3079***	0.3000***
	(0.0062)	(0.0208)	(0.0074)	(0.0382)
LSM	0.2618***	0.2712***	0.2573***	0.2950***
	(0.0057)	(0.0125)	(0.0084)	(0.0367)
Languages and humanities	0.2154***	0.2539***	0.1758***	0.2354***
	(0.0057)	(0.0121)	(0.0090)	(0.0350)
Arts	0.0898***	0.1734***	0.0339**	0.1328***
	(0.0097)	(0.0181)	(0.0149)	(0.0428)
Female (male=0)	-0.1384***	-0.0482***	-0.1687***	-0.0531***
	(0.0038)	(0.0124)	(0.0071)	(0.0174)
Medicine#Female			-0.1074***	-0.3965***
			(0.0276)	(0.1310)
Medical Related# Female			0.0196	0.0333
			(0.0156)	(0.0709)
Science# Female			0.0563***	-0.0190
			(0.0127)	(0.0470)
Maths# Female			0.0574***	0.0867*
			(0.0140)	(0.0449)
LSM # Female			0.0126	-0.0284
			(0.0113)	(0.0386)
Language# Female			0.0743***	0.0223
			(0.0116)	(0.0369)
Arts# Female			0.1089***	0.0507
			(0.0195)	(0.0470)
Observations	70,067	23,149	70,067	23,149
R-squared	0.2464	0.2018	0.2475	0.2028

Controlled for age, age-squared, region of employment, ethnicity, relationship status, yearly dummy variables.

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Confidence intervals with coefficients of column 3&4 are given in (Author's calculations)

Appendix 2-3 Figure *2-7* & Figure *2-9*

Table 2-7 shows the wage premium for full-time and part-time graduates compared to full-time and part-time workers with A-level qualifications only. Column 1 and column 2 show that both full-time and part-time workers with a degree earn a higher wage premium than those without. However, the returns of each subject are higher for full-time workers than for part-time workers in all subjects. We interact each subject category with gender to consider the male and female difference. The magnitude of graduate subject premium is higher for part-time workers, compared to the base category (Part-time workers with A-level qualifications only), than the wage premium for full-time workers[18] compared to the base category (Full-time workers with A-level qualifications only).

In Table 2-7, columns (3) and (4) report the gender differences and the interaction coefficients. Graduate women in all subject categories (except medicine) working full-time earn a higher wage premium compared to graduate men. The estimate for women working part-time is again negative and significant for medicine graduates but is positive and significant for the maths and engineering subjects. However, in other subjects, part-time women graduates do not earn significantly more or less than part-time male graduates, except in maths and engineering where the coefficient is positive and significant[19].

Table 2-7 shows that being female is associated with a lower wage premium. There is a smaller gap in the wage premium among men and women in part-time employment, compared to the wage premium gap among men and women in full-time employment.

Table 2-8 shows the total impact of being a female and graduated in a particular subject compared to A-level qualified males. As can be seen from Table 2-7, only some of the interaction terms are significant, it is these variables that we discuss in the table below. Females who graduated in medicine working either full-time or part-time earn a higher wage premium compared to men with A-level qualifications. Females who graduated in maths and engineering subjects also earn more than men with A-level qualification only. Women working full-time, who graduated in the Science, LSM and Languages,

[18] To test if the higher coefficients are not only because of reduced sample but there is an actual difference between the full-time and part-time workers graduate premium we estimate a model with a set of interaction variables between subjects and full-time workers. The estimates of these interaction terms are given in (Author's calculations)
Appendix 2-3, Table 2-21.

[19] This higher coefficient for women graduated in maths and engineering working part-time could possibly be because of female boost of employment in maths and engineering industry (Botcherby & Buckner, 2014).

education and humanities also earn a higher wage premium. The estimates also reveal that women graduated in arts working full-time earn a lower wage premium compared to men with A-level qualifications.

For women working part-time, wages are higher only in medicine, maths and engineering categories. In all other subject categories, there is no significant difference from the base category which is A-level qualified males working part-time. Women working part-time in medicine have the highest premium, this can be due to the fact that female doctors, as according to Grant-Kels (2019), are shifting towards part-time employment rather than full-time.

Table 2-8 Interaction term calculations from Table 2-7 (significant coefficients only)

Subject	**Full time**	**Part time**
Medicine # females	0.318	0.617
Medical Related # females	-	-
Science # females	0.099	-
Maths and Engineering # females	0.196	0.333
LSM # females	-	-
Languages and humanities # females	0.081	-
Arts # females	-0.026	-

(Author's calculations)

The interaction variables in Table 2-7 and Table 2-8 show that there is a significant difference between males and females among full-time and part-time individuals graduated in the different subjects, which calls for further investigation. Although Table 2-7 controls for region and ethnicity, it fails to explore these variables in detail and, therefore, we explore these further in the next part of the analysis.

2.6.3 Gender wage premium by region of employment

Individuals employed in London earn a significant wage premium, compared to those not employed in London. We consider this pattern in more detail, especially whether it differs across men and women. Table 2-9 shows the difference in wage premium between men and women living in London compared to other regions in the UK. We find interesting heterogeneity among medicine and medical related subjects compared to other subject choices. The interaction terms modelled in Equation 2.3, and reported in Table 2-9, show that male and female medicine and medical related graduates employed in London earn a lower subject premium compared to other region in UK. This contrasts to the pattern observed among all other subject choices. Individuals who graduated in LSM, particularly females, earn a higher wage premium if employed in London. Men and women graduated in Language and arts earn a higher premium if employed in London. This is also the case for law, economics, business, social-sciences, languages, humanities, history, geography, and arts.

Table 2-9 Wage Premium for graduates working in London

VARIABLES	All lhrpay	Females lhrpay	Males lhrpay
Base category: A-level qualified			
Medicine	0.5939***	0.5786***	0.6773***
	(0.0148)	(0.0178)	(0.0234)
Medical Related	0.1497***	0.2264***	0.1801***
	(0.0058)	(0.0065)	(0.0157)
Science	0.2723***	0.2882***	0.2233***
	(0.0066)	(0.0088)	(0.0098)
Maths and engineering	0.4206***	0.3890***	0.3280***
	(0.0064)	(0.0121)	(0.0081)
LSM	0.2660***	0.2785***	0.2596***
	(0.0059)	(0.0072)	(0.0094)
Languages	0.2190***	0.2677***	0.1742***
	(0.0058)	(0.0070)	(0.0098)
Arts	0.1015***	0.1559***	0.0260*
	(0.0097)	(0.0122)	(0.0158)
London (all other regions=0)	0.2623***	0.2274***	0.2643***
	(0.0102)	(0.0133)	(0.0149)
Medicine # London	-0.1317***	-0.1067**	-0.1805***
	(0.0364)	(0.0450)	(0.0554)
Medical related # London	-0.0683***	-0.0370*	-0.1485***
	(0.0169)	(0.0194)	(0.0409)
Science # London	0.0155	0.0337	0.0215
	(0.0180)	(0.0237)	(0.0266)
Maths and engineering # London	-0.0239	0.0360	-0.0266
	(0.0165)	(0.0301)	(0.0210)
LSM # London	0.0501***	0.0724***	0.0304
	(0.0147)	(0.0191)	(0.0220)
Languages # London	0.0420***	0.0472**	0.0488**
	(0.0153)	(0.0193)	(0.0241)
Arts # London	0.0461**	0.0545*	0.0732**
	(0.0224)	(0.0280)	(0.0365)
Constant	0.5917***	0.6139***	0.4262***
	(0.0249)	(0.0312)	(0.0395)
Observations	93,227	53,665	39,562
R-squared	0.2235	0.2017	0.2516

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Confidence intervals with coefficients of column 2 &3 are given in (Author's calculations)

Appendix 2-3 Figure *2-11* & Figure *2-4*

Table 2-10 is calculated from Table 2-9, giving the impact of graduates employed in London who graduated in different subjects compared to A-level qualified individuals in other regions in UK. We can see that men and women who graduated in Medicine and are employed in London earn a higher wage premium. Table 2-10 also shows that females who graduated in medical related subjects and LSM, employed in London, earn a higher premium compared to females with A-level qualification only, in other regions. Both men and women who graduated in languages and arts earn a higher wage premium if employed in London, compared to A-level qualified individuals employed in other regions in UK.

Table 2-10 Interaction term calculations from Table 2-9 (significant interaction coefficients only)

	All	Females	Males
Medicine # London	0.724	0.699	0.761
Medical related # London	-	0.416	-
Science # London	-	-	-
Maths and engineering # London	-	-	-
LSM # London	0.578	0.578	-
Languages # London	0.523	0.542	0.487
Arts # London	0.409	0.437	0.363

(Author's calculations)

Table 2-9 and Table 2-10 capture the effect of working in London compared to elsewhere in the UK on the wage premium for various subjects of men and women. We can see that there are certain subjects where individuals employed in London earn a higher wage premium compared to other regions in the UK. We wanted to explore this further and see if employment type (i.e. full-time/part-time) affects the wage premium coefficients. We split the sample into full-time and part-time males and females and presented in Appendix 2-2. This will reveal whether full-time or part-time employment for graduates in different subjects results in a different wage premium among male and female groups, employed in London, compared to their A-level qualified counterparts, in other regions in UK.

2.6.4 Gender wage premium by ethnicity

In this section, we will consider whether ethnicity affects the wage premium earned by men and women in different subjects. We will also consider whether this affects the gender difference in wage premia earned for different subjects. Table 2-11 shows the estimates of White individuals compared to the other ethnic minority graduates for different subject choices. White individuals earn a higher premium, compared to other ethnic minorities. However, the interaction terms between the subject graduates and White individuals show that White men and women graduated in medicine earn a lower premium compared to ethnic minority individuals graduated in medicine. For the graduates in medical related subjects, we can see that particularly White males earn a lower premium compared to ethnic minority males. Interaction between science subject and White individuals shows that White women earn a lower subject premium compared to ethnic minority females. The estimates for the languages and arts graduates also show that both white males and females earn a lower wage premium compared to ethnic minority males and females. An important insight is that the magnitude of lower wage premium is higher for men compared to women, which mean that within male and female' groups, white men earn lower premium compared to ethnic minority males. The estimates are not significant for the subjects of LSM, maths and engineering.

Table 2-11 Wage premium for white ethnicity graduates

VARIABLES	All lhrpay	Females lhrpay	Males lhrpay
Base category: A-level qualified			
Medicine	0.7024***	0.6568***	0.7372***
	(0.0229)	(0.0320)	(0.0310)
Medical Related	0.2038***	0.2393***	0.2412***
	(0.0156)	(0.0182)	(0.0347)
Science	0.3131***	0.3393***	0.2698***
	(0.0186)	(0.0241)	(0.0289)
Maths and engineering	0.4152***	0.4152***	0.3637***
	(0.0155)	(0.0264)	(0.0206)
LSM	0.3200***	0.3206***	0.3222***
	(0.0148)	(0.0191)	(0.0233)
Languages	0.3175***	0.3183***	0.3287***
	(0.0166)	(0.0208)	(0.0270)
Arts	0.2170***	0.2551***	0.1714***
	(0.0308)	(0.0382)	(0.0518)
White (all other ethnicities=0)	0.0950***	0.0578***	0.1617***
	(0.0105)	(0.0138)	(0.0160)
Medicine # White	-0.1794***	-0.1223***	-0.1392***
	(0.0282)	(0.0372)	(0.0423)
Medical Related # White	-0.0822***	-0.0255	-0.1131***
	(0.0166)	(0.0192)	(0.0381)
Science # White	-0.0400**	-0.0473*	-0.0492
	(0.0197)	(0.0256)	(0.0304)
Maths and engineering # White	0.0142	-0.0100	-0.0403*
	(0.0168)	(0.0292)	(0.0221)
LSM # White	-0.0245	-0.0128	-0.0332
	(0.0159)	(0.0204)	(0.0250)
Languages # White	-0.0890***	-0.0376*	-0.1464***
	(0.0176)	(0.0219)	(0.0286)
Arts # White	-0.0968***	-0.0772*	-0.1272**
	(0.0321)	(0.0399)	(0.0539)
Constant	0.6107***	0.6388***	0.4259***
	(0.0265)	(0.0334)	(0.0418)
Observations	93,227	53,665	39,562
R-squared	0.1943	0.1749	0.2225

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Confidence intervals with coefficients of column 2 & 3 are given in (Author's calculations)

Appendix 2-3 Figure *2-6* & Figure *2-8*

Table 2-12 gives the overall impact of white men and women who graduated in different subjects compared to A-level qualified individuals. Our results (column 2) show that white ethnicity females earn significantly higher premium if graduated in medicine, science, languages, and arts compared to A-level qualified ethnic minority females. Similarly white ethnicity males earn a significantly higher premium when graduated in medicine, medical related, maths, engineering, languages, and arts compared to ethnic minority males.

Table 2-12 Interaction terms calculations from Table 2-11 (significant interaction coefficients only)

	All	Females	Males
Medicine # White	0.618	0.592	0.759
Medical Related # White	0.216	-	0.289
Science # White	0.368	0.349	-
Maths and engineering # White	-	-	0.485
LSM # White	-	-	-
Languages # White	0.323	0.338	0.344
Arts # White	0.215	0.235	0.205

(Author's calculations)

Looking at the interaction terms and its calculations we can infer that overall, White graduates earn a lower wage premium compared to the ethnic minority graduates. However, White individuals earn a significantly higher premium than the a-level ethnic minority individuals or ethnic minority men and women earn much less in jobs after A-levels than White men and women do.

To explore subject-premium further by ethnicity we have also split the sample by males and females in full-time and part-time employment to understand the difference in between White and ethnic minority ethnicities, results are presented in Appendix 2-2.

Lastly with the regional and ethnicity differences within male and female groups presented above, we think it will be interesting to have a more specific focus and estimate the gender wage-premium difference among different subject choices for white males and females graduated in different subject choices and employed in London. Although this is not the focus of this chapter and demands further investigation of literature focused on the regional ethnicity dilemmas, therefore we have presented and discussed results in Appendix 2-2.

2.7 Conclusion

Our estimates in this chapter show that there is significant difference between the wage-premium associated with different subject choices. The highest premium is for graduates of medicine, maths and engineering degrees. Graduates in the subjects of creative and performing arts and medical related subjects such as nursing etc earn a lower wage premium compared to the A-level qualified individuals. This lower wage for arts graduates can be because arts qualified individuals enter the same job market as A-level qualified individuals but much later, this gives A-level individuals advantage over arts graduates as they gain extra experience (Britton et al., 2016). This is true for both full-time and part-time individuals.

There is a difference between males and females as A-level qualified females earn a lower premium compared to males. However, degree graduate females earn a higher premium compared to their male counter parts, especially for the subjects of maths, engineering, science, languages, and arts.

Individuals employed in London earn a higher wage premium maybe because it is harder to secure a job in London but particularly women who graduated in LSM working in London earn a higher wage premium. Alternatively, both males and females graduated in medicine and medical related subjects earn a lower wage premium if they are employed in London.

Individuals from white ethnicity also earn a higher premium compared to other ethnicities but this is not the case for graduates. Graduate males from ethnic minorities earn a higher premium when compared to white males for all subject categories. Graduate ethnic minority females in the subject categories of science and arts also earn a higher wage premium compared to white females.

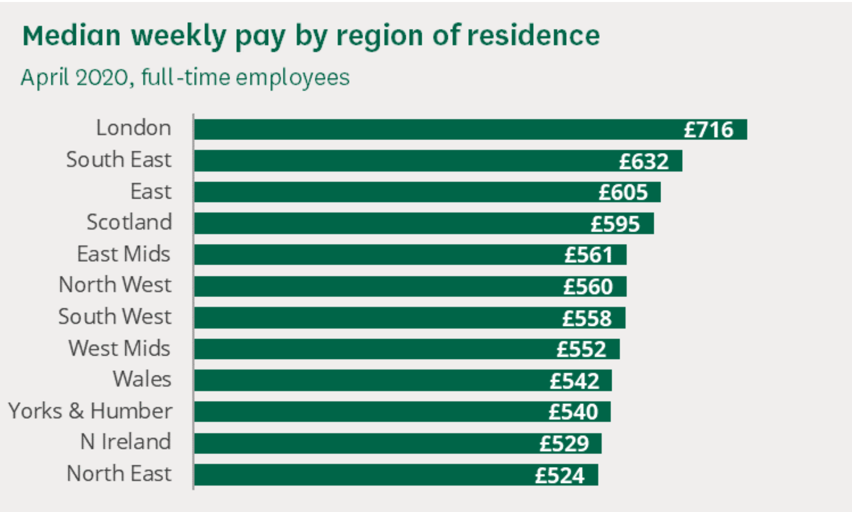
Finally, estimates for white males and females employed in London shows that graduate females earn a higher wage premium than white males for all subject categories except medicine. This is particularly true for the full-time workers, but the coefficients are insignificant for the part-time workers.

This can be useful in terms of understanding the males and females wage premium differences and improving on the policies based on reducing the gender wage gap. These results are also useful in looking at the policies related to the promoting the graduate degree subjects which are more in demand in the labour market.

2.8 Appendix

2.8.1 Appendix 2-1

Figure 2-2 Median Weekly pay by region of Residence



Source: https://commonslibrary.parliament.uk/research-briefings/cbp-8456/. Graph illustrating the median weekly pay by region of residence

Table 2-13 Median weekly pay for full time employees in different regions of UK

Median weekly pay, full-time employees (£)

2020 prices, adjusted for CPI inflation; data at April each year

	North East	North West	Yorkshire and The Humber	East Midlands	West Midlands	East	London	South East	South West	Wales	Scotland	Northern Ireland
1997	465	480	463	470	473	502	622	518	472	467	468	446
1998	461	485	479	476	489	514	639	535	480	471	479	455
1999	472	493	482	487	496	523	651	542	487	476	494	467
2000	492	509	501	494	509	535	687	564	502	489	506	479
2001	493	524	511	512	529	560	709	589	521	505	525	489
2002	503	537	525	528	535	573	731	612	532	510	542	499
2003	501	546	540	546	543	586	749	625	549	523	548	506
2004	530	565	558	554	564	601	774	641	561	549	560	533
2005	535	567	556	565	561	596	775	628	558	543	570	537
2006	539	570	559	573	564	602	778	641	565	547	585	550

2007	538	578	562	561	572	599	780	641	571	538	587	532
2008	544	581	571	575	580	606	792	647	577	543	598	540
2009	550	580	569	575	576	604	792	648	573	556	596	551
2010	539	568	560	566	569	594	781	637	560	548	594	532
2011	523	535	536	534	541	570	755	616	537	525	565	518
2012	514	531	525	525	530	560	737	606	528	511	563	517

Table 2-143 Median weekly pay for full time employees in different regions of UK (Cont.)

Median weekly pay, full-time employees (£)

2020 prices, adjusted for CPI inflation; data at April each year

	North East	North West	Yorkshire and The Humber	East Midlands	West Midlands	East	London	South East	South West	Wales	Scotland	Northern Ireland
2013	519	531	529	523	535	557	723	592	530	519	561	512
2014	519	523	519	517	519	546	715	587	526	514	563	499
2015	533	531	528	520	534	561	716	600	534	520	572	526
2016	535	546	540	523	552	572	726	612	548	535	579	534
2017	532	542	530	527	543	575	729	606	548	525	576	527
2018	522	545	536	531	552	574	734	606	547	524	580	533
2019	538	555	543	540	557	586	744	619	556	539	582	539
2020	521	560	539	552	553	575	761	609	550	538	593	529

Source: https://commonslibrary.parliament.uk/research-briefings/cbp-8456/. Graph illustrating the median weekly pay by region of residence

2.8.2 Appendix 2-2

GENDER WAGE PREMIUM BY REGION OF EMPLOYMENT AND EMPLOYMENT TYPE (FT/PT)

Table 2-15 estimates the subject-wage-premium for males and females employed full-time and part-time in London. Compared to all the regions in the UK, people employed in London earn significantly more for both full-time and part-time work.

The interaction terms themselves in Table 2-15 show that on average both males and female graduates in medicine and medical related subjects earn a lower wage premium if they are full-time employed in London compared to other regions. The interaction terms also show that females graduated in LSM subjects employed in London earn a higher wage premium compared to other regions in the UK. Another interesting estimate, which is not discussed in the literature, is that both males and females' part-time workers who graduate in arts and languages earn a higher wage premium if employed in London in other UK regions.

Table 2-15 Estimates for graduate men and women in different subject choices employed in London.

	Female Full time	Female Part time	Male Full time	Male Part time
	(1)	(2)	(3)	(4)
VARIABLES	lhrpay	lhrpay	lhrpay	lhrpay
Base category: A-level qualified				
Medicine	0.5032***	0.6678***	0.6256***	1.0357***
	(0.0200)	(0.0345)	(0.0225)	(0.1483)
Medical Related	0.1778***	0.2791***	0.1691***	0.2365***
	(0.0077)	(0.0112)	(0.0149)	(0.0738)
Science	0.2609***	0.2785***	0.2077***	0.2489***
	(0.0097)	(0.0175)	(0.0096)	(0.0473)
Math & engineering	0.3595***	0.3758***	0.3135***	0.2721***
	(0.0129)	(0.0259)	(0.0080)	(0.0412)
LSM	0.2589***	0.2484***	0.2523***	0.2533***
	(0.0082)	(0.0137)	(0.0093)	(0.0393)
Languages and Education	0.2455***	0.2461***	0.1700***	0.1827***
	(0.0080)	(0.0133)	(0.0098)	(0.0376)
Arts	0.1355***	0.1676***	0.0219	0.0797*
	(0.0142)	(0.0214)	(0.0166)	(0.0474)
London (all other cities=0)	0.2317***	0.1825***	0.2578***	0.2498***
	(0.0164)	(0.0215)	(0.0152)	(0.0550)
Medicine # London	-0.1441***	0.0381	-0.1902***	-0.1334
	(0.0508)	(0.0924)	(0.0513)	(0.2812)
Medical related # London	-0.0665***	0.0422	-0.1569***	-0.2275
	(0.0222)	(0.0382)	(0.0407)	(0.2107)
Science # London	0.0204	0.0536	0.0127	0.1505
	(0.0267)	(0.0494)	(0.0263)	(0.1353)
Maths and engineering # London	0.0175	0.0765	-0.0294	-0.0018
	(0.0332)	(0.0671)	(0.0210)	(0.1134)
LSM # London	0.0422*	0.1232***	0.0180	0.1262
	(0.0220)	(0.0388)	(0.0219)	(0.1073)
Languages # London	0.0203	0.1068***	0.0316	0.2177**
	(0.0220)	(0.0399)	(0.0241)	(0.1089)
Arts # London	0.0211	0.1146**	0.0567	0.2404*
	(0.0319)	(0.0569)	(0.0379)	(0.1232)
Observations	34,499	19,162	35,568	3,987
R-squared	0.2170	0.1947	0.2367	0.2436

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2-16 gives the total calculations of the interaction variables between subject choice and employed in London (full-time/part-time) compared to the A-level qualified males and females (full-time/part-time) in other regions in the UK. Both males and females individuals, graduated in Medicine and working fulltime in London, earn a higher wage premium than those with A-level qualifications. The estimates also show that females graduated in LSM subjects employed in London gain a significantly higher wage premium compared to the A-level graduates. Similarly, females graduate in LSM, languages, arts working part-time in London also earn a higher premium compared to the A-level qualified females in London. For males graduated in Medicine and Medical related subjects working in London full-time earn a higher premium compared to A-level qualified males. For part-time males graduated in languages and arts working in London also earn a higher premium compared to A-level qualified working part-time.

Table 2-16 Interaction term calculations from Table 2-15 (significant interaction coefficients only)

	Female Fulltime	Female Parttime	Male fulltime	Male Parttime
Medicine # London	0.590	-	0.693	-
Medical related # London	0.343	-	0.270	-
Science # London	-	-	-	-
Maths and engineering # London	-	-	-	-
LSM # London	0.532	0.554	-	-
Languages #London	-	0.535	-	0.650
Arts # London	-	0.464	-	0.569

(Author's calculations)

GENDER WAGE PREMIUM BY ETHNICITY AND EMPLOYMENT TYPE (FT/PT)

Next in Table 2-17 we show the wage-premium earned by white males and females who have graduated in different subject categories compared to their A-level qualified counterparts working full/part time. Both white males and females earn a higher wage premium compared to other ethnicities and this is significant for both part-time and full-time workers.

When interacting ethnicity and gender, we find that, generally, white men and women earn a lower wage premium compared to other ethnicity men and women. This is particularly the case for male full-time workers and females graduated in science and arts. White female medicine graduates working part-time earn lower wages than ethnic minority women graduated in medicine, although this is not the case for white females who are medicine graduate and full-time workers. Table 2-17 also shows that white men working full-time with a degree in medicine earn lower wage premium than their ethnic minority counterparts, as is the case for medical related graduate males and females. Looking at the science subject graduates we can observe that both white males and females working full-time earn a lower premium compared to ethnic minorities who are full-time employed science graduates. The estimates for the science graduates working part-time are insignificant for both males and females. We can also observe that white males with a degree in maths and engineering working full-time earn a lower premium than A-level white males in full-time work but if they (males) are part-time workers they earn a higher wage premium than A-level part-time white males, which could be the effect of the lower sample size.

Lastly, we can also observe that both white males and females earn a lower wage premium if they have graduated in Arts subject.

Table 2-17 Estimates for white ethnicity graduate males and females.

	Female Full-time	Female Part-time	Male Full-time	Male Part-time
	(1)	(2)	(3)	(4)
VARIABLES	lhrpay	lhrpay	lhrpay	lhrpay
Base category: A-level qualified				
Medicine	0.5098***	0.9883***	0.6951***	0.9674***
	(0.0349)	(0.0741)	(0.0316)	(0.1648)
Medr	0.1482***	0.3512***	0.2171***	0.2096
	(0.0214)	(0.0366)	(0.0349)	(0.1735)
Sci	0.3291***	0.2252***	0.2569***	0.1904**
	(0.0260)	(0.0527)	(0.0302)	(0.0907)
math_eng	0.3659***	0.3951***	0.3531***	0.1621**
	(0.0286)	(0.0645)	(0.0218)	(0.0654)
Lsm	0.2853***	0.2601***	0.3287***	0.1112*
	(0.0227)	(0.0359)	(0.0244)	(0.0655)
languages	0.2789***	0.2926***	0.3294***	0.2143***
	(0.0241)	(0.0417)	(0.0280)	(0.0831)
Arts	0.2688***	0.1453**	0.1410**	0.2254
	(0.0429)	(0.0692)	(0.0554)	(0.1454)
White (all other ethnicities =0)	0.0534***	0.0526**	0.1540***	0.0547*
	(0.0176)	(0.0210)	(0.0175)	(0.0359)
Medicine # White	-0.0472	-0.3692***	-0.1588***	0.0785
	(0.0412)	(0.0817)	(0.0417)	(0.2226)
Medical Related # White	0.0173	-0.0806**	-0.0968**	-0.0048
	(0.0227)	(0.0380)	(0.0379)	(0.1892)
Science # White	-0.0698**	0.0660	-0.0545*	0.0986
	(0.0278)	(0.0554)	(0.0317)	(0.1027)
Maths and engineering # White	0.0096	-0.0045	-0.0453*	0.1329*
	(0.0317)	(0.0695)	(0.0232)	(0.0786)
LSM # White	0.0002	0.0163	-0.0522**	0.2113***
	(0.0241)	(0.0383)	(0.0260)	(0.0775)
Languages # White	-0.0230	-0.0322	-0.1549***	0.0079
	(0.0254)	(0.0435)	(0.0296)	(0.0916)
Arts # White	-0.1182***	0.0508	-0.1017*	-0.0985
	(0.0450)	(0.0723)	(0.0577)	(0.1529)
Observations	34,499	19,162	35,568	3,987
R-squared	0.1862	0.1795	0.2060	0.2250

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Below Table 2-18 shows the total calculations of the interaction variables, giving the total impact of white males and females who graduated in different subjects compared to ethnic minority A-level qualified individuals. We can see that graduate white ethnicity males working full time earn significantly higher premium compared to A-level qualified males. The higher premium is also significant for part-time working white males with a degree in maths, engineering and LSM subjects. White females with a degree in Science and Arts earn a higher premium compared to A-level qualified and the estimates are also significant and positive for part-time white females graduated in medicine and medical related subject categories.

Table 2-18 Interaction term calculations from Table 2-17 (significant interaction coefficients only)

	Female Full-time	Female Part-time	Male Full-time	Male Part-time
Medicine # White	-	0.671	0.690	-
Medical Related # White	-	0.323	0.274	-
Science # White	0.312	-	0.356	-
Maths and engineering # White	-	-	0.461	0.349
LSM # White	-	-	0.430	0.377
Languages # White	-	-	0.328	-
Arts # White	0.204	-	0.193	-

(Author's calculations)

GENDER WAGE PREMIUM DIFFERENCE IN LONDON FOR WHITE ETHNICITY INDIVIDUALS

Finally, we turn to consider the wage premium of White males and females employed in London (Table 2-19). Although they rely on a reduced sample size, the estimates allow us to explore the differences in wage-premium for a particular region and ethnicity in more detail. To do this we restrict our sample to white individuals employed in London, we estimate the coefficients for both full-time and part-time workers and have gender interactions for different subject categories. Table 2-19 shows that the estimates for the subject categories for White ethnicity individuals graduated in different subjects living in London are similar to the ones estimated from previous models and reported in Table 2-5, Table 2-7, Table 2-9 and Table 2-11.

However, in comparison to the previous models, Table 2-19 illustrates that white males and females living in London earn a higher wage premium if they graduated in LSM and are working part-time (when compared to the estimates of part-time workers in Table 2-5 and Table 2-7), whereas maths and engineering graduates have slightly lower wage premium coefficients (when compared to Table 2-5 and Table 2-7). Another noticeable estimate is that the coefficient is higher for the individuals' who graduated in Languages and Humanities working part-time, and they earn approximately 49% more than A-level qualified individuals.

Looking at the gender interaction we can see that, besides the medicine graduate, white female graduates working full-time in all subjects including medical related and arts, earn a positive wage premium compared to white men employed in London. Estimates show that the gender difference is significant for degree qualified individuals who are working full-time but the coefficients are not significant for the part-time working individuals.

Table 2-19 Gender difference for white ethnicity individuals employed in London

White ethnicity individuals employed in London	Full lhrpay	Full time lhrpay	Part time lhrpay
Base category: A-level qualified			
Medicine	0.5106***	0.4265***	0.9907***
	(0.0708)	(0.0575)	(0.2948)
Medical Related	0.0253	0.0196	-0.1343
	(0.0488)	(0.0474)	(0.3496)
Science	0.2275***	0.2026***	0.4604***
	(0.0279)	(0.0273)	(0.1548)
Maths and engineering	0.2916***	0.2762***	0.3292**
	(0.0226)	(0.0222)	(0.1677)
LSM	0.2738***	0.2591***	0.3690**
	(0.0231)	(0.0227)	(0.1494)
Languages and education	0.1718***	0.1434***	0.4909***
	(0.0244)	(0.0243)	(0.1290)
Arts	0.0561	0.0381	0.2504*
	(0.0356)	(0.0366)	(0.1365)
Females (males=0)	-0.2694***	-0.2096***	-0.1869**
	(0.0216)	(0.0240)	(0.0810)
Medicine # females	-0.0856	-0.0590	-0.4937
	(0.0881)	(0.0843)	(0.3108)
Medical Related # females	0.1401***	0.0901*	0.3908
	(0.0539)	(0.0541)	(0.3522)
Science # females	0.0886**	0.0750*	-0.1336
	(0.0381)	(0.0404)	(0.1633)
Maths Engineering # females	0.1411***	0.1333***	0.0748
	(0.0421)	(0.0446)	(0.1850)
LSM # females	0.0795**	0.0449	0.0163
	(0.0313)	(0.0333)	(0.1546)
Languages # females	0.1326***	0.1229***	-0.1726
	(0.0319)	(0.0337)	(0.1353)
Arts # females	0.1405***	0.0981**	0.0430
	(0.0451)	(0.0483)	(0.1486)
Constant	0.9399***	0.7756***	1.3389***
	(0.0773)	(0.0778)	(0.1908)
Observations	11,317	9,360	1,957
R-squared	0.2013	0.1984	0.2091
Controlled for age, age-squared, relationship status, region of employment, ethnicity, yearly dummy variables			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Confidence intervals with coefficients are given in (Author's calculations)

Appendix 2-3 Figure 2-10 & Figure 2-12. It can be observed that confidence intervals are quite large, this is because of the reduction in sample size, hence coefficient are less precise.

Table 2-20 reports the overall interaction effects from the estimates of wage premia earned by graduate white women employed in London compared to white A-level qualified individuals employed in London. White ethnicity females who graduated in Maths and engineering, science, languages, and education employed in London earn the higher wage premium compares to graduate males. For individuals working full-time the estimates are positive and significant for science, maths and engineering, languages, and education. However, females in London who graduated in medical related subjects and arts working full-time earn a lower wage premium when compared to A-level qualified males.

Table 2-20 Calculated interaction terms from Table 2-19 (significant interaction coefficients only)

Subject	Both	Full time	Part time
Medicine	-	-	-
Medical Related	-0.104	-0.099	-
Science	0.047	0.068	-
Maths and engineering	0.163	0.199	-
LSM	0.083	-	-
Languages and education	0.035	0.057	-
Arts	-0.073	-0.073	-

(Author's calculations)

2.8.3 Appendix 2-3

Table 2-21 Estimates of full-time workers interacted with the graduate subject choice.

VARIABLES	(1) lhrpay
Medicine	0.6933***
	(0.0330)
Medical related	0.2469***
	(0.0104)
Science	0.2802***
	(0.0158)
Maths and engineering	0.3553***
	(0.0205)
LSM	0.2557***
	(0.0123)
Languages and Education	0.2394***
	(0.0119)
Arts	0.1651***
	(0.0179)

	(1)
VARIABLES	lhrpay
full-time	0.2700***
	(0.0069)
medicine#full-time	-0.1717***
	(0.0359)
medr#full-time	-0.1369***
	(0.0120)
sci#full-time	-0.0381**
	(0.0170)
math_eng#full-time	0.0143
	(0.0214)
lsm#full-time	0.0007
	(0.0135)
lang_sub#full-time	-0.0354***
	(0.0132)
arts#full-time	-0.0820***
	(0.0204)
Constant	0.5419***
	(0.0248)
Observations	93,216
R-squared	0.2536

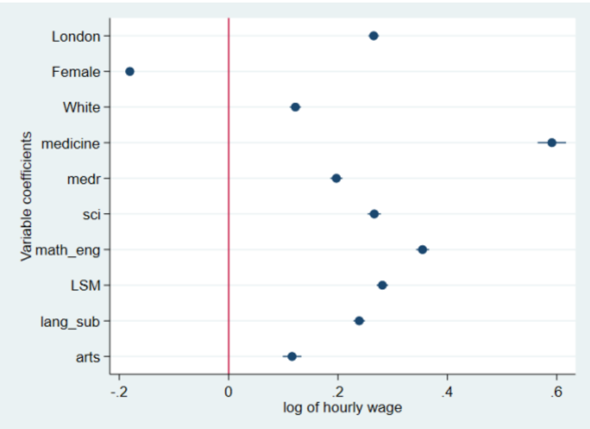
Controlled for age, age-squared, relationship status, region of employment, yearly dummy variables

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 2-3 Table 2-5 column 1 coefficients and confidence intervals

Figure 2-4 Table 2-9 column 3 coefficients and confidence (For Males)



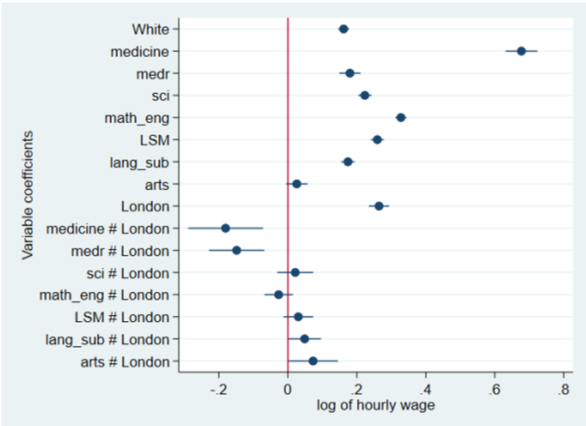


Figure 2-5 Table 2-5 column 2 (gender and subject interactions) coefficients and confidence intervals

Figure 2-6 Table 2-11 column 2 coefficients and confidence (For Females)

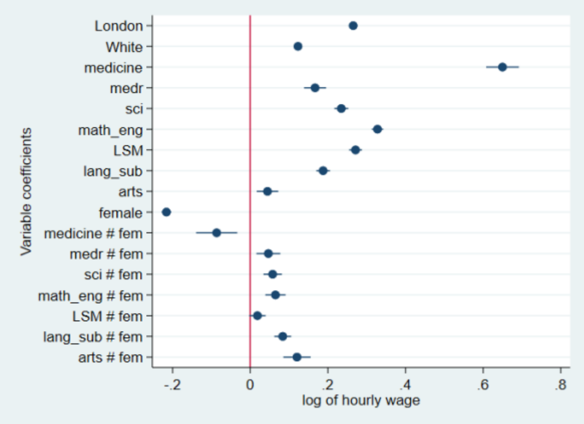


Figure 2-7 Table 2-7 column 3 coefficients and confidence intervals (Full-time workers)

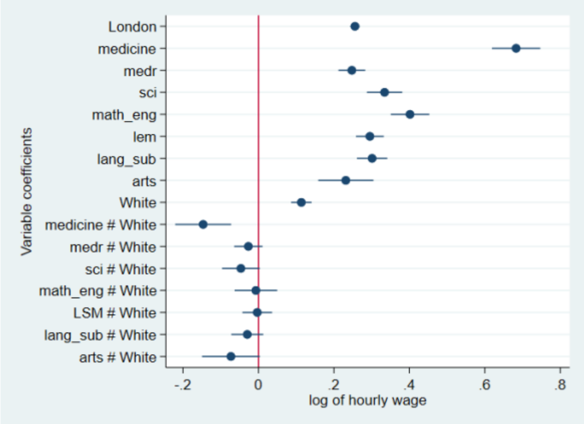


Figure 2-8 Table 2-11 column 3 coefficients and confidence (For Males)

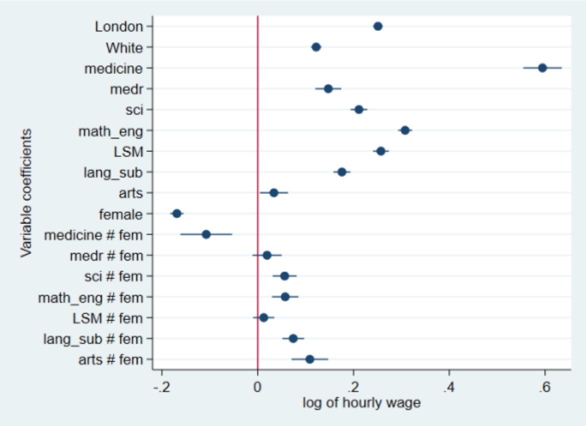


Figure 2-9 Table 2-7column 4 coefficients and confidence intervals (Part-time workers)

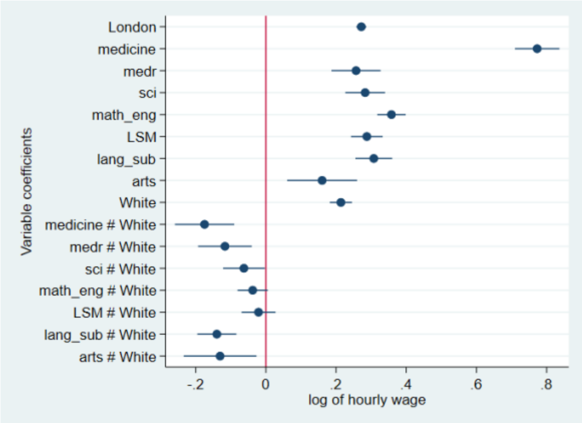


Figure 2-10 Table 2-17 column 2 coefficients and confidence (For Full-time)

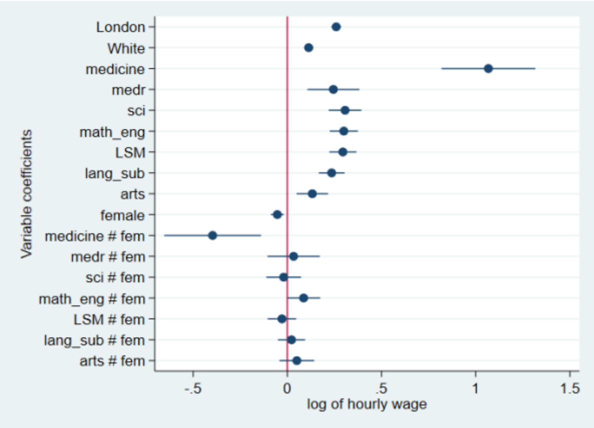


Figure 2-11 Table 2-9 column 2 coefficients and confidence (For Females)

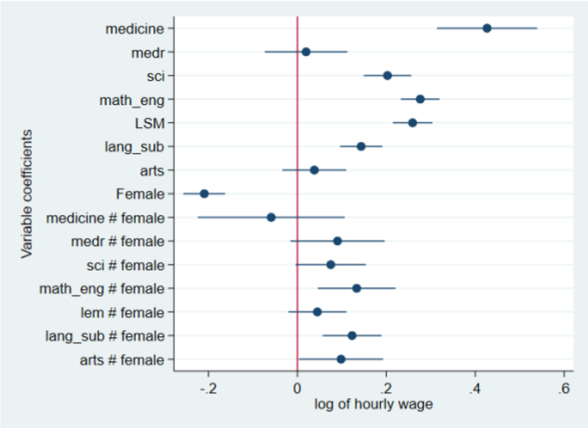
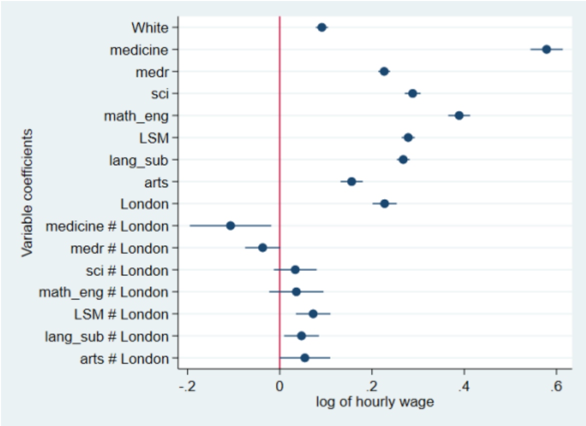
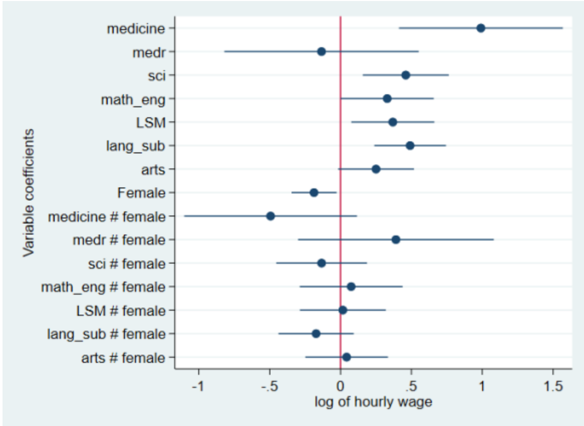


Figure 2-12 Table 2-17 column 3 coefficients and confidence (For Part-time)





3 New Graduates Educational Returns and Professional Vs Non-Professional Jobs: Impact of Financial Crisis 2008/09

3.1 Introduction

In this chapter, we consider the impact of the 2008 financial crisis on returns to subject in the UK. The 2008 crisis had wide-ranging effects on the labour market. According to Loh and Scruton (2018), by the end of 2011, almost 2.7 million people were looking for work, the unemployment rate had reached 8.4%, the highest rate since 1995. The unemployment rate returned to its pre-financial crisis level at the end of 2015. There was a significant decrease both in manufacturing jobs and in non-professional jobs during and after the crisis by approximately 33% in 2011. Earnings lagged prices for almost a full decade. The public sector had a pay freeze in 2011 and a pay cap was introduced in 2013, while in the private sector wage growth was also slow (Loh & Scruton, 2018).

In this chapter, we will consider the impact of the financial crisis of 2008/09 on the wages of individuals who graduated in different subjects from 2005-2018. As indicated above, unemployment reached a peak in 2011 and fell back to its pre-crisis level by 2015, so our chosen period covers both these years. Secondly, we focus on new graduates i.e., those who entered the labour market during this period. We expect that they are the ones who are most likely to have been affected by the crisis. Lastly, we will consider whether the financial crisis changed the probability of securing different types of jobs, in particular professional jobs[20] for which graduates are trained.

3.2 Literature

In examining the effect of economic crisis on the wages of individuals, it is important to understand that the main impact of a financial crisis on any labour market is to depress employment. Unemployment greatly reduced the incomes of those who were affected by financial crisis and with time put pressure on the wage premium of those individuals who were still in employment (O'Farrell, 2010). Changes in the labour market during the financial crisis of 2008/09 had three main effects on the wage premia:

1. There was an immediate positive effect on average wages because lower productivity - lower paid jobs were affected the most compared to higher productivity-higher paid jobs during the financial crisis (Pissarides, 2009).
2. Labour productivities tend to decrease during recessions (De long & Waldmann, 1997) because there is less demand in the market and companies have additional capacity. This places downward pressure on the wage premium. Redundancies have greater impact on the wage premium of lower productivity workers (for example those with less experience) than the wage premium of productive workers (with more experience). Additionally, when the number of working hours is reduced, it is usually the less productive workers who face the most impact.
3. With time, there will be a depressing effect on the wages of individuals, because of higher unemployment relative to the vacancies available, which makes it easier for employers to fill in the vacancies and more difficult for the workers to find suitable employment. As a result, employers are in a better position to bargain, and workers see a reduction in the nominal wage. This has a multiplier effect and will further reduce demand.

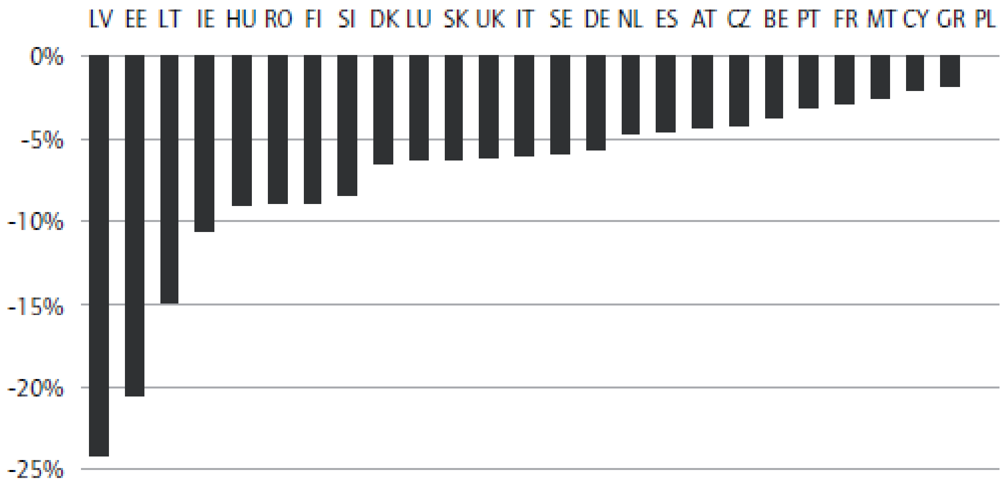
The financial crisis had significant impact on levels of employment in the UK as well as on wages. In the next section, we will discuss the Global Financial Crisis of 2008/9 in more detail and will have a look at how it affected wages in Britain.

3.2.1 FINANCIAL CRISIS OF 2007/08

[20] Shapiro (1975) defined non-professional jobs to include craftspeople, plumbers, electricians, installers, and food service workers or, in general, positions that primarily entail manual labour duties and trade skills learned through an apprenticeship or training program. Whereas professional jobs are defined as placements which require bachelor's, master's or a higher degree and include teachers, doctors, accountants, lawyers, engineers, scientists, nurses, and other specialist service jobs.

The collapse of Lehman Brothers marked the tipping point of the confidence in the financial sector. Figure 3-1 shows the decline in GDP across Europe from the time of a country's peak to the end of the third quarter of 2009. All European countries except Poland saw a real decline in GDP during the financial recession of 2008/09. This downturn also influenced the workers' wage share. The UK also saw a drop of 6% in real GDP.

Figure 3-1 Percentage decline in real GDP (from peak real GDP to the quarter 3 of 2009)



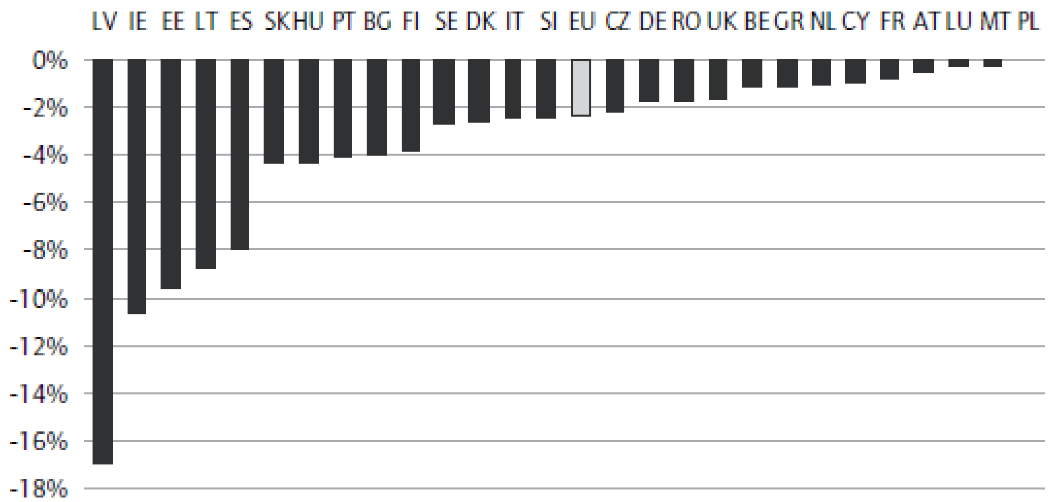
Source: Eurostat quarterly national accounts; seasonally adjusted data (taken from O'Farrell, 2010, pp. 7)

CHANGE IN EMPLOYMENT

European countries apart from Poland also observed a reduction in employment and working hours compared to a decrease in wages[21]. Figure 3-2 shows that countries which observe the largest fall in real GDP also observe the largest fall in the employment. The change in employment is not only affected by GDP but also by other policies such as short-term employment schemes (Leschke & Watt, 2010).

Figure 3-2 Change in employment (from the time of country's peak employment to Q3 2009)

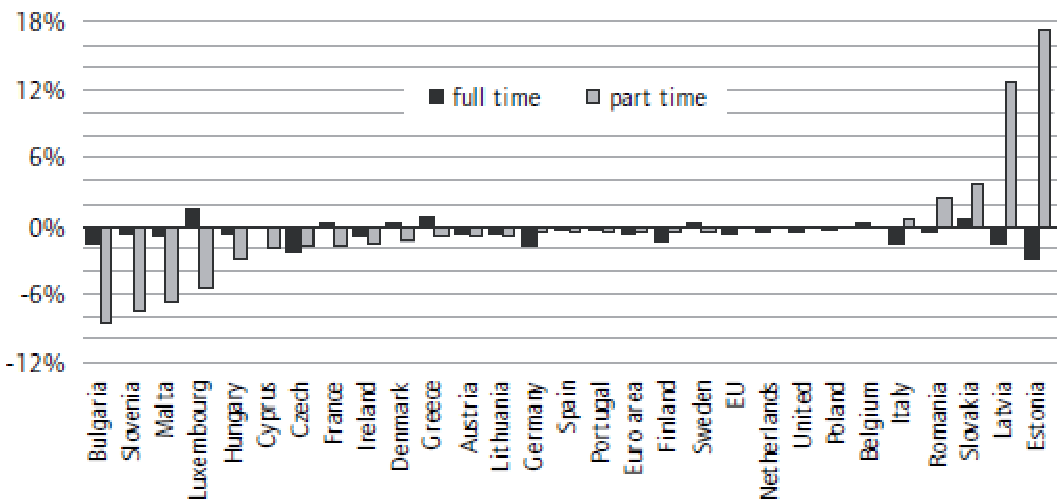
[21] Although there was a decline in the wages of individuals who were employed in the UK (see Figure 3-4), there was a higher degree of impact on the unemployment rate.



Source: Eurostat quarterly national accounts; seasonally adjusted data (O'Farrell, 2010, pp. 7)

In addition to the change in employment there was a change in working hours. Figure 3-3 below shows the change in actual hours worked in their main job. It can be observed that, between 2008 and 2009, there have been more pronounced changes in part-time than full-time working. This could be due to part-time workers normally having flexible arrangements. There was a general pattern of decreasing number of hours, although some countries, like Belgium, Greece, and Luxembourg, saw an increase in number of working hours. However, the UK did not experience much change in the number of hours worked. In what follows, we consider whether the impact of the crisis was different across groups: were existing (degree graduate) workers protected from the effects of financial crisis while new graduates entering the labour market faced difficulties? Therefore, it will be useful to know if there were any changes in the wages of new-graduates during/after the financial crisis compared to the wages of new-graduates before.

Figure 3-3 Change in hours worked (2008 to 2009)



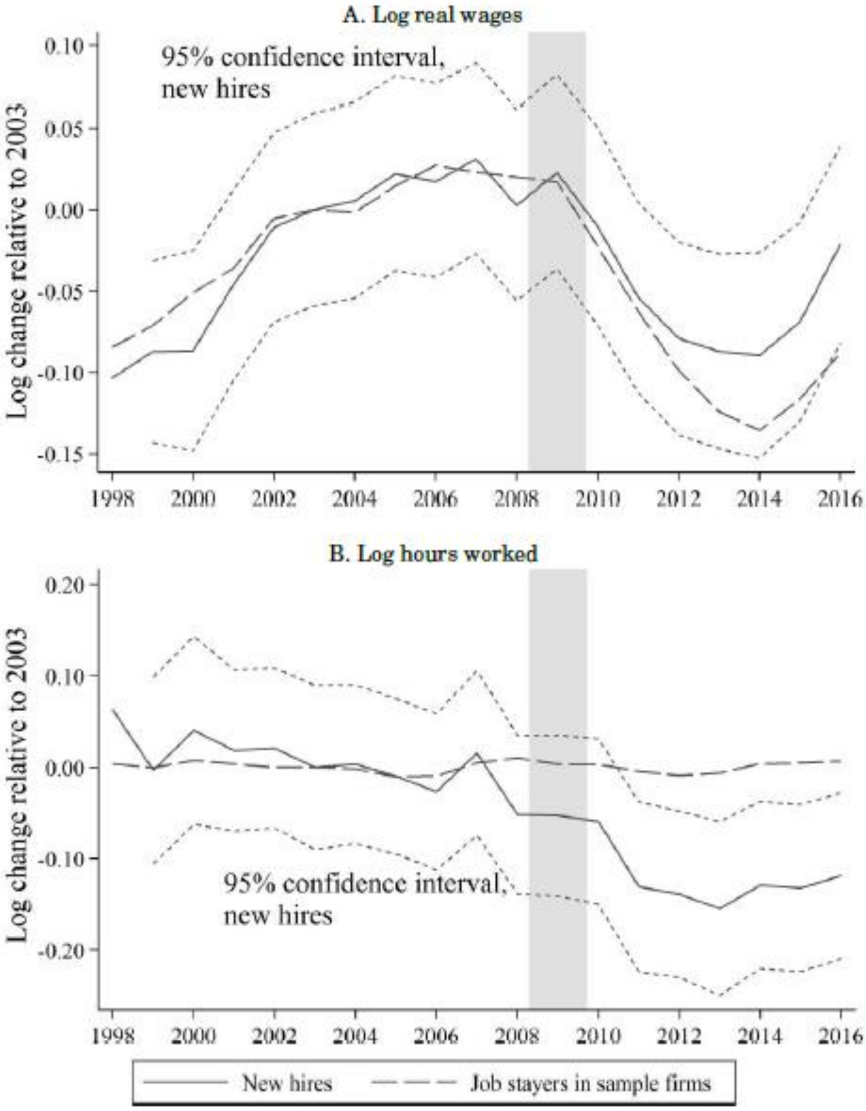
Source: Eurostat Labour Force Survey (O'Farrell, 2010, pp. 7)

The time before the economic crisis of 2008/2009 was a time of low growth in real average wage in Europe. The stagnation in wages began just before the stagnation in economic growth and this resulted in a falling labour share of income (O'Farrell, 2010). Overall, the employment and wages growth rates were not fast enough to maintain a steady labour share of income in different countries. There was a decline in both real and nominal wages (Weisbrot & Ray, 2010). While some countries in Europe saw an increase of 2.35% in real wages, this can be explained by a change in the composition of workforce, where higher skilled workers with higher wages stayed in jobs while the lower levels workers were laid off (O'Farrell, 2010). Overall, there were differences between industries and how wages have changed in Europe, countries which experienced the largest fall in the real GDP during the financial crisis, also experienced a decline in wages. These differences are due to the different policies being pursued by government to minimise the effects of the financial crisis.

In the UK, according to Blanchflower et al. (2017), real wages fell by 2% between 2008-2014 which was followed by a modest growth in 2015-2016. Similarly, the nominal wage had also continued to stall as employment fell from the last quarter of 2016 to the end of the first quarter of 2017.

According to Schaefer and Singleton (2018) real hiring (anybody being newly employed) wages were increased by 13 log points between 1998 and 2007 and the individuals who were already in jobs saw an increase of 14 log points in the same industry. Schaefer and Singleton (2018) also show that the hiring (anybody being newly employed) wages decreased by 12 log points between 2007 and 2014, whereas the job-stayers observed a decline in wages between 2008 and 2012 by 14 log points for men and 8 log points for women (Elsby et al., 2016). The changes in real log wages can be seen in the following Figure 3-4 given by Schaefer and Singleton (2018). Schaefer and Singleton (2018) also present evidence that, in comparison, there was a smaller drop in wages of new hires during the recession.

Figure 3-4: Estimated period-fixed effects for log real wages and log hours worked, including 95% confidence intervals for new hires, 1998-2016.

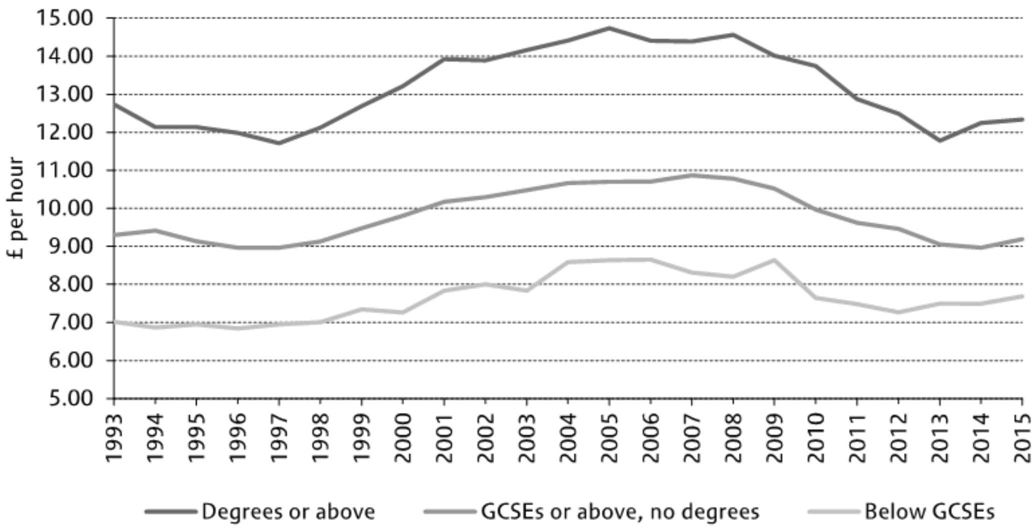


Source: Schaefer and Singleton (2018), pp 10. Notes for figure: "The 95% confidence interval for job stayers (not shown) is very narrow and almost indistinguishable from the long-dashed like. Standard errors are robust to clustering at the firm-level. Excluded reference category in first-step regression (1) is 1998 for new hires, and regression (3) excludes 1998 & 2016. Series normalised to zero in 2003. Shaded area marks official Financial Crisis 2008/2009. Series normalised to zero in 2003. New hires are for wages at entry level jobs where employees have less than twelve months of tenure. Job stayers are for jobs and employees who have tenure greater than twelve months, and only for firms which are ever represented in the CH firms' sample."

Figure 3-4 (b) shows the estimated series for hours worked by the individuals employed. It depicts that the hours worked by new hires decreased by 15 log points between 2007 and 2014. However, the hours worked by job-stayers saw no significant change during the financial crisis of 2008/09. In conclusion, once the cyclical composition bias is corrected the magnitude of impact of the financial crisis on real wages was much greater compared to previous studies.

Figure 3-5 from Blundell et al. (2016) reveals that the median hourly wage of new graduates fell by nearly 20% in between 2008-2013 (IFS briefing note BN185). The level in 2015 is about 15% below that in 2008 and is about the same as in the 1990s. The real median wage among school leavers also fell by 15% between 2008-2018, though the median wage differential between graduates and school leavers has essentially stayed flat at around 35% since 1990s for individuals aged 25-29 years.

Figure 3-5: Median real hourly wages of 25–29-year-olds, by education



Source: Blundell et al. (2016) The puzzle of graduate wages, Institute of Fiscal Studies briefing note BN185.

During the 2009-11 periods, when wage declines were most observed by the labour force, the earnings of 22 to 29-year-olds fell by 10.6%, compared with just under 7% for older age groups. Average pay for the over-60s recovered to its pre-crisis level by 2014; but it remained 9% lower than in 2008 for those aged 22 to 29 (Belfield et al., 2016). Therefore, in this chapter we look at the wage-premium of new graduates in different subject categories.

Ramsey (2008) examines Destinations of Leavers of Higher Education survey (DLHE) data for the UK graduating class of 2008 six months after graduation. The study attempts to determine whether since 2005 there were any significant differences in wages among new graduates coming from different educational backgrounds. The results show that there was a substantial variation in new-graduates' early salaries. Graduates from university earn a salary of £25000, which is almost three times more when compared to their peers (salary of £9000). The report also found that the starting salary among graduates from different subjects was linked to professions with defined careers and higher entry level training, such as medicine and teaching. Other subjects as mathematics, engineering, and computer science were also linked to higher professional level jobs compared to subjects like arts and design. In addition to this, differences in the graduate wage premium can also be related to individual characteristics, skill level and family background; for example, higher earning courses attract higher ability students from more advantaged backgrounds who would have the potential to earn a higher wage premium anyway.

Studies such as those of Elias and Purcell (2004) and Walker and Zhu (2008) suggest that the graduate wage premium has remained high; Walker and Zhu (2011) confirmed these findings up till 2009. O'Leary and Sloane (2011) study LFS from 1997-2006 and report that the returns to degree have been levelled and didn't increase or decrease after 2001 for both men and women. However, the most striking positive change in subject-premium was for males who graduated in medicine.

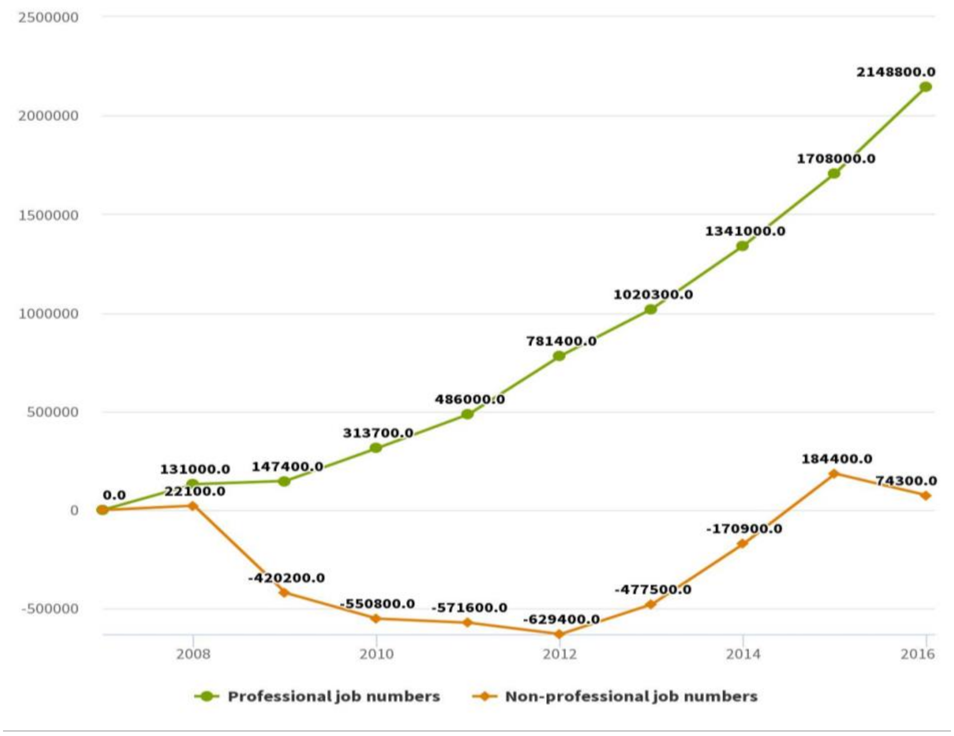
<u>New graduates and professional/non-professional jobs</u>

Next, we will consider the impact of the financial crisis of 2008/09 on the success of new degree graduates with different subject categories securing employment. When considering employment outcomes, the professions are split into Professional jobs[22] and non-professional jobs, with professional jobs seen as the ones that graduates would, ideally, be entering into. It has been recorded previously that university participation in the UK has increased during the last 4 decades (Chevalier 2010, 2011; Walker & Zhu 2005, 2011); for some a degree leads to better paid jobs, but the access to professional jobs is unequal amongst graduates.

The financial crisis of 2008/09 lasted from the second quarter of 2008 to the third quarter of 2009 and the UK very nearly re-entered recession during late 2011 and early 2012 due to a very slow recovery of the economic environment. The UK non-professional job market did not really recover until late 2011 and early 2012 due to a very slow recovery of the economic environment. The non-professional labour market also took seven years to recover to the point where there were more people in jobs than in 2008, despite adding nearly two million people in labour force during this period. In contrast, the professional job market was flat until 2009 but observed a rapid growth after that until 2016. Figure 3-6 gives the number of professional and non-professional jobs since 2007.

Figure 3-6 The increase in the number of professional and non-professional jobs since 2007

[22] Shapiro (1975) defined non-professional jobs include craftspeople, plumbers, electricians, installers, and food service workers or, in general, positions that primarily entail manual labour duties and trade skills learned through an apprenticeship or training program. Whereas professional jobs are defined as placements which require bachelor's, master's or a higher degree and include teachers, doctors, accountants, lawyers, engineers, scientists, nurses and other specialist service jobs.



Source: Grove (2018), Annual population survey, ONS

According to Grove (2018) "two categories among the non-professional jobs that is 1. administrative and secretarial occupations, and 2. skilled trade occupations were among the areas that saw the greatest decrease in employment numbers. Neither of these occupations has ever employed more people than they did in 2007".

Universities UK (2010) investigated the impact of the financial crisis in 2008/09 on graduates in different subjects. The focus of this report was on analysing the effects of degree subjects on the risk of being unemployed for graduates employed from 2006-2009. The findings were that graduates of medicine and engineering were at lower risk of being unemployed, whereas individuals who were at high risk had graduated in the subjects of arts, archaeology, cinema and photography during the financial crisis.

Universities UK (2010) results also suggest that in terms of the likelihood of new graduates finding a job, graduates in medicine and related subjects had an advantage during the financial crisis compared to all other subjects. Similarly, Chevalier (2011) examined the effects of degree subject on the earnings of new graduates. His findings also suggested that higher wage-premia are preserved for the degree subjects of medicine, maths and engineering, architecture, economics, education and computer science and these subject graduates are more likely to secure professional jobs compared to arts, linguistics, psychology, classics, and social sciences graduates, who are more likely to be in non-professional jobs. Macmillan et al. (2015) used DLHE data from students graduating in 2007 to report that graduates in medicine, law, economics, and business were more likely to secure professional jobs, while graduates in other subjects struggled to find professional jobs during the financial crisis.

This paper will add to the literature on the impact of the financial crisis of 2008/9 on the wage-premium of new graduates and the likelihood of finding professional employment, ten years after the crash. In summary, the existing literature shows that there was a fall in real GDP and employment during the financial crisis. Studies also show that there was a decrease in number of work hours of employed individuals. Following on from this, we ask in particular how the wage premium of graduates (employed) changed after the financial crisis. The next section will give a breakdown of the research questions we will consider in this chapter.

3.3 Research Questions

The previous literature shows that there was a significant effect of financial crisis of 2008/09 on both employment and wages. There has been less analysis of the impact of the crisis on graduates in different subjects and on professional vs non-professional occupations. In this chapter, we will analyse both the yearly subject-wage premium and the impact of the financial crisis on the subject wage premium of new graduates. In addition, we will also look at the impact of the 2008/09 financial crisis on the probability of securing a professional job for different subject graduates. In this chapter, we will do the following:

1. First, we will start by estimating the year-on-year wage premium for each subject category from 2005-2018 compared to A-level qualified individuals. This analysis will be useful in terms of knowing the graduate wage premium associated with different subjects compared to the individuals who do not have a degree. It also provides a link to our analysis in the previous chapter.

2. Secondly, we will estimate how the subject premia of new graduate cohorts graduating during and after the financial crisis (08/09) changed over the years from pre-financial crisis onwards? We will estimate the wage premium of individuals who graduated during and after the financial crisis and see how these premia evolved till 2018. In doing this, the focus will be on new graduates with minimum work experience, entering the labour market directly after graduation. While our base category in Chapter 2 was A-level qualified individuals, in this section of the chapter, we restrict ourselves to graduates and therefore our base category is those graduating in Law Social Science and Management degrees (LSM),

3. Lastly, we will consider whether the likelihood of new graduates obtaining professional jobs changed following the financial crisis?

3.4 Data and Methodology

As in Chapter 2, we use LFS data. Table 3-1 shows the percentage of new-graduates from the LFS data set for different time-periods (2005-2007, 2008-2010, onwards, so before, during and after the financial crisis). The table indicates that there were small changes in the proportion of students studying each subject following the financial crisis (2008-2011). From 2012 onwards, however, there was an approximately 4 percentage points increase in the graduates of LSM and Arts subject categories. During this period, there was also an approximately 8 percentage points decrease in the number of students graduating in languages and approximately 1-2 percentage points drop in the number of new graduates for Maths and Engineering.

Table 3-1 Percentage distribution of new graduates in each subject category for each time-periods

	2005-2007	2008-2011	2012-2015	2016-2018
Medicine	2.8%	2.4%	2.7%	2.3%
Medical related	7.0%	8.3%	8.8%	9.4%
Science	16.5%	15.4%	15.3%	15.9%
Maths & Eng	15.4%	16.5%	14.2%	14.4%
LSM	24.8%	22.4%	28.2%	28.1%
Languages	27.1%	28.4%	20.6%	20.2%
Arts	6.3%	6.5%	10.1%	9.7%

(Author's calculations using LFS)

Table 3-2 sets the context for our second research question by providing the frequency of different occupation types - professional and non-professional jobs[23] - which new graduates are employed in. Table 3-2 shows that the highest percentage of professional jobs are in the teaching and educational occupations, this is followed by corporate manager and directors and business, media, public service professionals.

Table 3-2 No of graduates in different occupations

Occupation main job	No. of Graduates	Variable Value
Professional Job Types		

[23] Defined by the Office National Statistics occupation classification (Salaries, 2017)

Corporate managers and directors	8,764 (14.50%)	'1' (Professional Jobs)
Other managers and proprietors	2,947 (4.87%)	
Science, research, engineering and tech	7,143 (11.82%)	
Health professionals	6,196 (10.25%)	
Teaching and educational professionals	9,891 (16.36%)	
Business, media and public service prof	8,723 (14.43%)	
Science, engineering and technology ass	1,666 (2.76%)	
Health and social care associate professional	1,588 (2.63%)	
Protective service occupations	1,083 (1.79%)	
Culture, media and sports occupations	3,102 (5.13%)	
Business and public service associate p	9,352 (15.47%)	
Un-Professional Job Types		
Administrative occupations	7,762 (26.36%)	'0' (Un-professional Jobs)
Secretarial and related occupations	1,728 (5.87%)	
Skilled agricultural and related trades	654 (2.22%)	
Skilled metal, electrical and electronics	1,178 (4%)	
Skilled construction and building trade	903 (3.07%)	
Textiles, printing and other skilled tr	895 (3.04%)	
Caring personal service occupations	4,102 (13.93%)	
Leisure, travel and related personal se	981 (3.33%)	
Sales occupations	3,657 (12.42%)	
Customer service occupations	1,556 (5.28%)	
Process, plant and machine operatives	831 (2.82%)	
Transport and mobile machine drivers an	1,061 (3.60%)	
Elementary trades and related occupations	478 (1.62%)	
Elementary administration and service	3,664 (12.44%)	
Total	89,905	

(Author's calculations using LFS)

3.4.1 Modelling the Evolution of Subject Premia over Time

Our analysis in this chapter begins, once again, with the wage model (Mincer, 1974). We begin by looking at whether the financial crisis of 2008/09 had an impact on subject premium. We estimate the wage premium of graduates in different subjects compared to A-level qualified individuals and observe how the wage premium has changed over the years for different subjects. We will consider female interaction with subject categories in order to capture the gender differences. In these estimates, we include the entire sample of men and women and consider how returns changed with the financial crisis.

$$log\, \boldsymbol{w}_{it} = \beta X_{it} + \; rS_{it} + \; \varphi_1 S_{it} * \; \boldsymbol{g}_{\eta} + \varepsilon_{it} \qquad Yearly_{2005-2018} \qquad \textit{Equation 3.1}$$

w_{it} shows the log of hourly wages for individual i and year t, S_{it} represents subject choices from 2005-2018 which is also interacted with female gender dummy $\boldsymbol{g}_{\eta}$. r gives the estimates of yearly subject wage premium and φ_1 gives the yearly wage premium earned by graduates at degree level and A-level qualified individuals for each year from 2005 to 2018. ε_i represents the error term. X_i represent the characteristics of individuals (gender, region of employment[24], marital-status and ethnicity).

3.4.2 Modelling the Effect of the Financial Crisis on Subject Premia

Second, we estimate the change in wage premium among new graduate cohorts, compared to the base category which is graduates in Law, Social Science and management (LSM). We restrict ourselves to new graduates and to a base category of LSM from amongst them (rather than A level graduates) so that we are analysing the outcomes for those who graduated at the same time and therefore have similar levels of work experience. Here, we assume individuals who graduate at the age of 22 will have minimum work experience, while individuals who enter the labour market after A-levels will have more work experience and will be incumbents at the time of the financial crisis, compared to new graduates.

To estimate the wage premium of individuals who graduated during and after the financial crisis and how wages evolve, we take the following steps:

i. To define new graduates, we create a variable that identifies the graduation year for each individual based on the assumption that individuals graduated at the age of 22. This is because, generally in the UK, individuals graduate at the age of 21 or 22 years (Britton et al., 2016; Dearden et al. 2008). This depends on the individual’s birth month because the month in which the individual turned 18 will determine the cohort when the individual started university, since the academic year starts in September. Second, with graduations from university taking place in July, we allow an extra year to categorise individuals as new graduates. Therefore, having individuals at the age of 22 in our data set will resolve this problem. We therefore also create the following variable “Year of Graduation” and use this together with age of 22 years to create the new graduates’ variable.

Year of graduation variable will be created as follows:

[24] We have used this for individuals living in London, instead of regional dummy. The reason for this is because we particularly wanted to see the difference in wages for individuals working in London compared to other parts of UK.

$$Year\ of\ Graduation = Current\ year - Current\ age + 22$$

Age subtracted from current year will give the year of birth of individuals and then we add 22 to get the year when individuals are of age 22. We retain those who are 22 years between 2006-2018 in our sample. However, for individuals who did their degree in medicine we used the age of 24 and 25[25] as it takes 5 years for individuals to complete a degree in medicine.

ii. Once we have the year of graduation for each individual, we drop all the individuals who graduated before 2005.

iii. Next, we create three cohorts for graduates in the following order:

   a. Cohort A: Individuals who graduated between 2005-2007
   b. Cohort B: Individuals who graduated between 2008-2010
   c. Cohort C: Individuals who graduated between 2011-2013

iv. We then create a dummy variable for the years in which the wage of each individual is recorded by the LFS as follows:

Table 3-3 Defining cohorts and the dummy variables for the time wages captured pre, during and post financial crisis.

		Wages Captured		
Cohort	Cohort graduation	1-3 years (D_A)	4-6 years (D_B)	7-9 years (D_C)
A	2005-2007	2005-2007 (pre financial crisis)	2008-2010(during financial crisis)	2011-2013 (post financial crisis)
B	2008-2010	2008-2010 (during financial crisis)	2011-2013 (post financial crisis)	2014-2016 (post financial crisis)
C	2011-2013	2011-2013 (post financial crisis)	2014-2016 (post financial crisis)	2017-2018 (post financial crisis)

Our data therefore consists of three cohorts (see Table 3-3), 2005-2007 graduates, 2008-2010 graduates and 2011-2013 graduates. Cohorts B and C of new graduates can be followed during the financial crisis and post financial crisis. $D_{A,B,C}$ will estimate the subject wage premium evolution for graduates (in different time periods) over the years.

Using the defined dummy variables, we run the following equation separately for each cohort.

[25] We have used both of the years only because some individuals could have turned 25 in the months before the graduation and we could potentially loose a significant sample of individuals who graduated in the same year.

$$\boldsymbol{w}_i^c = \beta X_i^c + rS_i^c + \text{ɒ}S_i^c * \boldsymbol{d}_i^c + \text{ɕ}\boldsymbol{d}_i^c + \text{ɘ}_i^c \qquad \text{Equation 3.2}$$

Here $\boldsymbol{w}_i^c$ represents the wages for each cohort (A, B and C). $\boldsymbol{d}_i^c$is a dummy variable representing the time-period for when wages are observed for the cohort. The ɒ coefficient for the interaction variable $S_c * D_c$ is controlling for wages being measured 4-6 or 7-9 years after graduation relative to 1-3 years for each subject choice. The dataset captures each individual at different points and so this variable will control for the impact that this might have on the estimates.

We define explicitly Equation 3.2, which estimates the evolution of the wage premium of individuals who graduated between 2005-2007, pre-financial crisis. $\text{ɒ}S_i^c * \boldsymbol{d}_i^c$ will calculate the how the subject wage premium of graduates (2005-2007) for the periods of 2008-2009, 2010-2013. We will re-estimate the model for each of our cohorts (those who graduated in 2008-2010 i.e. during the financial crisis and those who graduated between 2011-2013).

3.4.3 Modelling the Impact of the Financial Crisis on the Probability of Finding a Professional Job

Third, we consider whether the probability of obtaining a professional job changed following the financial crisis. In particular, we are considering if the probability of new graduates finding a professional job changes during and after the financial crisis, and whether they were forced into non-professional jobs which might have been unsuited to their qualifications. To estimate this probability, we created four cohorts[26] of new graduates who graduated as given in the following Table 3-4.

Table 3-4 Newly graduated cohorts from 2005-2018

	Cohorts			
	A	**B**	**C**	**D**
Graduation Year	2005-2007	2008-2010	2011-2013	2014-2016

[26] The reason we have four cohorts is because as we are calculating the likelihood of individuals in professional job and using the model Equation 3.3 we have the advantage of measuring the likely hood of securing a professional job for new-graduates in different periods.

For each cohort created in Equation 3.3 we estimate the following logistic model.

$$\boldsymbol{job\ type}_{Cohort} = \beta X_t + \propto_1 S_t + \epsilon_t \qquad \text{Equation 3.3}$$

Where cohort = A, B, C & D.

In Equation 3.3, the dependant variable ($\boldsymbol{job\ type}_{\boldsymbol{cohort}}$) is a binary variable that is 1 if the graduate is in a professional job and 0 otherwise. $\propto_1$ here will give the probability of a subject graduate being in a professional job compared to a non-professional job. The base for this probability is, once again, LSM graduates in each cohort (A, B, C & D). Marginal effects will be calculated, and pseudo values will be presented in the appendix.

Having done this, we explore whether individuals in our pseudo cohorts who graduated in subjects other than LSM, were more (or less) likely to be in non-professional jobs compared to LSM graduates, during and after the financial crisis. To analyse this, first we find the time period when the new graduate job type data is captured using the following table. We use cohort A, to demonstrate an example, if a graduate in a particular subject finds a professional job in 1-3 years, box labelled 2005-2007 will be associated with 1, and all other boxes in the row are 0. This is carried out for all graduates and all subject choices. We fall back to three cohorts as we will not be able to calculate the estimates for the change in probability for the years after 4-9 years for the cohort D (2014-2016).

Table 3-5 Defining cohorts and the dummy variables for the time Job-type captured pre, during and post financial crisis.

		Job Type Captured		
Cohort	Cohort graduation	1-3 years (D_A)	4-6 years (D_B)	7-9 years (D_C)
A	2005-2007	2005-2007 (pre financial crisis)	2008-2010(during financial crisis)	2011-2013 (post financial crisis)
B	2008-2010	2008-2010 (during financial crisis)	2011-2013 (post financial crisis)	2014-2016 (post financial crisis)
C	2011-2013	2011-2013 (post financial crisis)	2014-2016 (post financial crisis)	2017-2018 (post financial crisis)

We use OLS to find the interaction between subject choice and the job type, i.e. 1) Subject choice of new graduate, 2) Years in which job type is observed[27]. One limitation of the OLS method is that we are unable to constrain probabilities to be between 0 and 1, however if we are only interested in mean effects this is not an issue, since the results of the OLS produce similar effects to using a logit/probit.

[27] We here have particularly used OLS and not logit/probit because we are logit/probit doesn't allow us to measure the marginal effects of the interaction variables.

We estimate the following OLS model:

$$\boldsymbol{job\ type}_i^c = \beta X_i + \propto_2 S_i^c + \propto_3 S_i^c * \boldsymbol{d}_i^c + \epsilon_i^c \qquad \text{Equation 3.4}$$

$\propto_3$ will give the mean values of individuals securing a professional job (graduated in different subject categories over different time periods) compared to LSM graduates.

Table 3-6 gives the number of graduates in professional/ non-professional jobs in each cohort. Cohort D would only be used for Equation 3.3, but an important observation is that the percentage of individuals in the professional jobs for cohorts over the years has decreased.

Table 3-6 Number of individuals in professional/non-professional jobs for each cohort

	Non-Professional Jobs	Professional jobs
Cohort A	2878 (33.51%)	5710 (66.49%)
Cohort B	2825 (40.71%)	4115 (59.29%)
Cohort C	2045 (46.45%)	2358 (53.55%)
Cohort D	1287 (51.92%)	1192 (48.08%)

3.5 Empirical Analysis

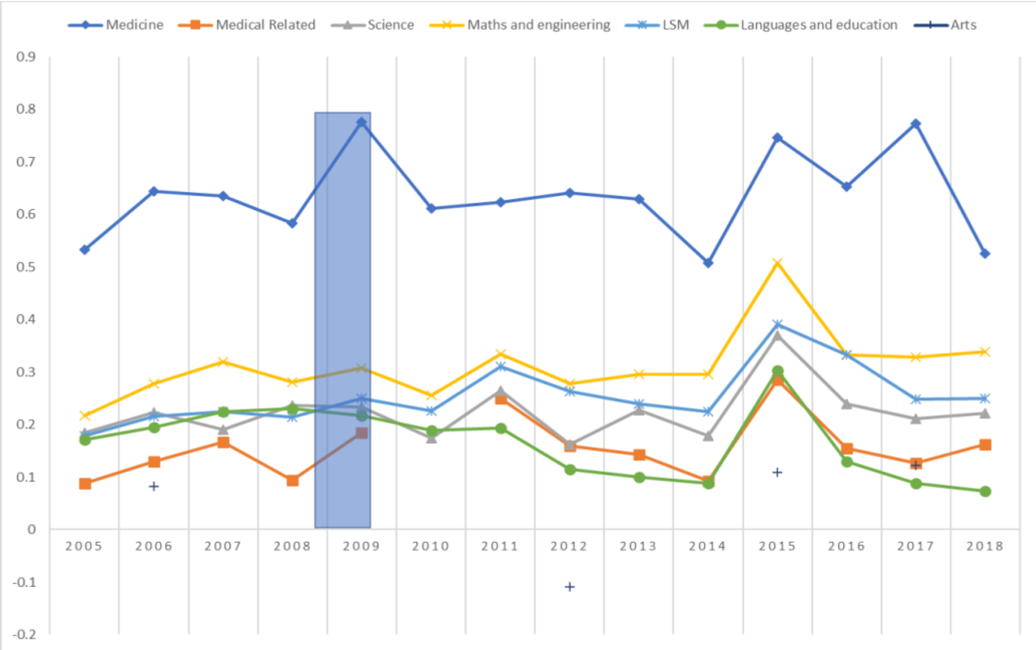
3.5.1 Evolution of Subject Premia over Time

We first analyse the evolution of the subject premium of graduates compared to their A-level qualified counterparts for each year in our sample using Equation *3.1*. This will give estimates of wage premia for the graduates in different subjects from 2005-2018 and will allow us to consider, on an annual basis, whether there was a change in returns to the various subjects after the 2008 financial crisis. Figure 3-7 is constructed using the estimates from Table 3-7 to make it easier to read yearly subject-wage premia. The estimates show that medicine graduates have the highest earnings and arts is the lowest and even negative for the year 2012. The graph illustrates that for medicine graduates there is a quite a bit of fluctuation, with three clear upward spikes in 2009, 2015 and in 2017, which can be explained by the changes in annual remunerations of medical professional as reported by BMA (2021)[28]. For other subject

[28] BMA, (2021) Available at: https://www.bma.org.uk/pay-and-contracts/pay/other-doctors-pay-scales/medical-academics-pay-scales (Accessed: 24th May 2021).

graduates, the wage premium is rather stable. The premium estimates dropped in 2008 perhaps because of financial crisis of 2007/08, after 2008 the subject premium was stable for most of the subject categories. Then in 2015 there is an upward spike in the graduate wage premium, this increase in the hourly wage premium is also reported by the Scruton (2015) in a report for ONS and showed that there is a 2% increase in the real wage of individuals.

Figure 3-7 Yearly subject premium for graduates compared to A-level individuals taken from Table 3-7



The graph illustrates the yearly wage premium for graduates in different subjects compared to the A-level individuals.

Table 3-7 Yearly gender difference between for individuals graduated in different subjects

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
VARIABLES	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay
Base category: A level qualified individuals														
Medicine	0.53***	0.64***	0.64***	0.58***	0.78***	0.61***	0.62***	0.64***	0.63***	0.51***	0.75***	0.65***	0.77***	0.53***
	(0.06)	(0.06)	(0.08)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)	(0.11)	(0.07)	(0.07)	(0.08)	(0.11)
Medical Related	0.09*	0.13**	0.17***	0.09	0.18***	0.08	0.25***	0.16***	0.14***	0.09*	0.29***	0.15***	0.13**	0.16***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Science	0.18***	0.22***	0.19***	0.24***	0.23***	0.17***	0.26***	0.16***	0.23***	0.18***	0.37***	0.24***	0.21***	0.22***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Maths and engineering	0.22***	0.28***	0.32***	0.28***	0.31***	0.26***	0.33***	0.28***	0.29***	0.30***	0.51***	0.33***	0.33***	0.34***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
LSM	0.18***	0.22***	0.22***	0.21***	0.25***	0.23***	0.31***	0.26***	0.24***	0.22***	0.39***	0.33***	0.25***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Languages and education	0.17***	0.20***	0.22***	0.23***	0.22***	0.19***	0.19***	0.12***	0.10**	0.09***	0.30***	0.13***	0.09**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Arts	0.04	0.08*	-0.05	0.06	0.07	0.00	0.02	-0.11**	0.04	0.02	0.11***	0.02	0.12***	0.07
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Females	0.21***	0.21***	0.18***	0.22***	0.18***	0.21***	0.20***	0.25***	0.23***	0.25***	0.23***	0.21***	0.23***	0.22***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
					-									
Medicine # females	0.01	-0.21**	-0.21**	-0.15	0.29***	-0.10	0.06	-0.07	0.15	0.09	0.01	-0.06	-0.22**	0.01
	(0.08)	(0.09)	(0.10)	(0.10)	(0.09)	(0.08)	(0.09)	(0.10)	(0.11)	(0.12)	(0.10)	(0.10)	(0.10)	(0.12)
Medical Related # females	0.02	0.01	-0.03	0.07	-0.02	0.12**	-0.03	0.04	0.06	0.14**	0.10	0.04	0.12*	0.02
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Controlled for age, age-squared, region of employment, ethnicity, relationship status, yearly dummy variables														

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3-7 Yearly gender difference between for individuals graduated in different subjects (Cont.)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
VARIABLES	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay	lhrpay
Base category: A level qualified individuals														
Sciences # females	0.06	0.05	0.04	0.07	-0.01	0.10**	0.02	0.10**	0.10**	0.11**	0.03	0.01	0.06	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Maths and engineering # females	0.08	0.04	0.03	0.06	0.01	0.09**	0.10**	0.11*	0.07	0.08	-0.01	0.07	0.09*	0.10**
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
LSM # females	0.06*	0.04	-0.03	0.06	0.02	0.02	-0.01	0.03	0.06	0.05	0.04	-0.07*	0.01	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Languages # females	0.07*	0.03	0.00	0.02	-0.03	0.05	0.04	0.17***	0.17***	0.18***	0.12***	0.12***	0.19***	0.16***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Arts # females	0.07	0.20***	0.19**	0.09	0.09	0.11	0.18**	0.19***	0.15**	0.10*	0.16***	0.08	-0.00	0.08
	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Constant	0.34***	0.36***	0.34***	0.53***	0.52***	0.44***	0.37***	0.52***	0.32***	0.47***	0.66***	0.65***	0.68***	0.86***
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.11)	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)	(0.09)	(0.08)	(0.08)
Observations	7,095	7,136	7,530	7,283	6,895	6,931	6,652	6,652	6,697	6,997	9,443	6,777	6,999	7,235
R-squared	0.25	0.24	0.24	0.23	0.23	0.23	0.26	0.25	0.23	0.25	0.27	0.24	0.22	0.21
Controlled for age, age-squared, region of employment, ethnicity, relationship status, yearly dummy variables														

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The interaction terms in Table 3-7 show that in general female graduates earn a higher premium than male graduates for all subject categories except medicine. Female medicine graduates have a lower premium than their male counterparts.

Interaction terms themselves show that new-graduate females in the subjects of science, maths, engineering, languages, and arts earn a higher wage premium compared to their male graduate counterparts. These results are similar to those of Chevalier (2007). The results are also closely linked to the analysis of McNabb et al. (2002), who argue that languages, humanities and arts are most popular among women, and it is likely that more women will be employed in these jobs at higher positions. On the contrary, men choose subjects with high financial returns while women are more risk averse and tend to choose subjects where they have greatest prospect of succeeding and scoring a higher grade. Smith (2011) found that women graduating in STEM subjects have a higher chance of employment and this trend has been increasing since 1986. In addition to this, according to a report by WISE[29] (2014), there has been an increase in the number of women in STEM-related apprenticeships, vocational qualifications, and degree qualifications. While Engineering is dominated by men, women who graduate in maths and engineering have observed a boost in employment and job market opportunities compared to men in the last decade.

Table 3-8 Calculated[30] estimates from interaction variables from Table 3-7(significant coefficients only)

Subjects	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Medicine	-	0.233	0.245	-	0.306	-	-	-	-	-	-	-	0.318	-
Medical Related	-	-	-	-	-	-0.016	-	-	-	-0.021	-	-	0.011	-0.038
Science	-	-	-	-	-	0.061	-	0.014	0.094	0.034	-	-	-	-
Maths and engineering	-	-	-	-	-	0.133	0.228	0.135	-	-	-	-	0.185	0.215
LSM	0.032	-	-	-	-	-	-	-	-	-	-	0.052	-	-
languages and education	0.030	-	-	-	-	-	-	0.032	0.036	0.012	0.193	0.032	0.044	0.012
Arts	-	0.076	-0.039	-	-	-	-0.004	-0.172	-0.043	-0.128	0.039	-	-	-

(Author's Calculation)

Table 3-8 gives the calculations of significant interactions from Table 3-7 for each subject category and this gives the change in yearly gender wage premium compared to the A-level individuals. The table demonstrates that there is not a particular pattern in the female wage premium compared to the A-level qualified individuals. But there is a negative wage premium

[29] WISE (Women in Science, Technology, Engineering and Mathematics is a campaign to support women in STEM subjects)

[30] The calculation of gender interaction term is done by adding the coefficient of subject, female, and the interaction term from Table 3-7.

for the females who graduated in medical related (for years 2010, 2014 and 2018) and arts (for year 2007, then negative returns continuously from 2011-2014) subjects. However, 2015 gives the positive premium for females who graduated in arts. For the subjects of medicine, LSM, maths and engineering and language and education categories, we can see that the females earn a positive wage premium over different years.

3.5.2 Effect of the Financial Crisis on Subject Premia

Next, we look at how the subject premia of individuals who graduated in different time periods changed over time. Table 3-9 gives the coefficients of subject premium of Cohort A, B and C after 4 to 6 and 7 to 9 years after graduation compared to 1 to 3 years of graduation. The estimates show that individuals in Cohort A (who graduated in 2005-2007) did not experience a substantial increase or decrease in their wage premium and this is the case for most of the subjects. Thus, the financial crisis does not seem to have affected the subject premia of these individuals. However, individuals who graduated in Arts observed a 16% lower subject premium 7 to 9 years after graduation compared to the LSM graduates. These results show that individuals who graduated in Arts just before the financial crisis were most affected by the aftermath of the financial crisis when it hit the labour market.

For Cohort B (individuals who graduated during the financial crisis) also, there was not a significant change in subject premia associated with the financial crisis. However, in two subject categories (medical related and the arts), graduates observed a substantial change in their subject premium 3-6 and 7-9 years after graduation as their subject premium was 19% (for medical related) and 15-25% (for arts) lower compared to LSM graduates. As these individuals graduated during the financial crisis, the most affected subjects were the medical related and the arts.

Lastly for Cohort C (individuals who graduated between 2010-2013), we can observe that individuals who graduated in medical related courses earned a lower subject premium compared to the LSM graduates but for this cohort, individuals who graduated in languages observed a higher wage premium (18%) compared to the LSM after 4-6 years.

Table 3-9 Wage premium of Cohorts A, B and C after 4-6 and 7-9 years of graduation

VARIABLES	Cohort A graduated in 2005-2007	Cohort B graduated in 2008-2010	Cohort C graduated in 2011-2013
LSM as Base category			
Medicine	0.2177***	0.3429***	0.2247***
	(0.0711)	(0.0619)	(0.0745)
Medical Related	0.0073	0.1931***	0.1486**
	(0.0863)	(0.0599)	(0.0597)
Science	-0.0648	0.0136	-0.0994*
	(0.0566)	(0.0554)	(0.0518)
Maths and Engineering	0.0670	0.0649	0.0064
	(0.0502)	(0.0581)	(0.0757)
Languages and humanities	-0.1165**	-0.0396	-0.1323**
	(0.0503)	(0.0587)	(0.0619)
Arts	0.0208	0.0540	-0.1899**
	(0.0522)	(0.0530)	(0.0758)
Wages observed from 4 to 6 years after graduation (Base Category: wages observed from 1 to 3 years since graduation)	0.0450	0.0170	-0.0369
	(0.0481)	(0.0503)	(0.0538)
Wages observed from 7 to 9 years (Base Category: wages observed from 1 to 3 years since graduation)	0.0922*	-0.0195	0.0490
	(0.0559)	(0.0599)	(0.0636)
Medicine # wages observed 4-6 years after	0.0628	-0.0920	-0.0486
	(0.0833)	(0.0772)	(0.1001)
Medicine # wage observed from 7-9 years	0.0128	-0.0803	0.0753
	(0.0945)	(0.0831)	(0.1081)
Medical related # wages observed 4-6 years after	0.0589	-0.1993***	-0.0678
	(0.0984)	(0.0769)	(0.0740)
Medical related # wage observed from 7-9 years	-0.0001	-0.1970***	-0.2119***
	(0.0962)	(0.0697)	(0.0767)
Science # wages observed 4-6 years after	0.0716	0.0166	0.0652
	(0.0672)	(0.0679)	(0.0667)
Science # wage observed from 7-9 years	0.0086	-0.0624	0.0041
	(0.0663)	(0.0669)	(0.0668)
Math engineering # wages observed 4-6 years after	0.0558	-0.0099	0.1169
	(0.0630)	(0.0703)	(0.0856)
Math engineering # wage observed from 7-9 years	0.0047	0.0757	0.0410
	(0.0629)	(0.0697)	(0.0894)
Languages # wages observed 4-6 years after	0.0507	-0.0182	0.1813**
	(0.0601)	(0.0684)	(0.0723)
Languages # wage observed from 7-9 years	0.0452	0.0430	0.0496
	(0.0612)	(0.0671)	(0.0751)
Arts # wages observed 4-6 years after	-0.0736	-0.1594**	-0.0553
	(0.0742)	(0.0674)	(0.0855)
Arts # wage observed from 7-9 years	-0.1608**	-0.2508***	-0.0609
	(0.0702)	(0.0712)	(0.0910)
Constant	-0.9591	-3.2381***	-3.0815**
	(1.0852)	(1.1666)	(1.4540)
Observations	2,800	2,778	2,285
R-squared	0.2580	0.2569	0.2870

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.5.3 Impact of the Financial Crisis on the Probability of Finding a Professional Job

Finally, we consider whether the likelihood of securing a professional job changed following the financial crisis. We also consider whether these probabilities varied by subjects using Equation 3.3. Table 3-10 displays the likelihood of securing a professional job for four cohorts who graduated before, during and post financial crisis. On average, graduates are more likely to secure a professional job than non-graduates (LSM individuals).

Table 3-10 Marginal effects of graduates with different jobs attaining Professional and non-professional jobs from 2005-2018

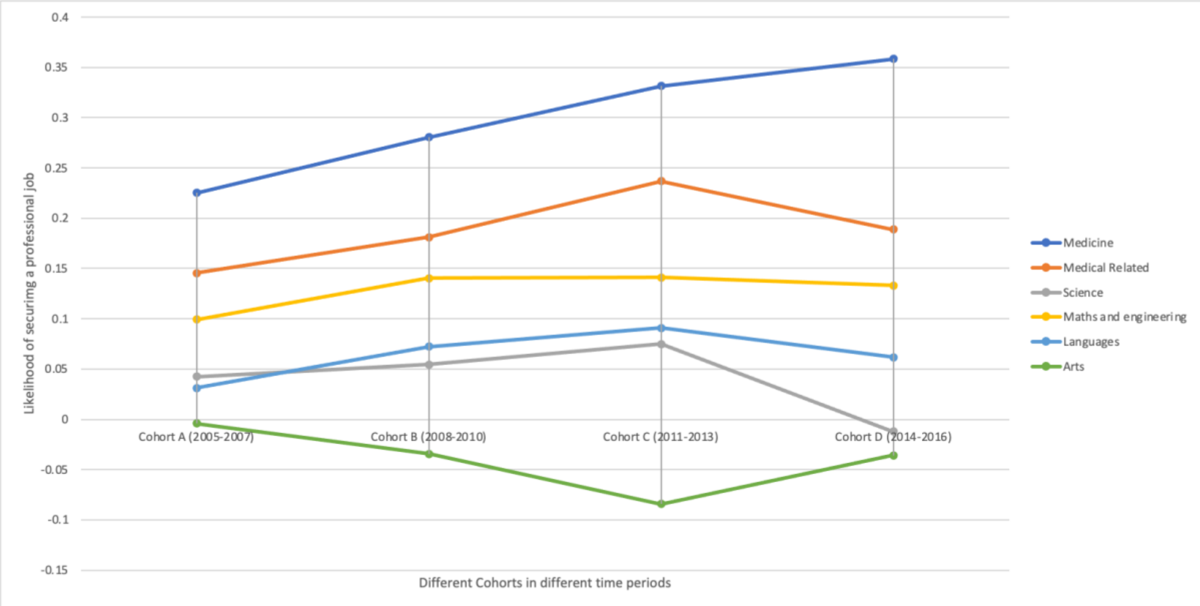
	Cohort A (2005-2007)	Cohort B (2008-2010)	Cohort C (2011-2013)	Cohort D (2014-2016)
	(1)	(2)	(3)	(4)
VARIABLES				
Medicine	0.2252***	0.2806***	0.3314***	0.3582***
	(0.0161)	(0.0182)	(0.0249)	(0.0407)
Medical Related	0.1455***	0.1811***	0.2368***	0.1887***
	(0.0196)	(0.0219)	(0.0284)	(0.0443)
Science	0.0423**	0.0543**	0.0747**	-0.0122
	(0.0206)	(0.0237)	(0.0292)	(0.0417)
Maths and engineering	0.0993***	0.1403***	0.1409***	0.1331***
	(0.0200)	(0.0222)	(0.0293)	(0.0431)
Languages	0.0311	0.0722***	0.0907***	0.0616
	(0.0190)	(0.0209)	(0.0262)	(0.0397)
Arts	-0.0042	-0.0345	-0.0842**	-0.0359
	(0.0265)	(0.0286)	(0.0345)	(0.0483)
Observations	4,220	3,864	2,673	1,378

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression model is controlled for age, age-square, region, relationship status, gender, and ethnicity.

We can observe that graduates in medicine have the highest probability of finding a professional job compared to LSM graduates and this probability has continuously increased over the years. This is followed by medical related subject graduates. Maths and engineering subject graduates are also more likely to find a professional job compared to the LSM graduates.

Figure 3-8 Likelihood of Cohorts A, B, C, and D graduate (in different subjects) securing a professional job compared to the LSM subject graduates (drawn from the values given in Table 3-10)



Comparing the probabilities of different cohorts over the time-period as depicted in Figure 3-8 shows that graduates in medicine have the highest probability of getting a professional job for all the time periods. This has been continuously increasing over the years and has not been affected by the financial crisis.

The likelihood for the cohort of medical graduates securing a professional job increased during and after the financial crisis but for cohort D (graduates 2014-2016) it has declined. This is also the case for languages and science graduates. The likelihood of securing a professional job for maths and engineering graduates increased until 2010 and since then it has been flat. The probability of arts graduates securing a professional job has decreased continuously until 2013 but for the period after that an increase is observed. However, it is less likely for arts graduates to secure a professional job compared to LSM graduates.

If we look at the 2008/09 financial crisis, we see that there was not an abrupt effect on the probability of individuals securing a professional job. But if we look at the big picture, we can observe that there is a wider gap among graduates in different subjects, particularly during 2011-2013, followed by a movement towards convergence. A point to remember here is that the professional jobs, by definition, include all doctors as professionals, so the findings are inherent in the definition.

Next if we look at how the probability of each cohort Table 3-11 who graduated in different time periods in different subjects has changed, we can see that for cohort A, who graduated in 2005-2007, the probability of being in a professional job decreases after 4-9 years of graduation compared to LSM graduates. For medical related subject graduates, the probability of being in a professional job also decreased 7 to 9 years of graduation.

For cohort B, who graduated in 2008-2010, there is a slightly different story as we can see that, although there is a decrease in the probability of medicine graduates securing a professional job after 7-9 years, there is an increase in the probability of securing a job for the maths and engineering graduates after 4-6 years and 7-9 years after graduation.

Lastly for cohort C, who graduated in 2011-2013, there is even a lower probability of securing a professional job than LSM graduates, among all the different cohorts, but here we can also observe that there is a higher probability of securing a job for graduates of science and language subjects after 4-6 years. In summary we cannot say that financial crisis 2008/09 had an instant effect on the probability of securing a job but it seems like there is a certain change in the labour market toward the demand of individuals in medicine, maths and engineering subjects after the financial crisis.

Table 3-11 Mean probability of securing a professional/non-professional job for different cohorts

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(1)	(2)	(3)
VARIABLES	job_type1	job_type1	job_type1
LSM as Base category			
london	0.0509***	0.0841***	0.0988***
	(0.0193)	(0.0187)	(0.0211)
married	-0.0302*	-0.0591***	-0.0560***
	(0.0159)	(0.0163)	(0.0178)
white	0.0989***	0.1161***	0.0789***
	(0.0205)	(0.0226)	(0.0259)
fem	-0.0553***	-0.0349**	-0.0801***
	(0.0164)	(0.0166)	(0.0180)
Medicine	0.4466***	0.4862***	0.4947***
	(0.0463)	(0.0505)	(0.0494)
Medical Related	0.2917***	0.1573**	0.2770***
	(0.0786)	(0.0799)	(0.0773)
Science	0.0211	0.0305	0.0108
	(0.0736)	(0.0718)	(0.0687)
Maths and Engineering	0.1008	0.0243	0.1404*
	(0.0687)	(0.0670)	(0.0785)
Languages and humanities	-0.0920	-0.0084	-0.0486
	(0.0601)	(0.0611)	(0.0628)
Arts	0.0461	-0.0240	-0.0691

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(0.0920)	(0.0984)	(0.0784)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3-11 Mean probability of securing a professional/non-professional job for different cohorts (Cont.)

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(1)	(2)	(3)
VARIABLES	job_type1	job_type1	job_type1
Job type observed from 4 to 6 years after graduation (Base Category: Job type observed from 1 to 3 years since graduation)	0.1052**	0.0427	0.0977*
	(0.0535)	(0.0532)	(0.0507)
Job type observed from 7 to 9 years (Base Category: Job type observed from 1 to 3 years since graduation)	0.1987***	0.1636***	0.1937***
	(0.0507)	(0.0502)	(0.0516)
Medicine Job type observed 4-6 years after	-0.1248**	-0.0599	-0.0970
	(0.0584)	(0.0596)	(0.0607)
Medicine Job type observed from 7-9 years	-0.2244***	-0.1804***	-0.2720***
	(0.0544)	(0.0553)	(0.0689)
medical related # Job type observed 4-6 years after	-0.1199	0.0622	-0.0267
	(0.0929)	(0.0939)	(0.0895)
medical related # Job type observed from 7-9 years	-0.1517*	0.0317	-0.0671
	(0.0859)	(0.0862)	(0.0879)
Science # Job type observed 4-6 years after	0.0113	0.0836	0.1351*
	(0.0865)	(0.0861)	(0.0810)
Science # Job type observed from 7-9 years	-0.0412	-0.0098	-0.0053
	(0.0826)	(0.0806)	(0.0836)
Maths/engineering # Job type observed 4-6 years after	0.0421	0.1600**	0.0174
	(0.0786)	(0.0806)	(0.0890)
Maths/engineering # Job type observed from 7-9 years	-0.0602	0.1260*	-0.0372
	(0.0767)	(0.0747)	(0.0885)
Languages # Job type observed 4-6 years after	0.0552	0.1012	0.1763**
	(0.0715)	(0.0740)	(0.0740)
Languages # Job type observed from 7-9 years	0.0730	0.0576	0.1450*
	(0.0687)	(0.0693)	(0.0750)
Arts # Job type observed 4-6 years after	-0.0579	0.0481	-0.0333
	(0.1118)	(0.1123)	(0.0935)
Arts # Job type observed from 7-9 years	-0.1086	-0.0200	-0.0325
	(0.1040)	(0.1082)	(0.0977)
Constant	0.5492***	0.5259***	0.5482***

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(0.0582)	(0.0581)	(0.0589)
Observations	3,191	3,253	2,673
R-squared	0.0799	0.0948	0.1110

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Conclusion

This chapter estimates the evolution of wage premia of new graduates in different subjects for different time periods before, during and after the financial crisis. In addition to this, we have also analysed the probabilities of getting professional jobs over the same time period.

The estimates show that individuals who graduated in 2005-2007 did not experience a substantial increase or decrease in their wage premium except for individuals who graduated in Arts who observed a 16% lower subject premium 7 to 9 years after graduation compared to the LSM graduates. These results show that individuals who graduated in Arts from 2005-2007 just before the financial crisis were most affected by the aftermath of financial crisis when it hit the labour market.

Individuals who graduated during the financial crisis particularly in medical related and the arts subject observed a substantial change in their subject premium 3-6 and 7-9 years after graduation as their subject premium was 19% (for medical related) and 15-25% (for arts) lowered compared to LSM graduates.

Lastly for individuals who graduated between 2010-2013 i.e. after the financial crisis, we observe that individuals graduated in the subject of medical related courses earn a lower subject premium compared to the LSM graduates and for this cohort individuals who graduated in languages observed a higher wage premium (18%) compared to the LSM after 4-6 years.

In terms of graduate professional and non-professional jobs, we see that individuals who graduated in medicine, maths, engineering, and medical related subjects were more likely to find a professional job compared to LSM graduates. Whereas individuals who graduated in arts may have found it difficult to secure professional jobs compared to the LSM graduates. Also, it is important for medicine graduates to get a professional job straight after the graduation as their probability to find a professional job after few years is reduced. Whereas on the contrary individuals graduated in maths, engineering and languages are more likely to find a professional job after a few years of graduation. This could possibly be because of the skills and experience they accumulate over the years. In totality we cannot say categorically that financial crisis 2008/09 had an impact on the probability of securing a job but it did had an impact on the labour market (we believe technological changes) which had an effect of higher demand for individuals graduated in medicine, maths and engineering. There are also some other variables that may influence the graduate wage premium but are not included in the model. For example, ability, family background and socio-economic status. The next chapter will consider these variables in more detail and will estimate the effect of these on individual wage premium.

3.7 Appendix

Here we look at the how wages of individuals graduated in different time periods change overtime using A-level as base category. Table 3-12 gives the coefficients of wage premium for Cohort A for the years of 2008-2010 and 2011-2013 of individuals graduated in 2005-2007. The estimates show that the individuals who graduated in 2005-2007 did not experience a substantial increase or decrease in their wage premium and this is the case for most of the subjects. Although individuals graduated in Languages and education saw an increase in their premium by 10% for the years 2011-2013.

Table 3-12 Wage coefficient for cohorts A,B and C pre, during and post financial crisis with the base category of A-levels

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
VARIABLES	lhrpay	lhrpay	lhrpay
A-Level as Base category			
london	0.2232***	0.1954***	0.2123***
	(0.0188)	(0.0193)	(0.0206)
white	0.1145***	0.0756***	0.0358
	(0.0198)	(0.0217)	(0.0227)
married	-0.0853***	-0.0674***	-0.0754***
	(0.0136)	(0.0135)	(0.0149)
fem	-0.0737***	-0.0903***	-0.1288***

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(0.0139)	(0.0135)	(0.0151)
Medicine	0.3675***	0.3895***	0.3792***
	(0.0678)	(0.0552)	(0.0674)
Medical Related	0.1744**	0.2003***	0.2855***
	(0.0824)	(0.0542)	(0.0516)
Science	0.0989*	0.0119	0.0293
	(0.0520)	(0.0490)	(0.0425)
Maths and Engineering	0.2206***	0.0632	0.1317*
	(0.0448)	(0.0538)	(0.0701)
LSM	0.1630***	0.0047	0.1353***
	(0.0409)	(0.0406)	(0.0443)
Languages and humanities	0.0451	-0.0338	-0.0040
	(0.0453)	(0.0527)	(0.0541)
Arts	0.1829***	0.0589	-0.0583
	(0.0469)	(0.0487)	(0.0699)
Wages observed from 4 to 6 years after graduation (Base Category: wages observed from 1 to 3 years since graduation)	0.0486	-0.1157***	-0.1322***
	(0.0400)	(0.0429)	(0.0384)
Wages observed from 7 to 9 years (Base Category: wages observed from 1 to 3 years since graduation)	0.0272	-0.1959***	-0.0471
	(0.0476)	(0.0489)	(0.0513)
medicine#wages observed 4-6 years after	0.0646	0.0635	0.0535
	(0.0798)	(0.0727)	(0.0937)
medicine#wage observed from 7-9 years	0.1018	0.1358*	0.1686*
	(0.0910)	(0.0763)	(0.0991)
medical related#wages observed 4-6 years after	0.0416	-0.0175	0.0531
	(0.0946)	(0.0723)	(0.0653)
medical related#wage observed from 7-9 years	0.0568	0.0590	-0.0819
	(0.0919)	(0.0634)	(0.0693)
science#wages observed 4-6 years after	0.0539	0.2030***	0.1899***
	(0.0626)	(0.0631)	(0.0571)
science#wage observed from 7-9 years	0.0668	0.1980***	0.1376**
	(0.0614)	(0.0603)	(0.0589)

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
maths_engineering#wages observed 4-6 years after	0.0416	0.1698**	0.2396***
	(0.0580)	(0.0666)	(0.0789)
maths_engineering#wage observed from 7-9 years	0.0676	0.3273***	0.1722**
	(0.0576)	(0.0647)	(0.0839)
LSM#wages observed 4-6 years after	-0.0162	0.1858***	0.1251**
	(0.0521)	(0.0517)	(0.0546)
LSM#wage observed from 7-9 years	0.0599	0.2585***	0.1304**
	(0.0513)	(0.0505)	(0.0592)
Languages#wages observed 4-6 years after	0.0346	0.1655***	0.3069***
	(0.0549)	(0.0636)	(0.0637)
Languages#wage observed from 7-9 years	0.1054*	0.2991***	0.1832***
	(0.0556)	(0.0607)	(0.0678)
Arts#wages observed 4-6 years after	-0.0878	0.0251	0.0670
	(0.0700)	(0.0639)	(0.0785)
Arts#wage observed from 7-9 years	-0.0989	0.0047	0.0706
	(0.0654)	(0.0669)	(0.0855)
Constant	-2.0623***	-1.6540**	-1.9191*
	(0.7827)	(0.8335)	(0.9870)
Observations	3,951	4,140	3,380
R-squared	0.3057	0.2560	0.3170

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 3-12 Cohort B (2008-2010) estimates show that medicine graduates from observed little change in wages from 4 to 6 years after graduation, however from 7 to 9 years we observe a notable increase in the wage premium of medicine graduates. Science, maths, engineering, LSM, languages and education Cohort B graduates all observed an increase in their wage premium from 4 to 6 and 7 to 9 years. Individuals graduated in science observed the highest wage premium from 2011-2013. Individuals graduated in maths and engineering observed the highest growth, since their average wage premium is highest in 2014-2016, followed by languages and LSM. Individuals graduated in medical related, and arts subjects did not observe any change in their wage premium.

In Table 3-12 Cohort C (2011-2013) estimates show that graduates in medicine observed a higher wage premium in 7 to 8 years. Science graduates earn a higher wage premium from 2014-2016 although this declines from 2017-2018. For Cohort C, languages and education graduates earned the highest wage premium 4 to 6 years after graduation, although for 7 to 9 years after graduation we observe a decrease in wage premium for languages subjects, as is the case for maths and engineering subjects. LSM graduates observed an increase in wage premium of approximately 13 percent after 7 to 9 years of graduation.

Analysing the wage premiums over the different time periods for Cohorts A, B and C, it can be observed that the Cohort A did not observe an increase in their wage premium during or after the financial crisis. Cohort B (2008-2010) Science, Maths, Engineering, LSM and Languages observed the highest wage premium. With the exception of Arts and languages the graduates in other subject categories observed an increase in wage premium after 4 to 6 years or 7 to 9 years after graduation.

3.7.1 Appendix 3-1

Table 3-13 Wage premium for each cohort with LSM as the base category.

	Cohort A graduated in 2005-2007	Cohort B graduated on 2008-2010	Cohort C graduated in 2011-2013
	(1)	(2)	(3)
VARIABLES	lhrpay	lhrpay	lhrpay
LSM as Base Category			
Medicine	0.2534***	0.2852***	0.2231***
	(0.0298)	(0.0294)	(0.0409)
Medical Related	0.0061	-0.0059	0.0373
	(0.0226)	(0.0238)	(0.0296)
Science	0.0058	-0.0175	-0.0730***
	(0.0186)	(0.0223)	(0.0259)
Maths and engineering	0.1053***	0.1231***	0.0766**
	(0.0193)	(0.0221)	(0.0298)
Languages	-0.0605***	-0.0246	-0.0389
	(0.0175)	(0.0201)	(0.0255)
Arts	-0.1175***	-0.1238***	-0.2398***
	(0.0238)	(0.0265)	(0.0292)
Constant	-1.3068***	-2.4104***	-2.4367**
	(0.3951)	(0.5589)	(0.9738)
Observations	5,033	3,814	2,320
R-squared	0.2867	0.2872	0.2907

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The model is controlled for ethnicity, region, gender and relationship status.

Table 3-14 Pseudo values for the logit model

	Cohort A (2005-2007)	Cohort B (2008-2010)	Cohort C (2011-2013)	Cohort D (2014-2016)
	(1)	(2)	(3)	(4)
VARIABLES	job_type	job_type	job_type	job_type
	LSM as base category	LSM as base category	LSM as base category	LSM as base category
age	0.8395**	1.1876***	1.9184***	2.6738***
	(0.4014)	(0.3672)	(0.4764)	(0.6466)
agesq	-0.0132**	-0.0193***	-0.0343***	-0.0518***
	(0.0066)	(0.0066)	(0.0094)	(0.0135)
london	0.4012***	0.4277***	0.5344***	0.4969***
	(0.1021)	(0.1002)	(0.1224)	(0.1615)
married	-0.2929***	-0.2994***	-0.2315**	-0.2754**
	(0.0867)	(0.0847)	(0.0942)	(0.1337)
white	0.3267***	0.5160***	0.4462***	0.4598***
	(0.1092)	(0.1132)	(0.1358)	(0.1747)
fem	-0.4465***	-0.1488*	-0.4222***	-0.2378*
	(0.0873)	(0.0842)	(0.0959)	(0.1318)
Medicine	2.6321***	2.6461***	2.5585***	2.6993***
	(0.4185)	(0.3689)	(0.3710)	(0.6206)
Medical Related	1.0710***	1.1310***	1.3684***	0.9487***
	(0.1750)	(0.1641)	(0.2024)	(0.2484)
Science	0.2456**	0.2767**	0.3543**	-0.0533
	(0.1217)	(0.1236)	(0.1414)	(0.1819)
Maths and engineering	0.6439***	0.8064***	0.7097***	0.6329***
	(0.1409)	(0.1409)	(0.1570)	(0.2144)
Languages	0.1771	0.3753***	0.4357***	0.2782
	(0.1090)	(0.1105)	(0.1278)	(0.1810)
Arts	-0.0226	-0.1622	-0.3701**	-0.1559
	(0.1437)	(0.1332)	(0.1506)	(0.2090)
Constant	-11.8561*	-17.2206***	-25.8530***	-33.6854***
	(6.1324)	(5.0707)	(6.0145)	(7.7672)
Observations	4,220	3,864	2,673	1,378

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4 Subject choice, skills and family background and their impact on labour market outcomes.

4.1 Introduction

Previously in chapters 2 and 3, we have analysed subject choice and subject premium using the Labour Force Survey. This enabled us to study how the earnings of graduates have changed from 2005 to 2018. However, the LFS does not allow us to control for family attributes, skills, and other characteristic variables and excluding these variables could bias our estimates. Earlier literature has also shown that the abilities and skills of individuals need to be controlled for, which is again not possible through the LFS. This motivated us to employ a more comprehensive dataset such as Next Steps which provides information on family background as well as individual abilities and skills.

This chapter analyses two dimensions of labour market outcomes: (i) the degree level subject choice of individuals and (ii) the impact of subject choice, skills, and family background on the wage premium. In the process, we are seeking to resolve the endogeneity problem in the returns to education model by minimising the omitted variable bias that arises from excluding family background and individual ability variables, which might be expected to have an impact on both education and also on wages more directly. We will start with an assessment of the association between skills and individual subject choices at degree level. This will be followed by an assessment of how family background is associated with the individual degree subject choices. An understanding of these two associations will then feed into an analysis of the effects of subject choice at degree level and skills on labour market wage premium.

Social scientists and economists have long recognised that both cognitive[31] skills and non-cognitive skills[32] are both influential in shaping lifetime opportunities and outcomes (Hall &

[31] Cognitive skills are usually identified with intelligence and ability to solve problems. Cognitive skills are usually measured by standardised test scores of numeracy, literacy, and science. It is a trait that is partly inherited and partly gained through the education and training (for further reading on the cognitive skills, see Devlin et al., 1997).

[32] Nyhus and Pons (2005) defines non-cognitive skills as the personality traits of Agreeableness, conscientiousness, emotional stability, autonomy, and extroversion.

Farkas, 2011). The relative importance of cognitive skills, measured by test scores, and non-cognitive skills such as behavioural traits, self-confidence, and work habits on lifetime earnings have long been a topic of debate in the skill-wage analysis literature (Herrnstein, 1973; Herrnstein and Murray, 1994; Jensen, 1969). One of the views is that inequalities in schooling, employment and earnings result primarily from differences in skills. Central to this view is the established argument that skills that are inherited at birth or learned in school determine individual productivity and earnings (Hall & Farkas, 2011).

In the next section, we will elaborate on each of the above-given points in separate sections which will form the basis of our research questions.

4.2 Literature

The term cultural capital refers to the stock of cultural knowledge that enables an individual to interpret and communicate signals in social settings (Davis et al., 2014). Early investigations by DiMaggio (1982) reveal that higher education choices are associated with the acquisition of cultural capital within social class differences. Cultural capital is therefore associated with individual expectations for the future. According to Bourdieu et al. (1990), the explanation for social class inequalities also lies in the distribution of 'cultural capital'. Cultural capital varies with social class and education, high cultural capital being held by those from more educated and higher socio-economic backgrounds (Van de Werfhorst et al., 2003). If individuals have accumulated higher cultural capital because of their relatively advantaged socio-economic background, they may be more likely to join the pool of scientists, researchers, journalists, and public sector employees than individuals from lower socio-economic backgrounds who have not been able to accumulate the same levels of cultural capital.

According to Erikson and Jonsson (1996), cultural capital is likely to increase individuals' preference towards the certain fields of education. Individuals coming from higher income and cultural backgrounds also perceive higher desirability and benefits of choosing subjects such as medicine, science, engineering, history, philosophy, education, and linguistics. Similarly, individuals coming from a higher economic background, but mid-level cultural background, are likely to choose subjects that develop their skills in commercial and financial management or go into fields with high financial yield. Individuals coming from lower socio-economic backgrounds with lower cultural and economic capital are more likely to take technical subjects and fields that lead to secure jobs market prospects (Kelsall et al., 1972).

The Rational Choice framework assumes that individuals coming from different social classes make rational decisions on whether to pursue further education, the rationality being based on opportune consideration of costs and benefits associated with the decision. These conscious decisions are found to be based on the social class they come from and on their parent's education and knowledge (Van de Werfhorst et al., 2003). The costs and benefits associated with each educational option vary with social class because ambition is relative to the social starting point of an individual (and social demotion is considered to have a higher costs) (Boudon, 1974). According to the Rational Choice theory, an individual coming from a relatively poor socio-economic background who wants to study in a subject associated with a lucrative employment option must be more ambitious than the individual coming from a higher socio-economic background. For the latter, it may be essential to pursue a more prestigious subject to avoid social demotion, but working-class individuals may avoid social demotion by going straight into the labour force. Boudon's (1974) research also finds that students from middle class backgrounds are more likely to pursue further education in prestigious subjects than working-class individuals at all levels of ability. Breen and Goldthorpe (1997) suggest that individuals would prefer to avoid downward mobility rather than have a chance of upward mobility. They argue that working-class individuals, wishing to move up the occupational class, might prefer to find employment instead of pursuing further education.

4.2.1 FAMILY/SOCIOECONOMIC BACKGROUND AND SUBJECT CHOICE

Interest in how students make their educational choices has resulted in research on the impact of family background on educational attainment. Parental education, family income and family head's occupation status were found to have a positive association with children's educational attainment (Biblarz & Raftery, 1999; Boggess, 1998; Sandefur & Wells, 1999). Turner et al. (2004) give evidence that more educated parents play an important role towards the individuals' attitudes towards facing barriers and fear of failing; and individual's attitudes towards fear of failing and facing barriers often lead them to rule out potential higher educational choices.

Studies also indicate that if family has a positive attitude towards science and maths it is more likely that individuals from those backgrounds study mathematical and scientific subjects in higher education (Novarro et al., 2007; Turner et al., 2004; Tang et al., 1999; Tai et al., 2006; Byars-Winston et al., 2008). This is because according to Chakravarty et al. (2013), parents can socially interact with children to create learning opportunities outside school and to establish positive attitudes towards certain subject choices. The role of parents in shaping children's career expands across all cultures and nations as demonstrated by Navarro et al. (2007) in Mexico, and Tang et al. (1999) while studying Asian American Youth in United States.

More recent research by Archer et al. (2014) also suggests that positive attitudes towards science subjects are shaped by factors such as home, family, parental education, peers and schools. Davis et al. (2014) shows that the intention of 16-year-olds to participate in HE in England is associated with parents' education, student culture and, more important, student's beliefs about the size of the graduate wage premium.

Not surprisingly, therefore, socioeconomic status is an important variable in individual studies. Davis and Guppy (1997) gave evidence that students from lower socioeconomic status households are more likely to choose more lucrative fields of study. However, Ware and Lee (1998) argue that men from higher socioeconomic background are more likely to choose science majors than the men from other background (Ware & Lee, 1998). Green (1992) also sums up, men from wealthier families are more likely to choose business majors than the women; in addition to this he also speculated that men were more motivated by the money and status in their college major choices regardless of their socioeconomic background. While women from less affluent backgrounds are motivated by money and status, women from higher socioeconomic backgrounds are more open to explore a wide variety of subjects and are not very keen on higher paid jobs. Trusty et al. (2000) also reported that the relationship between socioeconomic status and higher education choices were stronger for women than for men, showing that women are motivated to go into higher education if they come from less affluent backgrounds.

These arguments on family background and socioeconomic status and its relationship to higher education choices particularly matter for higher education policy. For example, in the UK and the US, higher educational policies have emphasised economic benefit as the motivation for participating in higher education (Davis et al., 2014). Higher education policies also need to consider the effect of cultural capital on participation rates from different communities. In the UK, for instance, universities spend a significant proportion of tuition fee to raise the participation of students from lower income backgrounds (Pollard et al., 2019).

4.2.2 Skills and subject choices

In addition to being influenced by family, it is likely that individuals choose subjects based on their skills and abilities. In fact, subject choices are based on many factors and previous studies have shown that individual comparative advantage in a particular subject or skill level is only one of these factors. For example, according to Van de Werfhorst et al. (2003), students' academic subject choice can be related to the skills inherited or learnt in school. Similarly, according to Jonson (1999), women have comparative advantage in arts and humanities subjects whilst men have an advantage in science and mathematics related subjects. These studies suggest that students will choose subjects where their comparative advantage lies. Comparative advantage helps to determine students' preferences within the set of available options. Van de Werfhorst et al. (2003) also argue that if a student has an 'A' grade in English and a 'B' grade in maths at the GCSE or A-level, they will be more likely to pursue humanities or non-technical subjects at degree level, as students believe that they have a higher rate of success where they have comparative advantage. Furthermore, previous research by Urez et al. (1999), argues that students from advantaged backgrounds are generally more likely to be encouraged to 'read' and participate in other forms of literacy-based activities – and may, therefore, have a higher comparative advantage in humanities and arts – than other students. Students coming from homes where they are encouraged to take part in science and technical related activities, they may find comparative advantage over others in these subjects.

The advantage of using comparative advantage (skill level) to explain subject choice is that it does not rely on students having labour market knowledge. Rochat et al. (2001) suggest that the assumption that students have labour market knowledge when making their degree subject decisions is weak compared to the assumption that students make decisions based on their skills in a certain subject and their family background. Skills are considered as a key determinant of subject choices as, according to Haveman (1995), the success of an individual is measured by schooling attainment, occupation or income level and a key determinant of success is the skill level of an individual and these include both cognitive and non-cognitive skills. A significant positive relationship between skills and educational choices has also been illustrated by Blanden et al. (2007) and Browne et al. (2009).

In the next sections we will discuss the impact of parental background and skills on subject choice.

4.2.3 Socio-economic Status and wage premium

So far, we have discussed the link between socioeconomic background and subject choice. Next, we want to discuss how these are linked to wage premium. Sewell et al. (1976) and Hauser et al. (1977) show that social background only had a significant effect with the increasing number of years of post-secondary school on individual income. Parental education had no effect, but parental income has a positive effect on individual's income.

The literature on socio-economic background and wage premium in the UK is limited (Britton et al., 2016) but a number of studies show that graduates from a higher socio-economic background, especially those educated at a private school, achieve a higher return to degree education (Bukodi & Goldthorpe, 2011; Crawford & Vignoles, 2014).

Other international research shows that individuals coming from households with lower household incomes earn lower wage premia. Dustmann (2004) using the German Socio-Economic Panel (GSOEP) finds that there is approximately 35% differential in wages between individuals born in lower educated/class families and individuals born in higher educated/class family. Similarly, Black et al. (2005), Bhuller et al. (2011) and Carneiro et al. (2015) used Norwegian data and show that parental income has a strong positive impact on children's education level and labour market wages.

4.2.4 Skill (cognitive and non-cognitive skills) and wages

We have already spoken about the impact of skills on subjective choice. We will consider literature relating to their impact on wages in this section. The importance of cognitive skills and non-cognitive skills in influencing individuals' future wage trajectories has also long been debated in the literature; however, the issue is still unsettled (Hall, et al. 2011).

According to Hauser et al. (1977), there is a linear relationship between earnings and the cognitive skills of individuals. In 1971, individuals with IQ over 120 earned on average 40 percent more than individuals with IQ under 80 (for all high school graduates)[33]. Similarly, Taubman and Wales (1974) showed that higher numeracy scores had a significant impact on the earnings of respondents[34].

Bishop (1992), using the National Longitudinal Survey of Youth from 1979 to 1986, analysed the effect of both mathematics and verbal composite scores on individual earnings and found that there is a positive effect of numeracy skills on individual earnings for men but not for women. However, the verbal composite score had a negative effect on male earnings and an insignificant effect on female earnings. Blackburn et al. (1993), using the Armed Services Vocational Aptitude Battery, report that none of the scores for arithmetic reasoning, mathematics knowledge, word knowledge or paragraph comprehension had any impact on earnings.

McIntosh and Vignoles (2001), employing the UK National Child Development Study (NCDS) and International Adult Literacy Survey Data sets (IALS), after controlling for education, reported that numeracy had a significant impact on earnings. Literacy was insignificant when using the NCDS but showed some positive effects when using the IALS. However, Cawley et al. (2001) reported that it is worth noting that skills and schooling are so highly correlated that it is very difficult to separate out their effects without imposing strong assumptions, such as that of a linear relationship of earnings with skills and education and measuring wage at one point of time despite wages varying with time for different individuals. In addition to these, cognitive skills are correlated with the earnings although they operate through the education attainment.

The role of non-cognitive skills on a range of life outcomes, including earnings trajectories, has received increased consideration, also as a result of the developments associated with human capital theory. Indeed, in the early days of human capital theory, human capital was

[33] Together schooling and skills contributed to 6.2 percent increase in income in 1968 and to 10.5 percent in 1971.
[34] The mathematical ability score was calculated by weighting 17 different tests. The test subjects ranged from simple math, algebra, trigonometry to advanced mathematical concepts. Using similar data, Willis and Rosen (1979) also reported significant positive results for higher numeracy ability.

essentially measured by years of education and cognitive skills (mostly proxied by IQ). The 'signalling hypothesis' (Spence, 1974 and 1978), however, put forward the idea that job market returns to education were only returns to human inherent ability and not to any skills acquired through education. As economists developed further understanding of the determinants of earnings, they emphasised that success in the labour market requires multiple soft skills too. These skills include conscientiousness, ability to work with others and other attributes identified by personality psychologists. Relevant market skills were understood to be heterogenous as different labour markets and life tasks require skills in different amounts and proportions (Heckman, 2019).

Despite the importance placed on achievement test scores in explaining various life outcomes, including labour market ones, studies show that they do not adequately capture non-cognitive skills such as personality and preferences, self-control, openness, resilience, humility, perseverance, conscientiousness, empathy, trust, attentiveness, tolerance, community engagement and self-esteem (Heckman at al., 2019, Cunha et al., 2010, Carneiro et al., 2007, Almlund et al., 2011; Borghans et al., 2008). These are all relevant to labour market success and until recently these skills have been ignored in evaluation of a person's lifetime prospects.

In recent research, economists and psychologists have constructed different measures of these skills and have given evidence that these are stable across a range of situations (Heckman et al, 2019). Also, skills are not purely determined by genes but can be fostered by early interventions in life. Interventions to improve skills are effective to different degrees for different skills at different ages, but importantly non-cognitive skills are more malleable at later stages in life than cognitive skills (Carneiro et al., 2007).

There is a growing body of research which shows that non-cognitive skills rival IQ in predicting labour market success, health, educational achievement and criminal activities (Heckman & Kautz, 2012, 2014a,b; Almlund et al., 2011). Both IQ and non-cognitive skills can be used to predict achievement scores but when predicting life success, non-cognitive skills do better.

Whetzel (1993) conducted an extensive analysis of which skills are most needed by the American labour force. The Commission categorised the necessary skills into four categories. First, basic skills which include reading, writing, speaking, listening and maths skills. Second, thinking skills which cover creative thinking, decision making, problem solving, ability to learn and reasoning skills. Third, personal qualities which include responsibility, honesty, integrity, sociability, and self-management. Lastly, workplace competencies were identified which include ability to allocate resources (e.g. time money and facilities), interpersonal skills (these include teamwork, leadership and collaborating with others), ability to learn new technology and information and work well with technology.

Authors like Deming (2017) also claim that between 1980 and 2012, jobs which required high levels of social interaction grew by 12 percentage points as a total share of the US labour market. In addition, social skills are complementary to cognitive skills and jobs which require a combination of both are becoming increasingly available. These skills allow workers to manage different tasks more effectively, build useful relationships and become ultimately more productive. Caines et al. (2017) show that the greatest growth in economic returns is related to cognitive and non-cognitive returns.

Holzer (1997) shows that employers' surveys reinforce the importance of non-cognitive skills. In a survey of 3,200 employers in four metropolitan areas in U.S.A., employers reported that qualities such as responsibility, integrity and self-management were important or in some cases most important. Another National Employer Survey of 3,300 employers in the mid-1990s showed that employers rank communication skills, work experience, attitude and credentials above years of schooling, grades and test scores (Zemsky, 1997). In 2007, a survey of employers in the state of Washington reported that employers found it more difficult to hire workers with appropriate teamwork, problem solving, communication, adaptability, and positive work ethic than adequate maths and literacy skills.

Evidence from the United Kingdom also supports these findings. A 1998 survey of approximately 4000 employers found that 16-24-year-olds were lacking technical, communication, customer handling and teamwork skills (Westwood, 2004). According to Hillage et al. (2002), a survey in 2002 of another 4000 employers in the UK showed that there was a shortfall of communication, teamwork, customer handling and problem-solving skills and least common were numeracy and literacy skills. Also consistent with these findings, the Confederation of British Industry defines employability of workers based on (1) values and attitude towards work (i.e., desire to learn, apply learning, improving and taking advantage of change); (2) literacy and numeracy skills; (3) communication, IT, improving on learning and performance, working with others, problem-solving were considered as key skills; (4) skills such as language and customer services; (5) job-specific skills and ability to manage one's own career progression. Caliendo et al. (2015) using a German survey shows that individuals with a higher locus of control end up with higher paying jobs and put more effort into job search and work. Using the same German data set Flinn et al. (2019) show that women score higher than men on the characteristic of 'agreeableness' and this costs them on their wages. Men, on the other hand, end up with higher wages because of higher bargaining ability.

4.2.5 Cognitive and non-cognitive skills measurement/issues

Cognitive skills are usually defined as the intelligence and the ability to solve abstract problems. Typical measures of cognitive skills are IQ test and other standardised tests available for literacy and numeracy (Heckman et al., 2014). Non-cognitive skills are personality traits that are related with measures of intelligence such as the IQ index. A widely accepted classification of personality traits in the literature is the Five-Factor Model, defined by the Nyhus and Pons (2005), which includes:

- *Agreeableness: the willingness to help others and act in accordance with other people's interests and the degree to which people are willing to cooperate.*
- *Conscientiousness: the preference to follow rules, regulations, and schedules to keep organised and attitude of being organised, dependable and hard-working.*
- *Emotional Stability: this encompasses the dimensions of being nervous versus relaxed, dependant versus independent and the degree to which an individual is insecure, anxious, depressed, confident, and cool.*
- *Autonomy: the individual's propensity towards taking control and initiative in different situations.*
- *Extroversion: the individual's preference towards human contact, being assertive, empathy and wishing to inspire people.*

These Big Five factors are widely used in psychology to define non-cognitive skills (Heckman et al., 2019). However, there are several other classifications such as Big Three, Big Nine and the MPQ, which are all conceptually related to the Big Five (Borghans et al., 2008; Almlund et al., 2011).

Robert (2009) and Almlund et al. (2011) suggest that all non-cognitive skill measurements are calibrated on measured behaviours or tasks. Tasks can include IQ tests, personality questionnaires, performance on job, participating in crimes, completing educational studies or performance in an experiment. Performance on different tasks depends on these factors to different degrees, as some people can be weak in one dimension but have strength in others. For example, a good IQ score requires both ability and effort, if a person lacks either one of those the IQ results could be misleading. Inferring skills from performance on tasks requires standardising all the other contributing factors that produce the observed performance. There are two issues that need to be addressed before designing the measures of skills based on the performance of any task. First is the individual's behaviour which depends on the created situation and, secondly, different incentives elicit different amounts of effort on the task used to measure skills. To accurately measure non-cognitive skills, it is required to standardise for the effort applied by the participants in any task. These issues are empirically relevant as incentives can increase the effort and can influence the performance of the participants. This problem is most commonly ignored in empirical research that studies how cognitive and non-cognitive skills affect the desired outcome (Heckman et al., 2012, 2019).

The most common practice in personality psychology questionnaires is self-reporting, which can lead to reference bias (John, 2000). Answers from the self-reporting measures can be misleading when comparing levels of personality skills. For example, the German Socio-Economic Panel asks respondents to rate themselves on the following statement 'I see myself as someone who tends to be lazy'. The scale ranges from 1=strongly disagree to 7=strongly agree. In answering this type of question people interpret the definition of being lazy by comparing themselves to others and if a group is comparing themselves to different reference points this can produce misleading results. This is called reference bias and is empirically important (John, 2000).

Heckman and Kautz (2014) comments that Ralph Tyler, who pioneered the development of achievement tests, also recognised its limitations, and suggested using measures of behaviours such as participation in student activities and other behavioural observations by teachers and school administrators to complement achievement tests when evaluating students and schools. Heckman et al. (2013) show that teachers' rating of elementary school children are strong predictors of adult outcomes and that early childhood interventions could promote these measures. Heckman et al. (2014) estimate the causal effect of cognitive and non-cognitive skills on life outcomes. They measure socio-emotional skills using risky behaviours measured at a young age. These measures include the behaviours of stealing from stores, damaging property, and conning someone. They show that non-cognitive skills promote educational attainment, health, and labour market outcomes. Jackson (2018) measures cognitive skills using achievement scores and for non-cognitive skills he uses behaviours such as absence, suspension, and grade progression. According to Heckman et al. (2019), behavioural measures for assessing non-cognitive skills help to predict life outcomes with similar strength to the cognitive test scores. Kautz and Zanoni (2014) also use early years behavioural measures to predict graduation and college attendance. Lleras (2008) uses tenth grade participation in sports, activities in school and academic clubs to measure non-cognitive skills. Benda (2005) uses both test scores and behavioural measures and finds that behavioural measures better predict criminal activity than psychological test scores.

4.2.6 Endogeneity in returns to education

So far, the wage-education model (Mincer (1974)) we have used is as follows:

$$ln\boldsymbol{w}_i = X_i\varphi + \beta\boldsymbol{s}_i + \epsilon_i \qquad \textit{Equation 4.1}$$

Where $\boldsymbol{w}_i$ is the wage, X_i is the vector of individual's characteristics, including the experience and its square and s_i is the number of years of schooling determined by:

$$\boldsymbol{s}_i = X_i'\gamma + \mu_i \qquad \textit{Equation 4.2}$$

This earning function gives the expected wage of an individual, given his characteristics and his years of schooling. Generally, the relationship is estimated using Ordinary Least Squares, and therefore β cannot be interpreted as a causal effect if $E(X_i\epsilon_i) = 0$ and $E(S_i\ \epsilon_i) = 0$, but $E(S_i\ \epsilon_i) \neq 0$. β can still be interpreted as the conditional expectation of wages given the characteristics and schooling but cannot give the causal effects since education is endogenous with respect to β. There might be unobserved characteristics that simultaneously determine education and are correlated with wage. In order to address this endogeneity issue and estimate a valid coefficient for returns to schooling, we need to isolate the effect of schooling on wages. This is not straight forward as $E(\mu_i\ \epsilon_i) \neq 0$.

Three issues could be associated with the estimation of Equation 4.1: i) measurement error that could bias the coefficient towards zero; ii) reverse causality associated with higher earnings that improve skills or higher paid jobs individuals that invest in further training and skill building courses, all of which tends to bias the errors upwards; iii) bias from omitted variables, due to the possible role of unobserved variables, such as cognitive and non-cognitive skills, family background, health, personality, employment prospects and others related to each individual.

An approach to deal with endogeneity is provided by the Instrumental Variables Model, which is based on the use of instrumental variables that are associated with education/ability but not with wages. For instance, in one of the first applications, Card (1993) uses institutional factors or elements of the budget constraint to create instruments. Harmon and Walker (1995) also used a change in the minimum school leaving age as an instrument. These instrumental variable estimates isolate the returns to education for the group whose education decision is most affected by the institutional features. The changes in the minimum school age can also be specific only to those who wanted to join the labour market as soon as they finish. In another example, Dickson (2009) used early age smoking to find how it can affect the schooling decisions.

In this chapter, we attempt to correct for the bias arising from omitted variables. However, it is difficult to remove this problem fully, because of the limited data availability, and considering that individuals skill level increases over time.

4.3 Data

This chapter uses Next Steps data which is also known as the Longitudinal Study of Young People (LSYP) in England. The study follows the lives of around 15,500 young people born in 1989-90 in England. It started in 2004, when participants were in year 9 aged 14-15 and attending independent and state schools. The survey has been linked to the National Pupil Dataset, which is a pupil level database that matches pupil characteristics and test score information to all the individuals surveyed in Next steps and therefore contains test score information at Key Stages 2, 3 and 4[35]. The first seven sweeps were continuous every year until

[35] In 2013, the management of the survey was transferred to the Centre of Longitudinal Studies at the UCL Institute of Education and in 2015 it reconvened to cover the lives of the members at the age of 25. The focus was maintained on education but the survey itself was broad and intended for use in multidisciplinary research.

2010[36], and in the first four waves' parents/guardians were also interviewed. The final survey was conducted in 2016 when the individuals were 25-26 years old.

One major strength of this data set is that it minimises major errors in skill measurement[37] as it takes numeracy and literacy scores directly from National Curriculum Exams for Key Stage 3. An advantage of using these scores is that they pre-date the choice of subjects at GCSE and A-level stages. These scores are therefore likely to be less endogenous than A-level or GCSE grades. This is because at A-level and GCSE stages, individuals might choose subjects based on a range of influencing factors, such as their ability but also teachers and parents' involvement and labour market knowledge. The data also allows us to control for individual characteristics such as ability and family background and other personal attributes. However, the downside of using this type of single cohort study is that the estimates exhibit the results for one particular cohort for a particular time period. It therefore does not illustrate if there are any wage differences among different cohorts over the time.

4.4 Research Question

We have analysed subject choice and subject premium using the LFS in previous chapters. The LFS allows us to use a large sample over a long period of time (2005-2018) and it therefore gives a broader picture of the returns to subjects in the UK. It also enabled us to look at how the earnings have changed over the years. However, it is not possible to control for attributes like family background, ability, and other character variables using the LFS data. Inability to control for these variables can cause bias in the returns' estimates. The Next Steps data helps us to correct for this bias. This chapter will therefore concentrate on the following question:

1. What impact do family background and individual skills (cognitive and non-cognitive) have on subject choices at university?

[36] These first seven sweeps were funded and managed by the department of Education and was focused on the young people's labour market experience. (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104, http://doi.org/10.5255/UKDA-SN-7104-4)
[37] Measurement errors can occur because if the relevant skills are not tested or respondents experience, emotional wellbeing, and environment also have an impact on the test. It is also a possibility that respondent solved a problem by chance or may cheat to solve the problem.

Once we have estimated the choice of subjects and their determinants using the Next Steps data, we will control for both cognitive and non-cognitive skills and see how they impact on the wage premium of individuals.

- How does the inclusion of cognitive and non-cognitive skills affect the subject-wage premium earned by graduates?

The literature on the returns to education has discussed the issue of estimating the causal effects of education on wages using instrumental variables. Here, by employing the Next Steps data, we will use the endogenous treatment model to test the causal effects of subject choice on wages. In addition to this we will also discuss gender differences and the difference in-between weekly and hourly wage estimates.

4.5 Model specification

One of the research questions in this chapter relates to whether individual subject choices are affected by individual characteristics, skills, and family background. In order to address the question posed, we begin with the following multinomial logit model:

$$\boldsymbol{sc}_i = \alpha + \beta_1 \boldsymbol{g} + \beta_2 \boldsymbol{pe_i} + \beta_3 \boldsymbol{inc}_i + \beta_4 KS_{3i} + \beta_5 SI_i + \beta_6 C_i + \varepsilon_i \qquad \text{Equation 4.3}$$

where:

$\boldsymbol{sc}_i$: *Subject Choice (Medicine, Medical Related, Science, Maths and Engineering, Law, Economics & Management, Languages & Education and Arts and Creative Arts)*

$\boldsymbol{g}$: $Gender$

$\boldsymbol{pe}_i$: $Parental\ Education$

$\boldsymbol{inc}_i$: $Household\ Income$

KS_{3i}: $Key\ Stage\ 3\ numeracy\ and\ literacy\ score\ representing\ cognitive\ skills$

SI_i: $Subject\ Identifiers$

C_i: $Controls\ (Ethnicity,\ region\ and\ health\ issues)$

The multinomial logit model is used because subject choice is a discrete variable where the choice between seven different categories of subjects is not ordered.

As in Chapter 4, our sample is restricted to those who went to university and have a degree. We will therefore be using a degree in Law, Social Science and Management (LSM) as the base category. β_1 will estimate the effect of gender (g); β_2 will estimate the effect of Parental Education on the subjects; β_3 will capture the effect of Household income (I) on subject choices and β_4 will capture the effect of Key Stage 3 (KS3) skills on the subject choice. Numeracy and literacy ability are the main skills that we consider. For example, according to Herman G. W. et al. (2002), higher numeracy means that individuals have skills to interpret data, process information, solve problems and make decisions based on logical thinking and reasoning. Similarly, higher literacy skills might reflect higher motivation for reading and writing, better narrative and comprehension skills and language awareness.

Numeracy and Literacy assessment scores measuring the skill level of an individual are highly correlated to each other (0.6687, which is significant at p-value<0.01). Therefore, we estimate three models: i) including only the numeracy variable; ii) including the literacy variable alone; iii) including both literacy and numeracy skills together to check if estimates change and which skills are more relevant.

Lastly, β_5 will capture the effect of subject identifiers. Subject identifiers are individuals' preferences in year 9 (we will define them in detail later in the variable section). Based on the work by Mendolia and Walker (2014), we assume that adolescent preferences are related to subject choices at the degree level.

In addition to model 3 which includes cognitive skills, we will also estimate a model with the non-cognitive skill variables, as follows:

$$\mathbf{sc}_\mathrm{i} = \alpha + \beta_1\mathbf{g} + \beta_2\boldsymbol{pe}_\mathbf{i} + \beta_3\boldsymbol{inc}_\mathbf{i} + \rho_1\mathrm{NC}_\mathrm{i} + \beta_4\mathrm{SI}_\mathrm{i} + \varepsilon_\mathrm{i} \qquad \textit{Equation } 4.4$$

NC_i variables represent the non-cognitive skills and ρ_1 will give the coefficients of non-cognitive skills on the subject choices.

4.5.1 Empirical Wage Model

In order to assess the relationship between skills and the wage premium, taking into account subject choices, we proceed in two steps and estimate two different regression models.

First[38], we employ OLS to estimate the extent to which wages differ by different degree subjects[39]. The base category is individuals who graduated in Law, Social Science and Management (LSM)[40]. The model will also control for the individual skills.

The equation is as follows:

$$\begin{aligned} \ln\mathbf{w}_\mathrm{i} = \alpha + \pi_1\mathbf{g} + \pi_2\boldsymbol{pe}_\mathbf{i} + \pi_3\boldsymbol{inc}_\mathbf{i} + \pi_4\mathrm{KS}_{3\mathrm{i}} + \pi_5\mathrm{NC}_\mathrm{i} + \pi_6\mathrm{SC}_\mathrm{i} + \pi_7\boldsymbol{uni}_\mathbf{i} \\ + \pi_8\boldsymbol{dc}_\mathrm{i} + \pi_9\mathrm{C}_\mathrm{i} + \varepsilon_\mathrm{i} \end{aligned}$$

Equation 4.5

$\boldsymbol{g}: Gender$

$\boldsymbol{pe_i}: Parental\ Education$

$\boldsymbol{inc_i}: Household\ Income$

$KS_{3i}: Key\ Stage\ 3\ numeracy\ and\ literacy\ score\ representing\ cognitive\ skills$

$NC_i: Non-Cognitive\ Skills$

$SC_i: Subject\ Choice\ at\ degree\ level$

$\boldsymbol{uni}_i: Prestige\ of\ the\ higher\ education\ institution\ (e.g. Russell\ Group)$

$\boldsymbol{dc_i}: Degree\ Class\ achieved$

$C_i: Controls\ (Ethnicity,\ region\ and\ health\ issues)$

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38 We will be using 'Ordinary Least Squares' to calculate the coefficients of subject premium for individuals graduated in different subject categories compared to A-level qualified individuals using the Mincer (1974) equation. This is the same method used in Chapter 4 but we re-estimate the model using Next Steps dataset, to give us a comparison with LFS dataset and also give an insight on how the estimates differ if we include cognitive and non-cognitive skill variables as an additional control. (The results and explanation will be given in 4.9.1).

39 The Least Squares implicitly assumes that the subject premium to specific degree subjects is homogenous, which means that all different types of students on average earn a similar wage premium as an outcome of studying a certain degree subject. This assumption is very strong because if the effect of degrees is heterogenous across graduates, the estimates will give weight to the average of different subject premia, and this may not be the true average treatment effect (that is effect for doing a certain degree). However, Dearden (1999), using the National Child Development study, reports that the OLS gives reasonable estimates of the true relationship between education and wages.

40 The main reason to select this category is because, according to HESA yearly data and the Next Steps, most of the graduates are in these subjects and there has been a continuous rising trend of university students in these subjects.

This estimation allows us to reassess the analysis done in Chapter 4 after including a range of additional variables but retaining the same (OLS) methodology. We can then consider whether the inclusion of these variables changes our estimates.

Second, we estimate an endogenous treatment model to compare each subject choice with the LSM subjects. The endogenous treatment model comprises of two stages: firstly, we estimate the subject choice equation and, secondly, we estimate the wage equation using the predicted estimates of subject choice from the first stage equation. This will capture the causal relation between the subject choice and wages.[41]

The motivation behind using this model is to correct for endogeneity, the presence of unobserved variables that drive both the wages and subject choices. More specifically, the factors influencing the selection of degree subjects at university, and which affect wages, are included in the model. The endogenous treatment model estimates the average treatment effect and the other parameters of a linear model augmented with an endogenous binary-treatment variable. Estimates are calculated by full maximum likelihood with a control function estimator.

In the first stage, the individuals choose a subject category for a degree qualification out of seven mutually exclusive choices. Let U_i denote the indirect utility by subject choice associated with the j_{th} treatment, where j_{th} is the identifier at an early stage of education for the individual i.

$$\mathrm{U_{ij}}|\boldsymbol{sc}_{\mathrm{i}} = \mathrm{SI_i}\alpha_{\mathrm{j}} + \sum_{\mathrm{k=1}}^{\mathrm{j}} \delta_{\mathrm{jk}}\,\mathrm{l_{jk}} + \eta_{\mathrm{ij}} \qquad \textit{Equation 4.6}$$

[41] We had two options to model wage and subject choice: one was the multinomial treatment model and the other was the endogenous treatment model. We choose the endogenous treatment model because of three reasons: i) the endogenous treatment model will be able to give us the causal relationship between the subject choice and wages, will adjust the coefficients and significant errors and will also allow us to factor the independent variables to uncover much more details on social class, parent's qualification, and prestige of university; ii) both model specifications use the same base categories, that is of LSM subject; iii) we tried to use the multinomial treatment model in secure access lab, and the commands for the multinomial treatment model did not work. This could be because of STATA do-files or the version of STATA, and UK data services was contacted numerous times and they did not know what was the reason, my supervisors are also aware of this.

SI_i is the set of identifiers that are related to subject choice (SC_i)[42] and we are assuming that they are exogenous to wages; η_{ij} are the i.i.d error terms. The subject choice utility variable U_i is also a function of unobserved characteristics that are common to the individual's choices, for example, latent variables such as motivation or ambition to excel in certain subjects, willingness to bear the costs of doing a degree (Vella & Verbeek, 1999), captured by the l_{jk}, which are assumed to be independent of η_{ij}. Although U_i is not observed, we do observe the choice of subjects in the form of binary variables d_i, as these are collected by vector $d_i = [d_{1j}, d_{2j}, \dots, d_{ij}]$, on the assumption that the probability of selecting a particular subject category other than LSM subjects, using the endogenous treatment logit model (Deb & Trivedi, 2006). The probability that a particular subject will be chosen is given by:

$$\Pr(\mathrm{d_i}|\mathrm{SI_i}, \mathrm{l_i}) = \frac{\exp\left(\mathrm{SI_i}\alpha_\mathrm{j} + \mathrm{l_{ij}}\right)}{1 + \sum_{\mathrm{k}=1}^{\mathrm{J}} \exp\left(\mathrm{SI_i}\alpha_\mathrm{j} + \mathrm{l_{ij}}\right)} \qquad \textit{Equation 4.7}$$

The second stage equation is given as:

$$\mathrm{E}(\mathrm{w_i}|\mathrm{d_i}, \mathrm{x_i}, \mathrm{l_i}) = \mathrm{x_i}\beta + \sum_{\mathrm{j}=1}^{\mathrm{J}} \gamma_\mathrm{i}\mathrm{d_i} + \sum_{\mathrm{j}=1}^{\mathrm{J}} \theta_\mathrm{i}\mathrm{l_{ij}} \qquad \textit{Equation 4.8}$$

Where w_i is the hourly wage for individual, x_i represent the set of other variables used such as parental background, skills, and other controls. γ_i is the treatment effect for choosing a subject category at degree level compared to the control choice of LSM subject category. In the second stage $E(w_i)$ is a function of latent characteristics; therefore, the outcome is affected by the unobserved characteristics.

4.5.2 Validity of Instruments

An important consideration when estimating the treatment model is related to the validity of instruments. In our model, we use the variable *'Subject Identifiers'* as the instruments. Valid instruments need to be relevant and exogenous. Relevance implies that the instruments should be correlated with the variable that they are instrumenting (Staiger & Stock, 1994). In our case,

[42] $SC_i = 1$ for subject category i and $Subjects_i = 0$ if LSM, where i = Medicine & dentistry; medical related subjects; maths & engineering, science, languages & education, or creative & performing arts.

this is subject choice. Secondly, exogenous instruments are uncorrelated to the error term in the second stage of the estimation, which, in our case, means that the instruments should be exogenous to the log of wages. To test the relevance of instruments, the procedure requires estimating the first stage of the regression model with the instruments as explanatory variables and the variable to be instrumented on the dependant side. These variables should be jointly significant.[43]

In order to test for the second condition related to the 'exogeneity of the instruments to wages', the general approach is to use the test for 'overidentifying restrictions'. This requires the model to be overidentified, having therefore a greater number of instruments than the endogenous variables. Although no equivalent of this test is being developed for the endogenous treatment model, we have used the instrumental variable (IV-regress) model[44] to test for overidentifying restrictions. The following section describes the variables we have used for estimating the model.

4.6 Variables[45]

4.6.1 Hourly and Weekly pay

Log of hourly and weekly pay will be used to estimate the returns to different subjects and to estimate the extent to which ability influences wages. We are using log values of both gross weekly and hourly wage as dependent variables. We convert the weekly wages to hourly wages by using the average number of hours worked each year. Table 4-1 gives the mean and standard deviations of weekly wage by subject categories and gender. It shows that the highest mean weekly wages are earned by men and women who graduated in Medicine, Maths and Engineering and LSM.

[43] The estimates are given and discussed in the empirical analysis section.

[44] The model is composed of: i) in the first stage, the subject choice at degree is regressed on the defined instruments (subject identifiers) and ii) in the second stage, the predicted values of the first stage are used to be regressed with our dependant variable (wages). To allow for heteroskedasticity we used general method of moments to obtain the Hansen, (1982) statistic for the validity of overidentifying restrictions. The estimates of IV regress is given in the Appendix 4-5, but the overidentifying restriction test values are as follows:

Test of overidentifying restrictions:
Score chi2(14) = 20.4171 (p = 0.1175)

[45] Data tables represented in this variable section are taken from using Next Steps (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

Table 4-1 Mean weekly pay (in British pounds £s) for different subject categories

Subject Groups		**Males**	**Females**
A-levels	Mean	361.82	308.61
	Standard Dev	656.42	376.81
Medicine	Mean	430.75	490.65
	Standard Dev	366.3	333.27
Medical-Related	Mean	332.98	398.78
	Standard Dev	471.34	240.91
Science	Mean	384.227	358.52
	Standard Dev	370.17	427.65
Maths and engineering	Mean	493.1	460.89
	Standard Dev	592.64	275.95
Law, social science and management (LSM)	Mean	459.1	436.84
	Standard Dev	464.98	1165.66
Languages and education	Mean	332.33	406.81
	Standard Dev	266.65	597.18
Arts	Mean	227.63	262.97
	Standard Dev	230.86	193.62

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

The number of hours worked per week are shown in Table 4-2. Converting the weekly wages to hourly by dividing the weekly pay by number of hours worked in a week will not represent the true hourly wage for degree graduates, as we can see that some degree graduates work more hours compared to others.

Table 4-2 Average number of weekly hours worked by individuals

Subject Groups		**Males**	**Females**
A-levels	Mean	32	24
Medicine	Mean	42	41
Medical-Related	Mean	33	33
Science	Mean	34	32
Maths and engineering	Mean	37	35
LSM	Mean	37	33
Languages and education	Mean	31	34
Arts	Mean	32	30

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.6.2 Parental education and Household Income

In our regression, we will be using the parent's qualification, taken from wave 2. The result will reflect the impact of parents on literacy and numeracy abilities and therefore on individual wages. Parent's qualification will also be a proxy for social class, given the relationship between educational achievement and socio-economic classification (Breen & Goldthorpe, 1997).

However, the correlation between education and social class has become weaker over time (Dustman et al., 2008); therefore, we also use household income. The income of the households in which the individuals lived when they were 13 and 14 years of age is taken from waves 1 and 2. It is divided into seven income group as in Table 4-3[46].

Table 4-3 shows that GCSE is the highest qualification achieved by most parents (almost 41 percent). Moreover, the highest percentage of individuals (more than 25 percent) come from a household with income between £20,800 and £33,800; this is followed by individuals coming from a household with income between £41,000 and £55,000 and those with income over £55,000.

Table 4-3 Main Parent qualification and household income

Main Parent' Highest qualification		**Bands for Household Income**	
No qualification (Base Category)	3087 (22.92%)	Under £10,400 (Base Category)	727 (10.16%)
Degree or Equivalent	1627 (12.08%)	£10,400 to £15,600	807 (11.28%)
Higher Education below degree level	1720 (12.77%)	£15,600 to £20,800	679 (9.49%)
GCE A Level or equivalent	1836 (13.63%)	£20,800 to £33,800	1810 (25.30%)
GCSE grades A-C or equivalent	3664 (27.21%)	£33,800 to £41,000	888 (12.41%)
Qualification at level 1	1124 (8.35%)	£41,000 to £55,000	1136 (15.88%)
Other Qualification	408 (3.03%)	Over £55000	1107 (15.47%)

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

[46] These groups are defined in the Next Steps Data and kept the same.

Zwysen and Longhi (2016) used parental occupation as a proxy for the parental background, we have also used this for the robustness check later in the analysis section.

Table 4-4 Main Parent Occupation

Main Parent Occupation	Frequency
Professional Occupation	453 (20.75%)
Administrative and Secretarial Occupation	653 (29.91%)
Personal Service Occupation	503 (23.04%)
Process, plant, and machine	296 (13.56%)
Elementary Occupation	278 (12.73%)

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

4.6.3 Key Stage 3 National Curriculum Scores

We will be using Key Stage 3 National curriculum scores for numeracy and literacy skills as a proxy for individuals' cognitive skills at the age 13-14. The scores are given in Table 4-5. We can see the highest percentage of individuals achieve a score level of 5 and 6 for both maths and literacy.

Table 4-5 Key Stage 3 literacy and numeracy skills (individual age 13-14 in 2003-2004)

National Curriculum level awarded at Key Stage 3	Numeracy	Literacy
2	91 (0.63%)	-
3	1139 (7.86%)	446 (3.92%)
4	2152 (14.85%)	2347 (17.34%)
5	3296 (22.74%)	5774 (42.65%)
6	4336 (29.92%	3611 (26.67%)
7	2849 (19.66%)	1361 (10.05%)
8	630 (4.35%)	-

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

The Key-Stage 3 assessment scores capture the skills of a student in mathematics and literacy. They also pre-date the A-level stage and, in this sense, reflect ability that is exogenous to our model. However, these variables cannot be entirely exogenous as many factors might influence literacy or mathematical skills from an early stage in individuals' life, including household background (Heckman et al., 2019). Including these variables, however, does help us to control for the impact that ability might have on subject choice and wage premia.

4.6.4 Subject Identifiers

As indicated above, we use Subject Identifiers as instruments in our estimation. Subject identifiers are individuals' school preferences recorded in February 2004 when individuals were in year 9. These variables are chosen as they are related to the individual subject choice; we made this inference on the basis of the literature on early childhood ability and its effects on later outcomes.[47] Subject Identifier variables (count variables) are as follows:

Table 4-6 Subject Identifiers frequency and percentages

How much do you like maths?		**How much do you like literacy?**		**Favourite School Subject**	
Like it a lot	4434 (28.75%)	Like it a lot	4977 (32.28%)	Science and Maths	4349 (28.77%)
Like it a little	6610 (42.86%)	Like it a little	7314 (47.43%)	Social Science and Humanities	6646 (43.96%)
Don't like it very much	4377 (28.38%)	Don't like it very much	3129 (20.29%)	Creative and Performing arts	4122 (27.27%)
Agreement with the statement	**I will choose only the subjects I am interested in**	**I will choose the subjects as same as my friends**	**I will choose the subjects because I like the teacher**		
Strongly Agree	8973 (58.53%)	335 (2.19%)	813 (10.33%)		
Slightly Agree	5057 (32.99%)	1309 (8.54%)	4963 (63.04%)		
Slightly Disagree	1077 (7.02%)	3490 (22.77%)	1418 (18.01%)		
Strongly Disagree	224 (1.46%)	10191 (66.50%)	679 (8.62%)		

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. [data collection]. 4th Edition. UK Data Service. SN: 7104)

4.6.5 Non-Cognitive Skills Variables

As discussed in previous sections, non-cognitive skills can be defined and measured in different ways. For our purposes, we use some of the basic drivers of non-cognitive skills as defined by Carneiro et al. (2007) and Lessof et al. (2016). In addition to this we also use some of the behaviour and attitude variables, which offer a better measure of non-cognitive skills than the self-reporting questionnaires (Heckman & Kautz, 2014).

[47] For details see Ashworth and Evans (2001), and Chowdry et al. (2010).

One of the important variables is Locus of Control, which has been shown to be a combination of three variables (Lessof et al., 2016), recorded on a scale from Strongly Agree to Strongly disagree:

1) People like me don't have much of a chance in life.
2) How well you get on in this world is mostly a matter of luck.
3) Even if I go well at school, I will have a hard time getting the right kind of job.

We have combined the self-reported answers for the above three statements and created a variable of Locus of Control. This variable is important in understanding the idea of individual self-control and attitude towards hard work. Caliendo et al. (2015), using a German survey, show that individuals with higher locus of control end up with higher paying jobs and put more effort in job search and work.

Next, we have created a variable for attitude towards a job that pays well, which is a combination of the following variables:

- I want to find a job that pays well.
- I want to find a job that leads somewhere.

According to Flinn et al. (2019) and Heckman et al. (2019), individuals who are more likely to look for a job that pays well are more likely to secure a higher paid job and also have higher bargaining skill.

We used answers to the following three questions to generate a variable for Risky Behaviour.[48]

- Whether ever vandalised public property?
- Whether ever shoplifted?
- Whether ever taken part in fighting or public disturbances?

In order to get the proxies for individual social skills, willingness to help others and satisfaction, which correspond to the Extroversion, Agreeableness and Emotional Stability of the Big Five measures of non-cognitive skills, we use the following:

[48] These variables are binary with yes and no answers.

Table 4-7 Frequency of respondents for each variable

Number of Friends (Count variable)		**Volunteered before (Binary variable)**		**Life Satisfaction (Count variable)**	
None	130	Yes	2846	Very Satisfied	2374
1	284	No	5550	Fairly Satisfied	4429
2-3	2310			Neither Satisfied nor Dissatisfied	1055
4-5	2791			Dissatisfied	669
6-9	1593				
10 or more	1420				

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.6.6 Subject Choice at The University

We will be using subject choices made by the individuals as a variable in all the models defined in the methodology section. The first column of Table 4-8 reports the 19 undergraduate degree subjects contained in Next Steps, which we have classified into 7 groups using JACS code[49] in the second column of Table 4-8. The distribution is similar to the one from the LFS data, with the highest percentage (almost 30 percent) of individuals graduating in Law, Social Sciences and Management (LSM) subjects.

Table 4-8 Number and percentage of individuals graduated in different subject categories.

A-level and Degree Subject Categories	**Frequency**	**Subject Groups**	
A-level	558	A-level	12.01%
Medicine and dentistry	115	Medicine	2.48%
Subjects allied to medicine	333	Medical-Related	7.17%
Biological Sciences	430	Science	14.96%
Veterinary and agricultural Sciences	32		
Physical Sciences	233		
Mathematical and Computer Sciences	290	Maths and Engineering	11.92%
Engineering	168		
Technologies	11		
Architecture, building and planning	85		
Social Studies	365	Law, social sciences, and management subjects	29.32%
Law	262		
Business and administrative studies	550		
Historical and Philosophical studies	185		
Mass communication and documentation	165	Languages and Education	

[49] Similar technique is followed by Herman G. W. et al., 2002

A-level and Degree Subject Categories	Frequency	Subject Groups	
Linguistics, classics and related subjects	196		
European languages	63		11.90%
Eastern, Asiatic, African and American languages	15		
Education	114		
Creative arts and design	476	Performing and Creative Arts	10.25%

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-9 gives the timeline in which the education variables are recorded. This will be useful in defining the specification of the endogenous treatment model explained in the next section. The subject identifiers, which we will use as instruments, were recorded in the first wave in February 2004; next, in July 2004, the literacy, numeracy and non-cognitive skills were recorded. Moving forward to wave 7, we can then link to the university subject choices, recorded in May 2010.

Table 4-9 Timeline of Recorded Variables

Timeline of Recorded Variables

February 2004 (Wave 1)	July 2004	May 2010 (Wave 7)
(**Subject-Identifiers**)Variables recorded in year 9 before Key Stage 3 assessment	Key Stage 3 assessment results	Subject Choice at University

• How much do you like maths?
• How much do you like literacy?
• Favourite School Subject
• Agreement with the statement
    ○ I will choose only the subjects I am interested in
    ○ I will choose the subjects same as my friends
    ○ I will choose the subjects because I like the teacher
	• National Curriculum Literacy ability level at Key Stage 3
	• National Curriculum Numeracy ability level at Key Stage 3
	• Non-cognitive skills
		• Medicine and Dentistry
		• Medical-Related Subjects
		• Science (Biology, Chemistry, Physics, agriculture, forestry and other related subjects)
		• Mathematics and Engineering Subjects
		• LSM
		• Languages, humanities and education
		• Performing and Creative Arts

4.6.7 Type of Institution

To control for the prestige of universities in the wage equation, we use the type of university individuals attended. This variable has the following three categories: Oxbridge, Russell Group and all other Universities. The frequency of each category is reported in Table 4-10, which shows that only 2% are graduated from Oxford and Cambridge and 19% are graduated from the Russell group universities. In our analysis, we combine the Oxbridge and Russell Group categories as the individuals from Oxbridge institutions represent only 2% of the sample.

Table 4-10 Percentage of individuals graduated from different university types

Type of University	**Frequency**
Oxbridge	87 (2.03%)
Russell Group	829 (19.37%)
All other Universities	3364 (78.60%)

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.6.8 Degree Classification

Our analysis considers all the students who were enrolled in undergraduate degrees (excluding any vocational courses below the degree level) and graduated in the academic year 2011-2013. We include the degree classification variable, distinguishing between first class, upper second class and lower class, to distinguish between the higher and the lower achievers, which is also used by employers to assess job applicants (Tims et al., 2015 and Psacharopoulos, 1994). The frequency of each degree classification is given in Table 4-11. It can be observed that almost 69% of graduates achieved either first class or upper second class.

Table 4-11 Percentage of individuals graduated in different classes

Degree Classification	**Frequency**
First Class	315 (18.16%)
Upper secondary class (2.1)	883

Degree Classification	Frequency
	(50.89%)
Lower second class/pass (2.2)	537
	(30.95%)

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Other control variables (as in Chapter 2) are gender, ethnicity, region (London) and marital status.

4.6.9 Correlation Between Cognitive and Non-cognitive Skills

The measures we are using for cognitive skills are literacy and numeracy test scores of individual Key Stage 3 national curriculum for the UK. We measure non-cognitive skills using 'locus of control', 'attitude towards a good job, 'risky behaviour', number of friends, life satisfaction, and volunteering activities (Lessof et al., 2016)

The following Table 4-12 gives the correlation matrix between cognitive and non-cognitive skills. We can see that there is a high positive correlation between key stage 3 numeracy and key stage 3 literacy skills (0.6687). Volunteering used as a proxy for helping people has a negative correlation with cognitive skills (-0.0875 for numeracy and -0.0665 for literacy). Attitude towards finding a job that pays well and number of friends has a positive correlation with cognitive skills (0.0978) but negative with volunteering (-0.0712). We can also observe a positive correlation between life satisfaction and individuals with higher cognitive skills (0.056) and higher number of friends (0.176). Individuals with higher locus of control are positively correlated with cognitive skills (0.246) have a higher number of friends (0.513), are more satisfied with their life (0.064). Locus of control has a negative correlation with risky behaviour, meaning individuals with lower locus of control are more likely to be involved in risky behaviours. Looking at these correlations we can assume that higher cognitive individuals are more ambitious and more extrovert and less inclined to consider volunteering.

Table 4-12 Correlation Matrix between cognitive and non-cognitive skills

	K3math	K3eng	Volunteer	Attitude towards job	Number of Friends	Life Satisfaction	Risky Behaviour	Locus of Control
KeyStage3numeracy	1							
Key Stage 3 literacy	0.6687*	1						
Volunteer	-0.0875*	-0.0665*	1					
Attitude towards job	0.0978*	0.0825*	-0.0712*	1				
Number of Friends	0.0989*	0.0600*	-0.0659*	0.0116	1			
Life Satisfaction	0.0562*	0.0624*	0.0634*	0.0408*	0.1756*	1		
Risky Behaviour	-0.1166*	-0.1332*	-0.0003	-0.0691*	-0.0068	-0.0572*	1	
Locus of Control	0.2462*	0.2078*	-0.0434*	0.0210	0.513*	0.0640*	-0.1045*	1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.7 Empirical Analysis for Subject Choice

Table 4-13 presents the results from the estimation of the multinomial logit model of model Equation *4.3*, which gives the likelihood of individuals taking different subject categories. To start with we can see that women are more likely than men to take medicine (by 2.3 percent), medical-related subjects (by 7 percent) and languages and education (by 6.8 percent). Women are less likely than men to take maths and engineering subjects (by 14.5 percent). In our data, there are no significant gender differences in the likelihood of taking Science, LSM and Arts subjects.

Table 4-13 Multinomial Regression for Subject Choice (marginal effects)

	VARIABLES	Medicine	Medical Related	Science	Maths and Engineering	Law, Social Science and Management	Languages and Education	Arts
Gender	Female	0.023***	0.070***	-0.001	-0.145***	-0.005	0.068***	-0.01
Favourite subject category at school (Base Category: Arts)	Science and Maths	0.038***	0.055***	0.032	0.038*	0.087***	-0.071***	-0.179***
	Social Science and Humanities	0.012**	0.005	0.081***	-0.012	0.133***	0.034*	-0.185***
Like Maths at school (Base Category: Don't Like Maths at all)	Like it a lot	-0.004	0.02	0.022	0.139***	-0.063*	-0.143***	-0.004
	Don't like it very much	0.019	0.025	0.034	0.060***	-0.083**	-0.058*	0.003
Like Literacy at school (Base Category: Don't like literacy at all)	Like it a lot	-0.043*	-0.037	0	-0.077**	0.051	0.100***	0.006
	Don't like it very much	-0.046*	-0.015	-0.018	-0.022	0.104*	0.012	-0.015
Agreement with the statement: I will choose the GCSE subject I am interested in (Base Category: Strongly disagree)	Strongly Agree	0.024***	0.068***	0.133	0.096***	0.234***	0.116**	0.212
	Agree slightly	0.005	0	0.008	0.011	0.018	0.005	0.007
Agreement with the statement: I will choose GCSE subjects as told by teacher (Base Category: Strongly disagree)	Strongly Agree	0.027	0.081	0.002	0.053	0.145**	0.017	0.036
	Agree slightly	0.031	0.082	0.041	0.088	0.127**	0.014	0.055
Agreement with the statement: I will choose GCSE subject that my friends do (Base Category: Strongly disagree)	Strongly Agree	0.034	0.079	0.014	0.091**	0.034*	0.056	0.057
	Agree slightly	0.008	0.111	-0.026	0.116**	0.086*	-0.077	0.020
Controls: Region, ethnicity Parental background, cognitive and non-cognitive skills and gender		×	×	×	×	×	×	×
Observations		2096	2096	2096	2096	2096	2096	2096

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

When looking at the likelihood of choosing specific subjects at university, given subject school preferences, we find that a person who preferred Science and Maths while at school, is significantly more likely than a person who preferred Arts to choose Medicine, Medical Related and LSM subjects at university and less likely to choose language and education and Arts. Someone with a preference for Social Science and Humanities is significant more likely than someone who preferred Arts to choose medicine (but to a less extent than the Science and Math person), Science, LSM, languages (more pronouncedly than the Science and Math person) and less likely to choose Arts.

Using the variable 'preference for maths or literacy' in the estimation, we also find that those individuals who 'like numeracy' are more likely to choose mathematics and engineering, and less likely to take on subjects like languages, education, and humanities at university. Similarly, individuals who like literacy at school are more likely to pick languages and education as subjects at university. We can conclude from this that enthusiasm for certain subjects at school extends into choosing those subjects at university. The results show that children who ‘like numeracy’ at Key Stage 3 Mathematics indicate that they are more likely to take Maths, Medicine, Engineering and Science subjects by 13.9 percent compared to individuals who ‘don’t like numeracy’. The estimates also indicate that individuals who ‘like math a lot’ are less likely than those who “do not like it at all” to take languages and education by 14.3 percent. It is therefore possible to infer that individuals’ (as children) with good numeracy skills at Key Stage 3 particularly favour the STEM subjects and are relatively less likely to take on the Humanities and arts disciplines. This also indicates that there is significant path-dependence in these preferences and that therefore they may relate to the cognitive skills, as cognitive skills develop from accumulation by focusing on these skills, gained by interested individuals when they are young in school.

Agreement with the statements that “I will only select subjects in GCSE I am interested in” has a significant impact on subject choice at degree level. We can see that it is 2.4 percent more likely for individuals to choose medicine if they strongly agree with the statement ‘I will choose the subject that I am interested in’ than if they strongly disagree. This estimate goes up to 23.4 percent for the degree level subjects of Law, Social Science and Management, 6.3 percent for medical related and 9.6 percent for the mathematics and engineering subject categories.

Agreement to the statement that “students will choose the subject at GCSE as their friends or as told by the teacher” is significant for the subject of Law, Social Science and Management, which suggests that the reason why the highest number of university students takes LSM is because individuals are influenced by peers, colleagues, and parents. The estimates are also significant for the subject category of Maths and engineering, which also depicts that in some cases some peer and teachers have a significant impact on maths and engineering choices.

As we have discussed earlier in this chapter, one of the problems in understanding the relationship between subject choices and wages is that the impact of cognitive skills is often missing in estimations. In this chapter, we can correct for this by including Key Stage 3 score of numeracy and literacy skills into our estimations.

Numeracy and literacy skills pick up different things, for example, higher numeracy ability individuals are more logical and better understand numbers and solve problems than individuals with lower numeracy skills. Individuals with higher literacy skills are better at awareness of language and comprehending different situations than lower literacy skilled individuals (Werfhorst et al., 2003; Heckman et al, 2018).

We estimate three separate models: one with the variable for Key Stage 3 numeracy scores (model (a) in Table 4-14); one with the variable for Key Stage 3 literacy scores (model (b) in Table 4-14); one with both Key Stage 3 numeracy and literacy scores together (model (c) in Table 4-14).

Table 4-14 Three models with literacy and numeracy skills estimated separately and together (marginal effects)

			Dependent variable (Subject choice)						
	Model	VARIABLES	Medicine	Medical Related	Science	Maths and Engineering	LSM	Languages and Education	Creative and Performing arts
(a)	Estimated model with Numeracy Skills: Numeracy Ability	Key Stage 3 numeracy	0.030***	-0.007	0.039***	0.019*	-0.032	0.000	-0.048***
(b)	Estimated model with Literacy Skills: Literacy Ability	Key Stage 3 literacy	0.025***	-0.012	0.033***	-0.017**	-0.017	0.035***	-0.066***
(c)	Estimated model with both Numeracy and Literacy Skills: KS3 Numeracy Skills	KeyStage3 numeracy	0.027***	-0.004	0.025*	0.047***	-0.045***	-0.024*	-0.029***
	KS3 Literacy Skills	KeyStage3 literacy	-0.004	-0.015	0.034*	-0.055***	0.021	0.053***	-0.043***
	Controls: Subject Identifiers, Gender, region, parental background, Non-cognitive skills		×	×	×	×	×	×	×
	Observations		2070	2070	2070	2070	2070	2070	2070

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

The estimates in model (a) indicate that individuals with higher numeracy skills are more likely to take medicine, science, maths, and engineering subjects than those with lower numeracy skills. The coefficient is highest for the subjects of science, maths, and engineering and negative for the arts subjects.

In model (b) individuals with higher literacy skills are better at awareness of language and comprehending different situations than lower literacy skill level individuals. Hence, individuals with higher literacy ability are more likely to take science and medicine subjects and less likely to take maths, engineering, and arts subjects.

It is often the case that high ability individuals may well be good at both numeracy and literacy skills and therefore not surprising that higher numeracy or literacy skill individuals choose medicine. This can be seen in the model (c) results where we have placed both cognitive skills variables together in one model; the estimates shows that numeracy skills outperform in terms of having an impact on the individual's subject choices at university level.

Table 4-15 shows the effect of parental background on subject choice: individuals from a household with a degree level education qualification are most likely to take medicine, LSM and arts than individuals from households with no qualifications. Additionally, if we look at household annual income, although most of the estimates are insignificant, individuals coming from middle-income households (with annual income of £33,800 to £41,000) favour maths and engineering degrees.

Table 4-15 Parental background and choice of degree subject (marginal effects)

	VARIABLES	Medicine	Medical Related	Science	Maths and Engineering	LSM	Languages and Education	Arts
Parents Qualification	Degree or equivalent	0.114**	-0.016	-0.006	0.017	0.112***	0.048	0.056**
(Base Category: No qualification at all)	Higher education below degree level	0.002	-0.017	0.011	0.01	0.105**	0.01	0.089***
	GCE A Level or equiv	-0.002	-0.036	0.015	0.026	0.094**	0.023	0.068**
	GCSE grades A-C or equiv	0.004	-0.027	0.027	-0.003	0.099**	0.035	0.063***
	Qualifications at level 1 and below	-0.016	-0.054*	0.066	-0.007	0.063	0.068	0.006
	Other qualifications	0.014	0.055	-0.072	0.079	-0.118	0.02	0.022
Household Income	10400.01 to 15,600	0.01	0.021	0.015	0.06	-0.03	-0.04	-0.036
(Base Category: Lower than 10,400)	15600.01 to 20800	0.011	0.001	-0.003	0.053	-0.031	-0.031	-0.001
	20800.01 to 33800	0.005	0.031	0.014	0.025	-0.051	-0.013	-0.012
	33800.01 to 41000	0.007	0.017	0.001	0.069**	-0.064	-0.024	-0.007
	41000.01 to 55000	0.001	0.007	0.007	0.023	-0.083*	0.041	0.004
	over 55000	0.013	-0.012	-0.01	0.041	-0.023	-0.006	-0.003
Controls: Subject Identifiers, Gender, region, parental background, cognitive skills and non-cognitive skills		×	×	×	×	×	×	×

Note: Table 4-15, Table 4-16, Table 4-17 are estimates of a single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

For a robustness check, we used the main parent occupation as a control instead of parental education and household income (Zwysen & Longhi, 2016) and found that, although most of the estimates are negative, individuals coming from families where parents had professional and administrative occupations appear more likely to take medicine than individuals coming from families where parents had elementary occupations.

Table 4-16 Parent's occupation's effect on degree subject choice (marginal effects)

	VARIABLES	Medicine	Medical Related	Science	Maths and Engineering	LSM	Languages and Education	Arts
Main Parent Occupation	Professional Occupation	0.039**	0.048	0.008	-0.047	-0.43	-0.044	0.038
(Base Category: Elementary Occupation)	Administrative and Secretarial Occupation	0.027**	0.063	0.075	-0.0615	-0.111	-0.008	0.014
	Personal Service occupation	0.017	0.038	0.046	-0.012	-0.177	0.004	0.083
	Process, plant and machine operatice	0.007	0.078	0.047	0.002	-0.099	-0.134*	0.109
Controls: Subject Identifiers, Gender, region, parental background, cognitive skills and non-cognitive skills		×	×	×	×	×	×	×
Observation		2096	2096	2096	2096	2096	2096	2096

Note: Table 4-15, Table 4-16, Table 4-17 are estimates of a single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Estimates in Table 4-17 gives the estimates of non-cognitive skill with the controls of parental background, cognitive skills, and subject identifiers. Most of the estimates given are insignificant but the numeracy skill estimates are significant.

Table 4-17 Cognitive and Non-cognitive skills' impact on degree subject choice (marginal effects)

variables	Medicine	Medical Related	Science	Maths and Engineering	Law, Social Science and Management	Languages and Education	Arts
Numeracy Ability	0.027***	-0.004	0.030***	0.024***	-0.030***	-0.004	-0.043***
Job_pay_well	0.003	0.019	0.005	0.006	0.055*	0.018	0.021
Volunteer	0.016*	0.017	0.004	0.026	0.045*	0.021	0.035*
Locus_control	0.001	-0.002	0.001	0.001	0.0018	0.006	0.004
Risky_behaviour	0.001	0.001	0.021	0.024	-0.043	0.013	0.027
Life Satisfaction	0.014*	-0.007	0.001	0.011	0.049**	-0.012	-0.028**
Controls: Subject Identifiers, Gender, region, parental background, cognitive skills	×	×	×	×	×	×	×
Observation	2096	2096	2096	2096	2096	2096	2096

Note: Table 4-15, Table 4-16, Table 4-17 are estimates of a single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Next in the Table 4-18 we give the estimates of non-cognitive skills without the inclusion of cognitive skills and the other parental background variables. One important thing to notice here is that individuals with higher non-cognitive skills are more likely to take medicine compared to individuals with lower non-cognitive skills, which is similar to the body of research that suggests that non-cognitive skills rival IQ in predicting labour market success (Heckman & Kautz, 2012, 2014a,b). The estimates show that non-cognitive skills also have some effect on individual subject choices. But if we compare the Table 4-17 and Table 4-18 we can see that numeracy skills have a higher impact on subject choices compared to non-cognitive skills, considering the coefficients of non-cognitive skills are insignificant if we include the numeracy skill variable in the model.

Table 4-18 Estimate of non-cognitve ability effects on the subject choice (marginal effects)

variables	Medicine	Medical Related	Science	Maths and Engineering	Law, Social Science and Management	Languages and Education	Arts
Job_pay_well	0.008*	0.018*	0.028*	0.006	0.083***	0.018*	0.021*
Volunteer	0.021***	0.017*	0.018	0.034**	0.020	0.016	0.027*
Locus_control	0.003***	0.001	0.002	0.001	0.004	0.003	0.005*
Risky_behaviour	-0.015	-0.016	-0.003	0.011	0.005	0.006	0.012
Life Satisfaction	0.012***	0.006	0.010	0.001	0.020*	0.012	0.020**
Controls: Subject choice, Gender, region, house hold Income, parental income.	×	×	×	×	×	×	×
Observation	2096	2096	2096	2096	2096	2096	2096

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

To summarize, we find students who enjoy maths and science subjects at key stage three are more likely to pursue STEM subjects in higher education compared to students who enjoy art subjects at key stage three. Furthermore, those students who excel in numeracy and literacy in key stage three are more likely to engage with STEM subjects at university compared to their counterparts. We also find students who pick their own subjects at GCSE are more likely to pursue maths and engineering in higher education; individuals who come from a more educated background are more likely to choose Medicine, LSM, and Arts subjects. Individuals who have higher non-cognitive skills, focus and life satisfaction, are more likely to study medicine subjects. These findings are important, since they suggest early years education, family background, and family education have a strong influence on future subject choice.

4.7.1 Wage analysis: The Graduate Sample

We start this section by estimating the wage Equation *4.5*. Our sample is restricted to graduates and the base subject category is LSM.[50] This allows us to look at the extent to which wages are related to subject choices but also to cognitive and non-cognitive skills as well as a range of other factors, such as prestige of university and degree class.

Table 4-19 Weekly wage premium estimates for subject choices

VARIABLES	(1) Weekly pay	(2) Weekly pay	(3) Weekly pay	(4) Weekly pay	(5) Weekly pay	(6) Weekly pay	(7) Weekly pay
Female	-0.095***	-0.065**	-0.109***	-0.071***	-0.053	-0.045	-0.050
	(0.026)	(0.026)	(0.027)	(0.027)	(0.036)	(0.042)	(0.037)
Medicine	0.326***	0.177**	0.258***	0.173**	0.188	0.241	0.159
	(0.074)	(0.085)	(0.086)	(0.085)	(0.141)	(0.174)	(0.139)
Medical Related	0.132***	0.154***	0.162***	0.159***	0.084	0.043	0.180**
	(0.046)	(0.046)	(0.047)	(0.046)	(0.074)	(0.097)	(0.077)
Science	-0.035	-0.040	-0.030	-0.037	-0.016	-0.062	-0.009
	(0.035)	(0.035)	(0.036)	(0.036)	(0.046)	(0.052)	(0.047)
Maths and Engineering	0.179***	0.149***	0.201***	0.157***	0.128**	0.099	0.102*
	(0.039)	(0.040)	(0.040)	(0.040)	(0.056)	(0.066)	(0.058)
Languages	-0.076*	-0.069*	-0.095**	-0.076*	-0.037	-0.058	-0.050
	(0.041)	(0.042)	(0.043)	(0.042)	(0.053)	(0.062)	(0.053)
Arts	-0.300***	-0.234***	-0.252***	-0.228***	-0.238***	-0.267***	-0.234***
	(0.042)	(0.043)	(0.044)	(0.043)	(0.061)	(0.067)	(0.063)
Key Stage 3 Maths		0.128***		0.117***	0.115***	0.096***	0.123***
		(0.013)		(0.015)	(0.023)	(0.027)	(0.023)
Key Stage 3 Literacy			0.106***	0.026	0.007	-0.004	0.005
			(0.016)	(0.019)	(0.026)	(0.032)	(0.027)
Controls:							
Ethnicity, region, and Health	×	×	×	×	×	×	×
Degree class and type of institution					×	×	×
Family background						×	×
Non-cognitive skills							×
Observations	2,392	2,236	2,211	2,204	919	610	855
R-squared	0.044	0.049	0.039	0.049	0.067	0.098	0.098

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

We have represented the estimates of weekly graduate premium in

[50] We also estimated the wage model with base category of A-levels, which is given in Appendix 4-1 Mincer wage equation with the base category of A-levels.

Table 4-19 and we believe, weekly estimates offer a more appropriate representation of individual wages than hourly wages, considering that a number of employed graduates work on fixed contracts and different hours during the week but we also calculated the same model for hourly wages given in

Table 4-20 to give a comparison.

Table 4-20 Hourly wage premium estimates for subject choices

VARIABLES	(1) Hourly Pay	(2) Hourly Pay	(3) Hourly Pay	(4) Hourly Pay	(5) Hourly Pay	(6) Hourly Pay	(7) Hourly Pay
Female	-0.042	-0.029	-0.061	-0.017	-0.017	0.034	0.024
	(0.041)	(0.043)	(0.043)	(0.044)	(0.063)	(0.076)	(0.065)
Medicine	0.184	0.020	0.112	0.019	-0.001	-0.109	0.080
	(0.123)	(0.143)	(0.142)	(0.142)	(0.243)	(0.303)	(0.242)
Medical Related	0.153**	0.182**	0.166**	0.166**	-0.060	-0.172	0.057
	(0.076)	(0.078)	(0.078)	(0.078)	(0.128)	(0.173)	(0.135)
Science	-0.204***	-0.210***	-0.197***	-0.214***	-0.283***	-0.250***	-0.240***
	(0.056)	(0.059)	(0.059)	(0.059)	(0.080)	(0.096)	(0.082)
Maths and Engineering	0.100	0.063	0.087	0.037	-0.135	-0.099	-0.111
	(0.064)	(0.066)	(0.066)	(0.067)	(0.097)	(0.121)	(0.101)
Languages	-0.264***	-0.257***	-0.257***	-0.233***	-0.129	-0.176	-0.096
	(0.066)	(0.069)	(0.070)	(0.070)	(0.094)	(0.115)	(0.095)
Arts	-0.322***	-0.278***	-0.309***	-0.285***	-0.346***	-0.250**	-0.319***
	(0.069)	(0.072)	(0.072)	(0.072)	(0.108)	(0.125)	(0.112)
Key Stage 3 Maths		0.097***		0.123***	0.124***	0.091*	0.124***
		(0.021)		(0.026)	(0.040)	(0.049)	(0.041)
Key Stage 3 Literacy			0.024	-0.061*	-0.050	-0.041	-0.027
			(0.027)	(0.032)	(0.047)	(0.059)	(0.048)
Controls:							
Ethnicity, region and Health	×	×	×	×	×	×	×
Degree class and type of institution					×	×	×
Family background						×	×
Non-cognitive skills							×
Observations	2,392	2,236	2,211	2,204	919	610	855
R-squared	0.044	0.049	0.039	0.049	0.067	0.098	0.098

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

The evidence shows that individuals with medical related subjects on average earn more than LSM graduates both hourly and weekly. Subject categories of languages, education and arts shows that the graduates in these subjects earn less than LSM graduates both weekly and hourly. For science subjects, the estimates are insignificant for weekly wages but are significant and negative for hourly estimates. If we look at the math and engineering subject category, we can see that the weekly wage premium is positive and significant compared to LSM graduates.

What happens to wage premia associated with different subject choices when we consider cognitive and non-cognitive skills? We find that the size of the coefficients decreases in the case of Medicine but not in the case of Maths and Engineering. For example in Table 4-19, a 32.6% increase in wages from choosing Medicine instead of LSM subjects, becomes 17.7% when we include the numeracy variable and insignificant when we add non-cognitive skills variables. On the contrary, graduates of maths and engineering subjects earn 13.2% more than LSM graduates; however, when we add skill variables, we see that the estimates increase. In this case if we look at the change in numbers, we can interpret it as the size of bias of numeracy and literacy skills. Comparing weekly wages given in
Table 4-19 and comparing it to hourly wages
Table 4-20 it can be assumed that individuals with higher cognitive skill earn higher wage premium.

Cognitive skills estimates show that individuals with higher numeracy skills are more likely to earn more hourly and weekly wage premium. This is also true for literacy skills but when both literacy and numeracy skill variables are used together, we can see in model (4) in
Table 4-19 that numeracy skills dominate literacy skills as its coefficient is significant and literacy skills variable is not[51].

Next Table 4-21 shows that the non-cognitive skills variables are insignificant when estimated together with the cognitive skill variables in model (1,3). But these variables are significant when estimated without the cognitive skills variables in model (2,4). Locus of control is positively associated with earnings as also reported in previous literature by Caliendo et al. (2015). The estimates also illustrate that individuals who have a positive attitude towards jobs that pay well earn almost 27.9% more than individuals who have a negative attitude towards jobs that pay well. Individuals who were involved in risky behaviour are likely to earn less than individuals who were not, which is also previously explained by Heckman et al. (2014). We use number of friends and volunteering as a proxy for communication skills and the empirical evidence suggests that individuals with a greater number of friends, or who have volunteered previously, are more likely to have higher earnings than individuals who have a smaller number

[51] These results are consistent with those from Dougherty (2003), Hall et al. (2011), and Heckman and Broecke (2016).

of friends or have not volunteered before. This evidence also supports the study by Almlund et al. (2011) and Borghans et al. (2008) on non-cognitive skills such as communication and network building.

Table 4-21: Wage premium estimates with the cognitive skills and non-cognitive skills

VARIABLES	(1) Hourly pay	(2) Hourly pay	(3) Weekly pay	(4) Weekly pay
Locus of control	0.009	0.049***	0.008	0.029***
	(0.013)	(0.007)	(0.008)	(0.004)
Attitudes towards job that pays well				
Matters a lot to me	0.098	0.246***	0.336***	0.279***
	(0.172)	(0.081)	(0.096)	(0.055)
Matters a little to me	-0.138	0.155*	0.238**	0.217***
	(0.175)	(0.083)	(0.098)	(0.056)
Life Satisfaction				
Very Satisfied	0.029	0.159**	0.184*	0.135***
	(0.171)	(0.063)	(0.094)	(0.044)
Fairly Satisfied	-0.051	0.189***	0.097	0.086**
	(0.166)	(0.060)	(0.091)	(0.041)
Neither Satisfied nor Dissatisfied	-0.321*	0.092	0.084	0.006
	(0.190)	(0.071)	(0.109)	(0.049)
Number of Friends	0.054*	0.074***	0.029*	0.039***
	(0.030)	(0.014)	(0.017)	(0.009)
Risky Behaviour	-0.014	-0.095***	-0.012	-0.048*
	(0.080)	(0.036)	(0.045)	(0.024)
Volunteered previously	0.019	0.048	0.009	0.069***
	(0.062)	(0.032)	(0.035)	(0.021)
Cognitive skills	×		×	
Controlled for: Gender, ethnicity, family background, subject choice, degree class, Institution type, health Region	×	×	×	×
Observations	855	4,276		
R-squared	0.098	0.068		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-22 reports the estimates associated with the prestige of educational institutions and different degree classes.

Table 4-22 Weekly estimates on Institutional prestige and degree class

VARIABLES	(1) Weekly pay	(2) Weekly pay	(3) Weekly pay	(4) Weekly pay	(5) Weekly pay	(6) Weekly pay	(7) Weekly pay
Key Stage 3 Maths		0.128***		0.117***	0.115***	0.096***	0.123***
		(0.013)		(0.015)	(0.023)	(0.027)	(0.023)
Key Stage 3 Literacy			0.106***	0.026	0.007	-0.004	0.005
			(0.016)	(0.019)	(0.026)	(0.032)	(0.027)
First					0.124**	0.135**	0.110**
					(0.050)	(0.059)	(0.052)
Upper Secondary Class					0.073*	0.094**	0.049
					(0.039)	(0.045)	(0.040)
Russell Group Universities					0.105**	0.117**	0.111**
					(0.043)	(0.050)	(0.045)
Non-cognitive Skills						×	×
Controls: Region, ethnicity, gender, Subject choice	×	×	×	×	×	×	×
Observations	2,392	2,236	2,211	2,204	919	610	855
R-squared	0.044	0.049	0.039	0.049	0.067	0.098	0.098

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

We see those individuals graduating from 'Russell Group' institutions earn a wage premium of 10.5% compared to individuals who graduate from other institutions. This is consistent with the study of Britton (2016) and Hussain et al. (2009), who also find that going to a prestigious university signals potentially enhanced personal skills to employers. The difference of almost 10% in wage premia between the Russell group and all other universities can be linked first to the theory of Rational Choice of subjects and then to the study by James et al.(1989), which concludes that it appears to be a very good investment for an individual to attend a prestigious university and to take mathematics and engineering subjects which require higher numeracy skills but it is even better for individuals with higher literacy skill to join a prestigious university in a non-numerical subject category as it has a positive peer group effects and also serves as an information signal to employers of the higher skill-set of the individual (James et al.,1989).

Degree Class estimates show that achieving First Class degrees or Upper second class also has a positive effect on weekly wages compared to individuals who achieve a lower-class degree. This effect is also diminished when degree class variables are estimated using the hourly wages.

Table 4-23 Estimates on parents' qualification and household income

VARIABLES	Wages compared with the A-level qualification individuals (1) Weekly	(2) Hourly	Wages Compared with the LSM Graduates (1) Weekly	(2) Hourly
Main Parent Qualification (Base Category: No qualification)				
Degree or equivalent	0.050*	0.074*	0.141*	0.168
	(0.006)	(0.007)	(0.090)	(0.166)
Higher education below degree level	-0.000	0.020	0.143	-0.205
	(0.062)	(0.063)	(0.089)	(0.165)
GCE A Level or equivalent	0.033	0.060	0.185**	0.022
	(0.060)	(0.061)	(0.090)	(0.169)
GCSE grades A-C or equivalent	0.060	0.073	0.150*	-0.080
	(0.054)	(0.055)	(0.086)	(0.160)
Qualifications at level 1 and below	-0.045	-0.043	0.041	-0.026
	(0.089)	(0.092)	(0.114)	(0.218)
Other qualifications	0.066	0.059	0.267*	-0.189
	(0.102)	(0.099)	(0.141)	(0.257)
House Hold income (Base Category: Under 10,400)				
10400-20800	0.153	0.185	-0.049	-0.253
	(0.084)	(0.087)	(0.085)	(0.159)
20800-33800	0.122	0.295**	-0.037	0.312**
	(0.087)	(0.087)	(0.083)	(0.155)
33800-41000	0.003	0.000	-0.020	-0.216
	(0.073)	(0.074)	(0.088)	(0.165)
41000-55000	0.013	0.014	0.069	-0.207
	(0.075)	(0.077)	(0.085)	(0.157)
over 55000	0.109	0.109	0.099	0.053
	(0.077)	(0.079)	(0.083)	(0.156)
Cognitive skill	×	×	×	×
Other controls: region, gender, subject choice, and ethnicity	×	×	×	×
Observations	1,190	1,181	546	610
R-squared	0.150	0.136	0.217	0.098

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Most of the estimates illustrating the impact of parental education and income on the wage premium are insignificant. But estimates which are significant reveal that main parent's degree level qualification has a positive impact on individual wages when compared to individuals coming from families with parents who had no degree qualification. The estimates are significant for weekly wage premium estimates when we compare graduates from LSM subjects. These estimates are contrary to the findings of Mitra (2002) who showed that parent's qualification does not influence wages. However, as discussed earlier, it is possible that individuals coming from families with more educated parents can make potential use of their parents' contacts to secure a place in the job market and possibly can benefit from a higher salary (Herman G. W. et al., 2002).

Household income estimates show that coming from a household with a higher income has a positive impact on the wage premium, suggesting that the effects of background are reinforced, making social mobility harder (Machin, 1996). Machin (1996) shows that members coming from a higher-income household are likely to earn more in the job market than those from a lower-income background. Individuals coming from households with household income of £21k-33k earn approximately 30% higher hourly wage than those from households with £10,400 and lower incomes. Dustmann (2004) finds that there is approximately 35% earning differential between individuals born in lower educated/class family and individuals born in higher educated/class family in Germany. He explains this by saying that parents' education and social class shape their taste and perception of what is an appropriate educational route for their child. Working class parents even in the absence of financial constraints can consider a lower educational track or an early labour market entry as a good option for their child.

We summarise the above findings. Individuals who graduated in medical related subjects earn a higher wage premium than the LSM graduates. Maths and Engineering subjects also earn significant and positive wage premium compared to LSM. Individuals with higher numeracy and literacy skills earn a higher hourly and monthly wage premium. Inclusion of numeracy and literacy skills reduces the magnitude of coefficient of degree subject choice, which shows that numeracy and literacy skills have a higher impact on the wage premium compared to the degree subject choice itself. Non-cognitive skills such as locus of control, positive attitudes and less risky behaviour are likely to earn a higher wage. Individuals who come from a higher income household have a higher wage premium, deepening social mobility.

4.7.2 Estimates of an Endogenous treatment model

The endogenity problem between wages and subject choice has been studied extensively (Dickson, 2009; Heckman, 1999). Studies have controlled for the effect of ability biasness by including IQ scores as measures of skills and ability. According to Lang (1993), adding these ability and skill variables may not necessarily improve the explanatory power but instead may perverse the signs for the coefficients of these variables because non-cognitive skills are generally correlated with cognitive skill (as shown in Table 4-12). Another approach employed data on twins/siblings, under the assumption that this will eliminate the differences of ability but Bound and Solon (1998) suggested that this methodology is culturally biased considering that twins and siblings are brought up in a similar culture and may be identical in terms of view towards entering the labour market and other cultural and social skills. An alternative strategy is the instrumental variable technique - as for instance in Dickson (2009) - which is based on finding a variable related to schooling but not to the wages. Using this variable as an instrument will lead us to the consistent estimator of the returns to education. The endogenous treatment model is based on a similar technique: the idea is to isolate the effects of choice of degree subjects on wages from other latent variables.

We estimate three endogenous treatment models with weekly wage as the independent variable: i) Model with cognitive skill; ii) Model with non-cognitive skills; iii) Model with both cognitive and non-cognitive skills.[52] Having the three models will illustrate how the wage premium coefficients for each subject category compared to the LSM differs with cognitive and non-cognitive skill. We will also discuss how the coefficients for cognitive and non-cognitive skills differ.

[52] We also estimated endogenous treatment model with hourly wages given in Appendix 4-3 (*Table 4-35 Endogenous treatment model with Hourly Wage as the dependant variable*)

Table 4-24 Subject Wage premium estimates (Second Stage) compared to LSM subject[55]

VARIABLES	(1) lwpay	(2) lwpay	(3) lwpay
med_vs_lsm	0.094*	0.082**	0.846
	(0.027)	(0.113)	(0.851)
medr_vs_lsm	0.150	-0.006	0.202
	(0.253)	(0.282)	(0.272)
sci_vs_lsm	0.466	-0.197	-0.087
	(0.299)	(0.299)	(0.274)
math_vs_lsm	0.401**	0.521***	0.362*
	(0.025)	(0.164)	(0.177)
ling_vs_lsm	-0.168	-0.056	0.085
	(0.196)	(0.175)	(0.179)
art_vs_lsm	-0.563***	-0.570***	-0.425***
	(0.207)	(0.151)	(0.154)
Cognitive skills	×		×
Non-cognitive skills		×	×
Other controls: region, ethnicity, family background, degree class, institution type	×	×	×

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Table 4-24, Table 4-25 and Table 4-26 are estimates of single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

The estimates given in Table 4-24 are the second stage[53] estimates, these are causal estimates considering the fact that it is calculated using the treatment model, where we isolate the degree subject choice in first stage and also use the individual characteristics as skills, degree class, institution type and family background. Model (1), which controls for cognitive skills, shows that individuals who choose medicine, maths and engineering subjects are able to earn 9.4 and 40.1 percent more than LSM graduates respectively. Model (2) controls for non-cognitive skills and we can see that individuals with medicine and maths and engineering subject categories earn approximately 8.2 and 52.1 percent more than LSM graduates. The 10-percentage point difference in the maths and engineering premium in model (1) and (2) can be associated with the inclusion of cognitive skills variables in model (1). Model (3), which includes both the cognitive and non-cognitive skills as controls in the estimation, shows that the wage premium of individuals with degree subject in maths decreases to 36.2 percent. However, arts graduates

[53] The first stage estimates are given and discussed in the Appendix 4-4

earn approximately 56 percent less than LSM graduates in model (1) and this is changed to 42.5 percent less compared to LSM in model (3).

Table 4-25 Endogenous model cognitive skills estimates (second stage)

VARIABLES	lwpay	lwpay	lwpay	lwpay	lwpay	lwpay
med_vs_lsm	0.094**					
	(0.027)					
medr_vs_lsm		0.150				
		(0.253)				
sci_vs_lsm			0.466			
			(0.299)			
math_vs_lsm				0.401**		
				(0.025)		
ling_vs_lsm					-0.168	
					(0.196)	
art_vs_lsm						-0.563***
						(0.207)
Key Stage 3 Numeracy	0.096**	0.099**	0.098***	0.090**	0.099***	0.112***
	(0.043)	(0.044)	(0.036)	(0.040)	(0.038)	(0.038)
Key Stage 3 Literacy	0.070	0.066	0.077*	0.007	0.015	0.032
	(0.052)	(0.054)	(0.043)	(0.048)	(0.045)	(0.046)
Degree Class						
First Degree Class	0.190*	0.264***	0.097	0.104	0.216**	0.185**
	(0.098)	(0.101)	(0.080)	(0.089)	(0.086)	(0.087)
Upper Secondary Class	-0.011	0.095	0.018	-0.022	0.053	0.057
	(0.077)	(0.076)	(0.060)	(0.069)	(0.064)	(0.067)
Russell Group	0.250***	0.182**	0.158**	0.211***	0.225***	0.152**
	(0.077)	(0.078)	(0.066)	(0.069)	(0.065)	(0.073)
Observations	197	215	308	252	256	249

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Table 4-24, Table 4-25 and Table 4-26 are estimates of single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-25 shows that most of the effect on wages is captured by the Key Stage 3 numeracy skill while the coefficient for Key Stage 3 literacy skill is insignificant. The estimates show a wage premium of between 9 and 11 percent associated with having a higher ability score. The estimates also show that degree class and institution type have a significant impact on individual wages, individuals from Russell group universities receiving around 20 percent higher wages than individuals attending other universities.

Table 4-26 Endogenous model non-cognitive skills estimates (second stage)

VARIABLES	lwpay	lwpay	lwpay	lwpay	lwpay	lwpay
med_vs_lsm	0.082**					
	(0.113)					
medr_vs_lsm		-0.006				
		(0.282)				
sci_vs_lsm			-0.197			
			(0.299)			
math_vs_lsm				0.521***		
				(0.164)		
ling_vs_lsm					-0.056	
					(0.175)	
art_vs_lsm						-0.570***
						(0.151)
locus_control	0.020*	0.020**	0.015*	0.010	0.022**	0.017*
	(0.011)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
Attitude towards Job that pays well						
Matters a lot to me	0.120	0.101	0.208*	0.191	0.115	0.205
	(0.146)	(0.132)	(0.117)	(0.117)	(0.124)	(0.132)
Matters a little to me	-0.056	-0.043	0.075	0.058	-0.047	0.050
	(0.150)	(0.135)	(0.120)	(0.121)	(0.128)	(0.135)
Life Satisfaction						
Very Satisfied	0.077	0.103	0.036	0.044	0.110	0.063
	(0.133)	(0.118)	(0.102)	(0.106)	(0.107)	(0.115)
Fairly Satisfied	0.015	0.024	-0.016	-0.048	0.027	-0.041
	(0.129)	(0.115)	(0.099)	(0.102)	(0.103)	(0.112)
Neither Satisfied nor Dissatisfied	0.065	0.053	-0.029	-0.053	0.089	0.000
	(0.149)	(0.133)	(0.114)	(0.118)	(0.120)	(0.130)
Number of Friends	0.051**	0.044**	0.041**	0.038**	0.061***	0.046**
	(0.023)	(0.021)	(0.018)	(0.019)	(0.020)	(0.021)
Risky Behaviour	-0.025	-0.034	-0.021	0.001	-0.032	-0.006
	(0.065)	(0.058)	(0.049)	(0.053)	(0.054)	(0.056)
Volunteered previously	0.019	0.023	0.004	0.024	0.047	0.043
	(0.050)	(0.044)	(0.039)	(0.041)	(0.043)	(0.044)
Observations	722	826	1,026	925	897	868

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Table 4-24, Table 4-25 and Table 4-26 are estimates of single model.

Source: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Subsequently next if we look at Table 4-26 with the estimates of non-cognitive skill. The results illustrate that individuals with higher locus of control earn a higher wage premium by approximately 2 percent. But individuals with higher number of friends which we are using as a proxy for extroversion earn approximately 5 percent higher wage premium compared to individuals with lower number of friends which we can relate to the social and networking skills of individuals as described in literature (Heckman et al., 2019; Heckman et al., 2016; Carneiro et a., 2007). Our estimates also show insignificant effect of risky behaviour, volunteering, and life satisfaction.

4.8 Conclusion

In this chapter we have focused on the effects of family background, and academic achievement at Key Stage 3 on subject choices made at degree level and wage premium of graduates. Our analysis shows there is strong link between family background and academic achievement at Key Stage 3 on both subject choice and the wage premium of graduates. We find in particular a significant association between good numeracy skills at key stage three and STEM subjects at degree level, whilst strong literacy skills are associated with a greater likelihood to pursue art like subjects.

We summarize our detailed findings. Our findings show university degree subject choice is strongly influenced by numeracy and literacy skill levels at key stage 3. Individuals who were good at reading and literacy compared to mathematics at the age of 13 and 14 are more likely to pursue degrees in arts, media studies, languages, and education. Those who are comparatively good at mathematics are more likely to choose mathematics, engineering, technology, law and economics subjects. Individuals with higher levels of numeracy and literacy are also more likely to pursue Medicine at degree level; those with strong non-cognitive skills such as locus of control, positive attitude, less risky behaviour are also more likely to choose medicine at degree level.

Our findings also suggest subject selection at degree level is influenced by enjoyment of subjects at Key Stage 3. We find individuals who enjoy maths and science subjects at Key Stage 3 are more likely to pursue medicine, math, engineering, and science subjects in higher education compared to students who enjoy art and humanities subjects at Key Stage 3. In addition, students who pick their own subjects at GCSE are more likely to pursue maths and engineering in higher education; individuals who come from a more educated background are more likely to choose Medicine, LSM, and Arts subjects. Individuals who have higher non-cognitive skills, focus and life satisfaction, are more likely to study medicine subjects.

We have also found that individuals with high numeracy and literacy skills are more likely to earn a higher wage premium. There is also a positive association of non-cognitive skills with the wage premium, especially for individuals who have a high locus of control and social skills are more likely to earn a higher wage premium. Lastly, individuals who come from a strong financial background are more likely to earn a higher wage premium compared to the individuals who come from a lower income background. These findings are important since they suggest subject choice at degree level and wage premium is not only influenced by success in literacy and numeracy at Key Stage 3, but also by enjoyment of subjects in early years education, family background and family education.

4.9 Appendix

4.9.1 Appendix 4-1 Mincer wage equation with the base category of A-levels

The following estimates allow us to provide a comparison with the estimates in of Labour Force Survey as in previous chapters as we are using the A-levels as the base category. The estimates are calculated for both weekly and hourly wages for graduates with the base category of A-levels.

Table 4-27 Hourly and Weekly wage premium for different subject choices compared to A-level qualified individuals with ability controls

	(1)		(2)		(3)		(4)	
VARIABLES	Hourly	*Weekly*	Hourly	*Weekly*	Hourly	*Weekly*	Hourly	*Weekly*
Cognitive Skills								
kS3 numeracy ability			0.129***	*0.091****			0.121***	*0.091****
			(0.011)	*(0.011)*			(0.010)	*(0.010)*
kS3 Literacy ability					0.101***	*0.093****	-0.035	*0.057****
					(0.019)	*(0.019)*	(0.013)	*(0.013)*
(A-level as base category)								
Medicine	0.487***	*0.520****	0.199***	*0.432****	0.285*	*0.467****	0.217***	*0.398****
	(0.076)	*(0.076)*	(0.086)	*(0.086)*	(0.087)	*(0.087)*	(0.090)	*(0.090)*
Medical-Related	0.406***	*0.370****	0.401***	*0.319****	0.431***	*0.322****	0.393***	*0.281****
	(0.065)	*(0.065)*	(0.061)	*(0.061)*	(0.067)	*(0.067)*	(0.048)	*(0.048)*
Science	0.198**	*0.191****	0.079	*0.101***	0.104**	*0.135****	0.098	*0.085***
	(0.061)	*(0.061)*	(0.041)	*(0.041)*	(0.064)	*(0.064)*	(0.035)	*(0.035)*
Maths and Engineering	0.440***	*0.376****	0.251***	*0.274****	0.319***	*0.339****	0.249***	*0.274****
	(0.068)	*(0.068)*	(0.048)	*(0.048)*	(0.071)	*(0.071)*	(0.040)	*(0.040)*
Law, social science and							0.252***	*0.130****
Mgt	0.395***	*0.243****	0.263**	*0.160***	0.302**	*0.171***		
	(0.060)	*(0.060)*	(0.034)	*(0.034)*	(0.063)	*(0.063)*	(0.027)	*(0.027)*
Languages and Education	0.131*	*0.176***	0.012	*0.107***	0.061	*0.091**	0.047	*0.081*
	(0.063)	*(0.063)*	(0.043)	*(0.043)*	(0.066)	*(0.066)*	(0.043)	*(0.043)*
Arts	0.130*	*-0.032*	0.060	*-0.032*	0.077	*-0.032*	0.024	*-0.073*
	(0.075)	*(0.069)*	(0.049)	*(0.049)*	(0.071)	*(0.071)*	(0.041)	*(0.041)*
Non-cognitive skills							×	×
Controlled for ethnicity, gender, region, house hold Income, parental income, marital status and illness	×	×	×	×	×	×	×	×
Observations	2733	*2393*	2574	*2258*	2488	*2201*	2479	*2192*
R-squared	0.121	*0.121*	0.144	*0.144*	0.124	*0.124*	0.136	*0.136*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-27 illustrates that ability variables at Key Stage 3 have a positive and significant impact on wages. Higher numeracy skills on average have an effect of 11.6% increase in hourly wage premium and 8.5% increase in weekly wages. Similarly, literacy ability had a positive significant effect on the weekly premium of individuals of 9.3% and 4.5% on hourly wages. If we look at the estimation of numeracy and literacy skills together in (4), we see that numeracy ability have a higher impact on the wages of individuals than the literacy skills on both hourly and week wages, in fact the effect of literacy skills is insignificant.

These regression effects of ability are larger than those presented in the previous literature. McIntosh and Vignoles, (2000) using the UK National Child Development study (NCDS) and International Adult Literacy Survey (IALS) data sets, reports that numeracy ability had a significant 6% impact on the earnings of individuals after controlling for education. Although they did not find a significant impact of literacy on wages using NCDS data but they found numeracy have a 10% significant effect on wages with IALS. Dougherty, (2003) finds that individuals with higher numeracy ability experience a 9.5% gain in earnings whereas in case of literacy the gain is only 1.4% and insignificant. The larger effect of numeracy ability on wage premia is also confirmed by the key findings represented by IZA World of Labour report by Broecke, (2016) that numeracy skills have a higher impact on wage premia than literacy skills and on average higher skilled workers have higher wages. He also depicted that England and Northern Ireland had the highest difference in wages between the high and low skilled workers among all the European countries, USA, Canada and Japan.

Individuals earning higher wage premia for higher numeracy and literacy ability in different degree subjects can also be observed in Table 4-28 below where we have used interaction between ability and subject choice.

Table 4-28 Interaction between subject choice and ability

VARIABLES	(1) Log of weekly pay	(2) Log of weekly pay
Medicine * Numeracy ability	0.127	
	(0.178)	
Medical-related * Numeracy ability	0.053	
	(0.033)	
Science * Numeracy ability	0.047**	
	(0.019)	
Mathematics & engineering * Numeracy ability	0.066**	
	(0.027)	
LSM * Numeracy ability	0.052**	

VARIABLES	(1) Log of weekly pay	(2) Log of weekly pay
	(0.020)	
Languages and education * Numeracy ability	0.038	
	(0.037)	
Arts * Numeracy ability	0.039	
	(0.033)	
Medicine * literacy ability		0.115
		(0.166)
Medical-related * literacy ability		0.023
		(0.037)
Science * literacy ability		0.069*
		(0.040)
Mathematics * literacy ability		0.061*
		(0.035)
LSM * literacy ability		0.024
		(0.026)
Languages and education * literacy ability		0.078*
		(0.043)
Arts * literacy ability		0.061
		(0.038)
Controlled for Subject choice, ethnicity, region, degree class, prestige of university, household income, parent's qualification, cognitive & non-cognitive skills and marital status	×	×
Observations	4,966	4,786
R-squared	0.152	0.117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-28 indicates that higher numeracy ability contributes to even a higher wage premium for the subjects which are more numerical in nature. The interaction between the numeracy ability and subject categories of maths and engineering, science and LSM are significant by 4.7 and 6.6% respectively. Interaction between literacy ability and subject categories of maths and engineering and science have significant impact on wages by 6.1 and 6.9% respectively; but coefficient is higher and significant for the languages and education by 7.8% at the significant level of 10%, which indicates that higher literacy ability will give a boost to wage premium of language and education graduates. If an individual takes a graduate subject and have higher ability in it, he is more likely to perform better.

Table 4-29: Wage premium for males and females with different subject choices compared to A-level qualified individuals with ability controls

VARIABLES	(1) Lwpay, Males sample controlled for math ability	(2) lwpay, Females sample controlled for maths ability	(3) lwpay Males sample controlled for literacy ability	(4) lwpay Female sample controlled for literacy ability
Cognitive Skills				
kS3 numeracy ability	0.137***	0.106***		
	(0.028)	(0.020)		
kS3 Literacy ability			0.144***	0.082***
			(0.032)	(0.023)
A-level as base category				
Medicine	0.324***	0.364***	0.314**	0.455***
	(0.121)	(0.109)	(0.132)	(0.109)
Medical-Related	0.197	0.257***	0.129	0.281***
	(0.160)	(0.070)	(0.159)	(0.070)
Science	0.023	0.048	-0.007	0.085
	(0.109)	(0.069)	(0.115)	(0.070)
Maths and Engineering	0.259**	0.154*	0.288***	0.234***
	(0.104)	(0.088)	(0.111)	(0.088)
Law, social science and Mgt	0.097	0.148**	0.068	0.175**
	(0.106)	(0.069)	(0.113)	(0.069)
Languages and Education	0.064	0.149**	0.029	0.154**
	(0.110)	(0.073)	(0.117)	(0.075)
Arts	-0.204*	-0.117	-0.256**	-0.100
	(0.123)	(0.080)	(0.128)	(0.081)
Controlled for Subject choice, ethnicity, region, degree class, prestige of university, house hold income, parent's qualification, cognitive skills, non-cognitive skills and marital status	×	×	×	×
Observations	497	693	490	691
R-squared	0.160	0.165	0.154	0.143

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

The estimates show that numeracy skills at Key Stage 3 contributes to an increase in weekly earnings of 13.7% for men, while higher literacy ability contributes 14.4%. For women, the impact of higher ability is less when compared to men. Females with higher numeracy ability gain 10.6% on their wages and women with higher literacy ability are 8.2%. These results are also illustrated by Mitra, (2002) for US where higher mathematics skills lead to positive wage premiums, with men gaining 8% higher than the women in the labour market with higher level of numeracy skills. This research also reports that only men experience significant returns to verbal skills while females do not. This is surprising as females generally score higher on verbal/literacy tests. This also true in our data set as shown in the following Table 4-30.

Table 4-30 Frequency of number of males and females for KS3 national curriculum level for Numeracy and literacy

	Numeracy		Literacy	
KS3 National Curriculum level	Males	Females	Males	Females
2	15 (53.47%)	13 (46.43%)		
3	180 (43.90%)	230 (56.10%)	88 (55%)	72 (45%)
4	357 (43.27%)	468 (56.73%)	483 (54.33%)	406 (45.67%)
5	603 (41.47%)	851 (58.53%)	1230 (45.45%)	1476 (54.55%)
6	925 (41.44%)	1307 (58.56%)	807 (38.34%)	1298 (61.66%)
7	791 (47.51%)	874 (52.49%)	292 (38.64%)	551 (65.36%)
8	252 (57.53%)	186 (42.47%)		

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Murnane et al., (1995) found similar results and explain that higher ability is often correlated with certain positive personal characteristics, such as confidence, ambition, motivation, and analytical skills.

Looking at degree subjects' premia in Table 4-27, we can see that Medicine graduates earn the highest compared to the A-levels, this is followed by maths and engineering and then by medical related subjects, LSM, languages and finally the Arts. If we compare the hourly and weekly wages the estimates illustrate that medicine graduates earn a higher weekly wage premium but lower hourly wage premia. This is because of the higher number of hours worked by medicine graduates as shown in Table 4-2. Other subject category with the similar pattern is education and languages which shows the similar pattern. The subject categories where hourly wage premia are higher than the weekly wage premia are medical-related, science, maths and engineering and LSM and this is because these graduates work similar number of hours as the A-level individuals but get paid a higher hourly wage.

Creative and performing arts estimates are insignificant for weekly wages but significant and positive for the hourly wages when estimated without the skill controls. Britton et al., (2016) while analysing yearly wages find a negative premium for Arts graduates and conclude that the subject is associated characteristics which are associated with lower demand in the job market. Secondly, when comparing them to A-level qualified individuals, they find that A-level qualified individuals enter the job market earlier and gain extra experience of few years over the Arts graduates who enter the job market much later.

In Table 4-29 we can also see that women with higher numeracy and literacy skills also do better in the languages and educational professions, as they have a higher chance of progress. Whereas for men the estimate for subject category of Languages and education are insignificant. The insignificant estimates for males can be explained as Joy, (2006) shows that teaching and medical related professions are female dominated and they have a higher success rate. A similar pattern is also portrayed in Next Steps as given in the following table. Also, if we look at the mean weekly wages in "Table 4-1 Mean weekly pay (in British pounds £s) for different subject categories" we can see that weekly wages for women who have graduated in medical related subjects or languages have higher mean wage than women with A-levels and when compared to men.

Table 4-31 Number of individuals graduated in different subject categories.

Subject Group	Male	Female
Medicine	27	54
Medical-Related	55	**176**
Science	214	295
Maths and engineering	298	86
Law, Social Science and Management	377	550
Languages and Education	102	**306**
Arts	127	195

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.9.2 Appendix 4-2

Table 4-32 Hourly wage premium estimates for subject choices

VARIABLES	(1) Hourly Pay	(2) Hourly Pay	(3) Hourly Pay	(4) Hourly Pay	(5) Hourly Pay	(6) Hourly Pay	(7) Hourly Pay
Female	-0.042	-0.029	-0.061	-0.017	-0.017	0.034	0.024
	(0.041)	(0.043)	(0.043)	(0.044)	(0.063)	(0.076)	(0.065)
Medicine	0.184	0.020	0.112	0.019	-0.001	-0.109	0.080
	(0.123)	(0.143)	(0.142)	(0.142)	(0.243)	(0.303)	(0.242)
Medical Related	0.153**	0.182**	0.166**	0.166**	-0.060	-0.172	0.057
	(0.076)	(0.078)	(0.078)	(0.078)	(0.128)	(0.173)	(0.135)
Science	-0.204***	-0.210***	-0.197***	-0.214***	-0.283***	-0.250***	-0.240***
	(0.056)	(0.059)	(0.059)	(0.059)	(0.080)	(0.096)	(0.082)
Maths and Engineering	0.100	0.063	0.087	0.037	-0.135	-0.099	-0.111
	(0.064)	(0.066)	(0.066)	(0.067)	(0.097)	(0.121)	(0.101)
Languages	-0.264***	-0.257***	-0.257***	-0.233***	-0.129	-0.176	-0.096
	(0.066)	(0.069)	(0.070)	(0.070)	(0.094)	(0.115)	(0.095)
Arts	-0.322***	-0.278***	-0.309***	-0.285***	-0.346***	-0.250**	-0.319***
	(0.069)	(0.072)	(0.072)	(0.072)	(0.108)	(0.125)	(0.112)
Key Stage 3 Maths		0.097***		0.123***	0.124***	0.091*	0.124***
		(0.021)		(0.026)	(0.040)	(0.049)	(0.041)
Key Stage 3 Literacy			0.024	-0.061*	-0.050	-0.041	-0.027
			(0.027)	(0.032)	(0.047)	(0.059)	(0.048)
Controls:							
Ethnicity, region and Health	×	×	×	×	×	×	×
Degree class and type of institution					×	×	×
Family background						×	×
Non-cognitive skills							×
Observations	2,392	2,236	2,211	2,204	919	610	855
R-squared	0.044	0.049	0.039	0.049	0.067	0.098	0.098

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Table 4-33 Hourly estimates on Institutional prestige and degree class

VARIABLES	(1) Hourly pay	(2) Hourly pay	(3) Hourly pay	(4) Hourly pay	(5) Hourly pay	(6) Hourly pay	(7) Hourly pay
Key Stage 3 Maths		0.097***		0.123***	0.124***	0.091*	0.124***
		(0.021)		(0.026)	(0.040)	(0.049)	(0.041)
Key Stage 3 Literacy			0.024	-0.061*	-0.050	-0.041	-0.027
			(0.027)	(0.032)	(0.047)	(0.059)	(0.048)
First					-0.025	-0.038	-0.045
					(0.089)	(0.108)	(0.092)
Upper Secondary Class					0.024	0.005	0.006
					(0.068)	(0.084)	(0.071)
Russell Group Universities					0.130	-0.018	-0.186
					(0.075)	(0.090)	(0.078)
Non-cognitive Skills						×	×

VARIABLES	(1) Hourly pay	(2) Hourly pay	(3) Hourly pay	(4) Hourly pay	(5) Hourly pay	(6) Hourly pay	(7) Hourly pay
Controls: Region, ethnicity, gender, Subject choice	×	×	×	×	×	×	×
Observations	2,392	2,236	2,211	2,204	919	610	855
R-squared	0.044	0.049	0.039	0.049	0.067	0.098	0.098

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.9.3 Appendix 4-3

Endogenous treatment model first stage firstly shows that we have valid instrument as we have significant results for the variables used that is numeracy likeness, literacy likeness, favourite subject in school and the agreement statements. Estimates in Table 4-34 shows that individuals whose favourite subject is maths and science compared to arts subjects are more likely to choose medicine, medical related, maths, engineering, languages and education subjects and less likely to choose arts subjects. In addition, individuals who like social sciences are more likely to choose languages and medicine (but to a lesser extent) and are less likely to choose arts subjects.

Individuals who like numeracy at early ages are more likely to choose maths, science and medicine and less likely to take languages, education and arts. Whereas individuals who like literacy are more likely to take medical related and languages subjects and less likely to take the maths subjects.

Estimates for the agreement with different statements show different results but most promising estimates are from the individuals who strongly agree with the statement that they will choose the GCSE subjects they are interested in. The estimates show that individuals are more likely to choose medicine, medical related, maths, engineering and linguistics if they strongly agree to the statement given in previous statement compared to individuals who strongly disagree.

Table 4-34 Endogenous Treatment model (First Stage)

VARIABLES	(2) med_vs_lsm	(5) medr_vs_lsm	(8) sci_vs_lsm	(11) math_vs_lsm	(14) ling_vs_lsm	(17) art_vs_lsm
Science and Maths	0.620**	0.078*	0.082	0.035*	-0.603**	-0.643**
	(0.057)	(0.008)	(0.251)	(0.002)	(0.293)	(0.283)
Social Science and Humanities	0.046*	-0.446	0.190	0.136	0.436**	-0.767***
	(0.007)	(0.368)	(0.198)	(0.253)	(0.211)	(0.212)
Agreement with the statement: I will choose the GCSE subject I am interested in (Base: Strongly disagree)						
Strongly Agree	0.035**	0.092**	0.187	0.159**	0.327*	0.287
	(0.016)	(0.025)	(0.160)	(0.019)	(0.092)	(0.199)
Agree Slightly	0.502	-0.224	-0.151	-0.370	-0.311	0.247
	(0.737)	(0.506)	(0.306)	(0.385)	(0.412)	(0.353)
Agreement with the statement: I will choose GCSE subjects as told by teacher (Base: Strongly disagree)						
Strongly Agree	0.097	0.052	0.041	-0.868*	0.616	0.424
	(0.984)	(0.847)	(0.528)	(0.505)	(0.644)	(0.695)
Agree Slightly	3.850	-0.015	0.399	-0.864*	0.271	0.370
	(0.985)	(0.723)	(0.514)	(0.480)	(0.634)	(0.676)
Agreement with the statement: I will choose GCSE subjects that my friend choose (Base: Strongly disagree)						
Strongly Agree	0.806	-0.878	-0.415	0.093	0.008	0.989
	(0.293)	(0.241)	(0.850)	(0.956)	(0.041)	(0.243)
Agree Slightly	0.755	-0.709**	-0.342	0.467	0.962	0.047**
	(0.293)	(0.068)	(0.806)	(0.956)	(0.041)	(0.003)
Like Math at school (Base Category: Don't like it)						
Like it a lot	0.036**	-0.146	0.183**	0.456**	-0.495**	-0.221**
	(0.008)	(0.372)	(0.010)	(0.069)	(0.239)	(0.027)
Don't like it very much	0.881	0.011	0.168	0.056	-0.331	-0.014
	(0.705)	(0.345)	(0.186)	(0.255)	(0.211)	(0.221)
Like Literacy at school (Base Category: Don't like it)						
Like it a lot	0.528	-0.176***	0.042	-0.436*	0.320**	0.120
	(0.786)	(0.043)	(0.218)	(0.255)	(0.065)	(0.272)
Don't like it very much	0.347	-0.292	0.022	-0.322	-0.014	0.175
	(0.706)	(0.317)	(0.210)	(0.236)	(0.275)	(0.267)
Observations	197	215	308	252	256	249

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.9.4 Appendix 4-4

Table 4-35 Endogenous treatment model with Hourly Wage as the dependant variable

VARIABLES	(1) lhpay	(4) lhpay	(7) lhpay	(10) lhpay	(13) lhpay	(16) lhpay
Female	-0.238**	-0.128	-0.060	-0.250**	-0.126	-0.040
	(0.114)	(0.110)	(0.094)	(0.105)	(0.100)	(0.098)
ethnicity						
Mixed	-0.007	0.002	-0.018	0.092	0.004	-0.022
	(0.284)	(0.286)	(0.208)	(0.282)	(0.229)	(0.205)
Indian	-0.138	-0.006	-0.209	-0.246	-0.120	-0.079
	(0.213)	(0.193)	(0.213)	(0.193)	(0.184)	(0.206)
Pakistani	-0.263	-0.167	-0.390	-0.128	-0.344	0.013
	(0.254)	(0.245)	(0.262)	(0.285)	(0.255)	(0.252)
Bangladeshi	0.205	0.542	0.222	0.145	0.150	0.381
	(0.358)	(0.371)	(0.372)	(0.330)	(0.341)	(0.359)
Black Caribbean	0.420	0.490	0.032	0.300	0.235	0.206
	(0.531)	(0.579)	(0.377)	(0.576)	(0.454)	(0.352)
Black African	0.739*	0.634	0.389	0.634*	0.284	0.580
	(0.438)	(0.418)	(0.384)	(0.356)	(0.394)	(0.403)
Other	-0.080	-0.175	-0.504*	0.217	-0.089	-0.327
	(0.329)	(0.330)	(0.285)	(0.297)	(0.324)	(0.294)
Living in London	0.008	-0.048	0.228	0.010	0.045	0.052
	(0.162)	(0.159)	(0.151)	(0.152)	(0.143)	(0.148)
No health issues	0.205	0.171	0.237**	0.146	0.388***	0.055
	(0.145)	(0.145)	(0.113)	(0.137)	(0.122)	(0.121)
med_vs_lsm	-1.723***					
	(0.650)					
KeyStage 3 Numeracy	0.196***	0.219***	0.049	0.154**	0.201***	0.194***
	(0.074)	(0.073)	(0.063)	(0.072)	(0.065)	(0.062)
KeyStage 3 Literacy	-0.021	0.006	0.049	0.021	-0.096	-0.009
	(0.090)	(0.089)	(0.076)	(0.085)	(0.080)	(0.076)
Parents Qualification						
Degree or equivalent	-0.168	0.026	0.014	-0.355*	-0.181	0.183
	(0.234)	(0.227)	(0.228)	(0.214)	(0.205)	(0.217)
Higher education below degree	0.035	0.183	0.021	-0.203	-0.155	0.314
	(0.235)	(0.225)	(0.230)	(0.212)	(0.205)	(0.214)
A-level or equivalent	-0.018	0.213	0.068	-0.017	0.051	0.318
	(0.234)	(0.236)	(0.236)	(0.221)	(0.203)	(0.219)
GCSE or equivalent	-0.018	0.101	0.160	-0.050	-0.059	0.325
	(0.225)	(0.218)	(0.224)	(0.206)	(0.200)	(0.211)
Qualification at level 1	-0.348	-0.047	0.040	-0.274	-0.323	-0.034
	(0.313)	(0.279)	(0.283)	(0.295)	(0.283)	(0.304)
Other qualification	0.300	0.555	0.382	0.128	0.062	0.523
	(0.376)	(0.362)	(0.378)	(0.347)	(0.297)	(0.340)
5200-10400	-0.198	-0.218	-0.190	-0.232	-0.213	-0.173
	(0.206)	(0.204)	(0.186)	(0.202)	(0.190)	(0.181)
15600-20800	-0.094	-0.037	-0.146	-0.160	-0.257*	-0.073
	(0.184)	(0.183)	(0.158)	(0.175)	(0.151)	(0.158)
20800-33800	-0.370**	-0.364**	-0.366**	-0.374**	-0.490***	-0.358**
	(0.163)	(0.164)	(0.143)	(0.157)	(0.143)	(0.141)
33800-41000	-0.347*	-0.282	-0.458***	-0.127	-0.148	-0.208
	(0.178)	(0.179)	(0.149)	(0.164)	(0.157)	(0.156)
41000-55000	-0.375**	-0.340**	-0.361***	-0.311**	-0.379***	-0.302**
	(0.159)	(0.164)	(0.137)	(0.147)	(0.140)	(0.141)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4-36 Endogenous treatment model with Hourly Wage as the dependant variable (Cont.)

VARIABLES	(1) lhpay	(4) lhpay	(7) lhpay	(10) lhpay	(13) lhpay	(16) lhpay
Degree Class						
First Degree Class	0.149	0.219	-0.101	-0.034	0.016	0.159
	(0.173)	(0.172)	(0.142)	(0.154)	(0.151)	(0.143)
Upper Secondary Class	-0.068	0.053	-0.100	-0.095	-0.063	0.068
	(0.134)	(0.128)	(0.108)	(0.123)	(0.113)	(0.110)
Russell Group	0.139	-0.056	-0.022	0.196	0.133	0.079
	(0.134)	(0.131)	(0.113)	(0.122)	(0.114)	(0.121)
medr_vs_lsm		0.596				
		(0.449)				
sci_vs_lsm			-0.527			
			(0.531)			
math_vs_lsm				-0.248		
				(0.364)		
ling_vs_lsm					-0.631*	
					(0.333)	
art_vs_lsm						-0.327
						(0.333)
Observations	213	234	339	275	279	269

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

4.9.5 Appendix 4-5

Table 4-37 IV-regress estimates

VARIABLES	(1) lhpay
sub2	-0.038
	(0.094)
Female	0.034
	(0.079)
Mixed	-0.092
	(0.193)
Indian	-0.137
	(0.157)
Pakistani	-0.502*
	(0.260)
Bangladeshi	-0.324
	(0.275)
Black Caribbean	0.060
	(0.136)
Black African	0.357**
	(0.146)
Other	-0.457
	(0.351)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4-38 IV-regress estimates (Cont.)

VARIABLES	(1) lhpay
Living in London	0.210**
	(0.093)
No health issues	0.292***
	(0.095)
k3math	0.081
	(0.051)
k3eng	-0.029
	(0.056)
Degree or equivalent	-0.194
	(0.161)
Higher education below degree	-0.232
	(0.161)
A-level or equivalent	-0.018
	(0.160)
GCSE or equivalent	-0.143
	(0.158)
Qualification at level 1	-0.055
	(0.213)
Other qualification	0.041
	(0.204)
5200-10400	-0.056
	(0.134)
15600-20800	-0.287**
	(0.115)
20800-33800	-0.363***
	(0.111)
33800-41000	-0.280**
	(0.116)
41000-55000	-0.280**
	(0.109)
Household income: over 55000 (Base Category)	-
First Degree Class	-0.039
	(0.110)
Upper Secondary Class	0.006
	(0.078)
Russell Group	-0.029
	(0.101)
Observations	584
R-squared	0.072

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: (University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. 4th Edition. UK Data Service. SN: 7104)

Test of overidentifying restrictions:

Score chi2(14) = 20.4171 (p = 0.1175)

5 Conclusion and Discussion

Over the past few decades, the number of new graduates in the UK has risen substantially. Despite this, in recent years the returns to degree education have stabilised (Walker et al., 2011, Blundell et al., 2005; Blundell et al., 2016). The labour market has become very complex as a result of technological developments and there has been an increase in demand for workers whose skills are complementary to these changes and developments. This study is particularly based on finding how the wage premium earned by graduates has changed over the years, what are the variables involved and also present the heterogeneity analysis of wage premium.

In conclusion, this study finds that there is significant differences between the wage-premium associated with different subject choices. The highest premium is for graduates in subjects of medicine, maths, and engineering degrees. Graduates in the subjects of creative and performing arts and medical related subjects such as nursing etc earn a lower wage premium compared to A-level qualified individuals. This lower wage for arts graduates can be attributed to the fact that arts qualified individuals enter the same job market as A-level qualified individuals but much later, so that A-level individuals have an experience advantage over arts graduates (Britton et al., 2016). There is a significant difference between the graduate male and female wage premium: graduate females earn a higher premium compared to their male counterparts, especially for the subjects of maths, engineering, science, languages, and arts.

Individuals employed in London earn higher wage premia perhaps because of higher competition in the labour market and the higher London wages, this is particularly true for women who graduated in LSM and are working in London earn a higher wage premium. On a similar note, individuals from white ethnicity also earn a higher premium compared to other ethnicities but this is not the case for graduates. Graduate males from ethnic minorities earn a higher premium when compared to white males for all subject categories. Graduate ethnic minority females in the subject categories of science and arts also earn a higher wage premium compared to white females. Our estimate also show that white graduate females employed in London earn a higher wage premium than white males for all subject categories except medicine. This is particularly true for the full-time workers.

It can be inferred by looking at the gender wage variation that there is higher variance in the wage premium earned by males, which is a result of variation in higher and lower end jobs, contrary to this, women are clustered more towards the middle level/wage jobs.

The evolution of wage premia shows that individuals who graduated in 2005-2007 did not experience a substantial increase or decrease in their wage premium except for individuals who graduated in Arts who observed a 16% lower subject premium 7 to 9 years after graduation compared to the LSM graduates. These results show that individuals who graduated in Arts from 2005-2007 just before the financial crisis were most affected by the aftermath of financial crisis when it hit the labour market. Medical related and Arts subject graduates during the financial crisis observed a substantial change in their subject premium 3-6 and 7-9 years after graduation as their subject premium was 19% (for medical related) and 15-25% (for arts) lowered compared to LSM graduates. Lastly individuals, who graduated from 2010-2013 in the subject of medical related courses earned a lower subject premium compared to the LSM graduates. In this cohort individuals graduated in languages also observed a higher wage premium (18%) compared to the LSM after 4-6 years.

In terms of graduate professional and non-professional jobs, we see that individuals who graduated in medicine, maths, engineering, and medical related subjects were more likely to find a professional job compared to LSM graduates. Whereas individuals who graduated in arts found it difficult to secure professional jobs compared to the LSM graduates after the financial crisis. Also, it is important for medicine graduates to get a professional job straight after the graduation as their probability to find a professional job after a few years is reduced. Whereas, on the contrary individuals graduated in maths, engineering and languages are more likely to find a professional job a few years after graduation. This can possibly be because of the skills and experience they accumulate over the years.

Our analysis also shows there is strong link between family background and academic achievement at Key Stage 3 on both subject choice and the wage premium of graduates. We have found a significant association between good numeracy skills at Key Stage 3 and STEM subjects at degree level, whilst strong literacy skills are associated with a greater likelihood to pursue Arts and Literature subjects.

Our findings also show that university degree subject choice is strongly influenced by numeracy and literacy skill levels at Key Stage 3. In addition, individuals with strong non-cognitive skills, such as locus of control, positive attitude and less risky behaviour, are also more likely to choose medicine subjects at degree level.

Our results also show that individuals from higher social and financial backgrounds are more likely to choose Medicine, LSM, and Arts subjects. We have also found that individuals with high numeracy and literacy skills are more likely to earn a higher wage premium. There is also a positive association of non-cognitive skills with the wage premium. Individuals who have a high locus of control and social skills are especially more likely to earn a higher wage premium. From our results it can also be assumed that non-cognitive skills are crucial to any job market and individuals with higher non-cognitive skills are at a higher financial and social ladder compared to the individuals with higher cognitive and lower non-cognitive skills.

The results provide an insight into the potential wage premium may earned by different degree subject students, when choosing to go to university and how this wage premium is affected by university choice. The resutls also provide valuable information to policy makers on the effectiveness of the higher education system and potential steps to take when considering further expansion of the education system. It also presents the information to policy makers on the importance of children ability levels at Key Stage 3. According to our estimates, this plays a crucial role in the individual's choice of university, degree subject and lifetime earnings.

While we do not claim that our empirical results for the organisational change explanation are definitive, we believe that they do provide a coherent explanation of the remarkable stability of the education wage differential from the early 1990s until the mid-2010s in the UK, that occurred despite unprecedented increases in the share of entry workers with degree level education over the same period. This points to the UK responding to the substantial increase in university education through an adjustment in the organizational structure of work. We caution that it is dangerous to extrapolate. The UK has already surpassed the US in the Arts Degree proportion for the cohorts born after 1975, and it may exceed the US in the Arts Degree proportion for the entire workforce. It is plausible that the organisational technology is fully utilised so that a further educational expansion, in the absence of the arrival of a new technology, would result in declines in the education wage differential. There is already some sign of this decline in the private sector. The wage differential, though, remains substantial.

6 Reference

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