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Growth in Within Graduate Wage Inequality: The Role of Subjects, Cognitive Skill Dispersion and Occupational Concentration.

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Abstract

UK graduate wage inequality has increased over the previous three decades. This paper demonstrates that most of the growth has occurred within degree subjects, with the largest occurring in non-STEM subjects. The paper therefore investigates two potential explanations. The first is the increase in the variance of childhood cognitive test scores amogst graduates in the same subject. This increase differs across subjects, and is again in the non-STEM subjects where the variance of test scores has increased the most, especially during the second period of rapid higher education expansion in the 1990s. The second potential explanation explored is the fall in the occupational concentration of subjects. Graduates of some subjects (like Medicine and Education) are highly concentrated into only a few jobs whereas others are much more widely dispersed. Generally, all subjects have become more widely dispersed across occupations over time, but some more so than others. The paper then shows that both of these factors have played a role in explaining growing graduate wage inequality within subjects, though the largest is by far from the widening in the variance of test scores. The path of graduate wage inequality would have been relatively flat without the accompanying increase in the variance of cognitive skills.

Keywords: Wage Inequality, Subject of Degree, Graduates.

JEL Codes: J2; J24; J31

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1. Introduction

Large increases in Higher Education (HE) participation have produced increased numbers of graduates in the labour markets of advanced countries. This in turn has produced numerous research studies into the effect of such an increase on labour market outcomes (see, for example, Elias and Purcell, 2004; McIntosh, 2006; O'Leary and Sloane, 2005; Walker and Zhu, 2008 in the UK, and Card and Lemieux, 2001; Katz and Murphy, 1992; Topel, 1997 in the US). In terms of the mean wage differential between graduates and non-graduates, there is little evidence that this has been affected by the increased number of graduates in the market.

Simple focus on average differences, however, can miss much variation around the mean. Indeed there is much variation in wages *within* education categories. It has been argued that much of the overall increase in wage inequality has been due to an increase in this residual inequality within education groups, for example by Juhn *et al.* (1993), Katz and Autor (1999) and Lemieux (2006a) in the US or Gosling *et al.* (2000) in the UK.

There are various characteristics by which graduates could be differentiated, in order to examine within-graduate wage inequality. For example, one area of study could be variation in quality of university attended (for example see Hussain *et al.*, 2009), while another could be degree classification (first class, second class etc.). In this paper we focus on the distribution of graduates by subject of degree. A small number of studies in the economics literature have also considered subject choice. In the UK, for example, O'Leary and Sloane (2005) consider degree subject in their analysis of changing returns over time. Walker and Zhu (2011) calculate a full net rate of return to investments in different degree subjects, allowing for the increase in fees introduced in the UK from 2012. Chevalier (2011) demonstrates the variation in graduate wages by subject, but shows there is still more variation in wages within subjects than between. Machin and Puhani (2003) consider degree subject in both the UK and Germany and find that in both countries, wages vary by subject, and furthermore that differences in subject choices between men and women explain a small part of the gender wage gap. More recently, in the US, Altonji *et al.* (2012) consider wage differentials to subject majors, within the context of a theoretical model which takes account of subject choice. One limitation of this study is that the data does not allow for the analysis of changes over time.

In this paper, we document UK employment shares, wage differentials and inequality measures by subject of degree over time. The paper goes beyond mere documentation however, by focussing in on two potential drivers of growing graduate wage inequality. By doing this, the paper makes a unique contribution to the literature. Both of the potential drivers are linked to the expansion of the HE sector and the fact that more individuals are now accepted onto degree courses. The first is the extent to which there has been a widening in the range of cognitive skills of graduates and whether this can partly explain the growing graduate wage inequality we observe. Second, we find little evidence of falling wage differentials for any subject, suggesting that the increase in the supply of graduates is likely to have been have been met by similar increases in employer demand for graduates. However, Figure 1 (taken from the CBI Education and Skills Survey) shows employers have a greater preference for STEM (Science, Technology, Engineering and Mathematics) subjects on average. This is likely to have increased the competition for the available graduate jobs in some subjects more than others, which may in turn have led to a wider range of jobs being performed and hence an increase in the variance of wages. We therefore also investigate changes in the occupational dispersion of subjects as a second potential explanation of growing wage inequality.

To preview our results, we find that the variance of cognitive skills has increased for all subjects, but more so for non-STEM subjects than STEM. We also find that all subjects have become more occupationally diverse (less concentrated) over time, but again that some have experienced larger changes than others. We therefore estimate graduate inequality equations and find that even after conditioning on supply and composition effects, the increase in the variance of cognitive skills and the dispersion of occupations has increased graduate wage inequality, with the former having a larger effect than the latter.

The rest of the paper is organised as follows. The next section provides background information on changes in employment shares and wage differentials by broad education categories, over time in the UK. Section 3 then compares changes over time in graduate employment shares and wage differentials by subject of degree. Section 4 looks at the extent of within-subject wage inequality, whilst Section 5 presents trends in cognitive skills by subject. Section 6 investigates the extent to which changes in occupational concentration differ across subjects. Section 7 then estimates subject level inequality equations to explain growing graduate wage inequality through the potential drivers we consider. The final section concludes.

2. Background

We begin by documenting the overall changing pattern of graduate labour supply and wages in the UK. We focus on recent trends (between 1994 and 2011) because this is the period of analysis for subjects that will follow later in the paper. For this we use the Labour Force Survey (LFS) which is a quarterly survey of households but which provides us with an annual series.[1] We focus on workers aged 23-45 to increase the proportion of graduates we have in our sample, given we will be estimating separately by subject of degree later. Note that the `graduate' group contains all undergraduates, whether or not they went on to obtain a postgraduate degree, because our data only provide information on the subject of the first degree, and so subject of postgraduate degree could not be analysed separately. [2]

Table 1 supports what we already know from the existing literature, that there has been an increase in the supply of educated labour in the UK, with women seeing the larger increase, of a similar magnitude to that in the US. The largest compensatory fall has been in terms of the proportion of individuals acquiring no qualifications. Table 2 shows that there has also been an increase in graduate wage differentials, relative to those with intermediate qualifications.[3] The figures show an increase in the size of the graduate wage differential for both genders. The larger increase in the graduate pay differential (0.042 log percentage points) has been for men, who have also experienced the smaller change in graduate employment share. For women, the change in the graduate wage differential is statistically insignificant.[4] So clearly there are gender differences, although explaining these is not the main focus of our paper.

The rising supply of graduate labour, accompanied by rising graduate wage differentials are well-documented facts in the UK and the US, and have been shown to be an important driver of the growth in wage inequality (for example, by Goldin and Katz, 2007, and Lemieux, 2006b, in the US and Lindley and Machin, 2013, in the UK). But within graduate wage inequality is a relatively less researched area. Table 3 shows various measures of wage inequality over time both for the full sample of workers and separately for graduates. Firstly the growth in overall wage inequality captured by the 90-10 log wage ratio has been larger for graduates (0.16) than it has been for all workers (0.09) between 1994 and 2011. Furthermore, for all workers the growth in inequality over the 1994 to 2011 period has mainly been at the top end of the earnings distribution since the change in the 90-50 ratio (0.06) is double the change in the 50-10 ratio (0.03). This difference is however not as marked for graduates since the changes at the bottom (0.07) and the top (0.09) are more similar.

Given these trends, our initial approach to explaining this rising graduate wage inequality is to look at labour supply changes by subject and then look at the subject specific wage changes. We therefore initially consider between subject changes as a source of rising variation.

3. The Change in the Employment Shares and Earnings by Subject of Degree

In this section we examine the change in the number of graduates and the change in graduate wage differentials over time by subject for the period 1994-2011, since the first full LFS survey year with subject information was in 1994. We present these separately for STEM and non-STEM subjects. Following Walker and Zhu (2011) we define STEM subjects as Medical, Medical Related (including Nurses), Biology/Agricultural Science, Physical Science, Maths/Computing and Engineering/Technology, whilst we define non-STEM subjects as Law, Economics, Management/Business, Other Social Sciences, Arts/Humanities, Education and Combined subjects.

Table 4 reports the change in the composition of graduate employment shares by subject using the LFS cross sections 1994, 2000, 2005 and 2011. Amongst graduates the largest increases in employment shares have been in Management/Business (0.064), Medical Related (0.053) and Arts/Humanities (0.044), with Other Social Sciences (-0.006) and Combined degrees (-0.153) experiencing a relative fall. Overall, Table 4 shows that the subject composition of graduates has changed over time, with only the proportion of Medics remaining constant at around 2-3 percent of all graduates. In 2011, over 20 percent of all graduates aged 23-45 had degrees in Arts/Humanities, whilst almost 15 percent had Management/Business degrees.

Given the increase in the relative supply of graduates, we might expect to see changes in the subject specific graduate wage differentials at the same time.[5] However, Table 5 shows that changes in these wage differentials have remained relatively flat. Only Engineering/Technology, Economics, Other Social Science and Combined degree graduates have significantly increased their wage differentials relative to those with intermediate qualifications, with log point increases (standard errors) of 0.108 (0.033), 0.139 (0.063), 0.074 (0.044) and 0.086 (0.029) respectively. Medical degrees provide a much larger payoff relative to intermediate qualifications and this is consistent over time, whilst Arts/Humanities provide the lowest. In 2011 Medical graduates earned 0.820 log points (127 percent) more than workers with intermediate qualifications, whilst for Arts/Humanities graduates this wage premium was only 0.281 log points (32 percent), on average.

The fact that the employment shares of some subjects (like Management/Business, Medical Related and Arts/Humanities) have increased, whilst at the same time graduate wage payoffs have remained relatively flat (and have increased only for Engineering/Technology, Economics, Other Social Science and Combined degrees), suggests that demand may have shifted in favour of some subjects more so than others.

4. Within-Subject Wage Inequality

The previous sections showed substantial growth in within graduate wage inequality, but also that changes in subject specific returns have mostly remained flat. This suggests that the variance of wages has been growing more within subjects than between them. We therefore decompose the variance of the graduate log wage, *Var*(lw_{ijt}), into that which is within and that that which is between subjects:

$$Var(lw_{ijt}) = \left[\frac{\sum(lw_{ijt} - \overline{lw}_{jt})^2}{N_t}\right] + \left[\left(\frac{\sum(\overline{lw}_{jt} - \overline{lw}_t)^2 N_{jt}}{N_t}\right)\right] \quad (1)$$

for graduate *i* of subject *j* in year *t*, where N_t is the number of graduates in each year. The first square bracket contains the within subject variance of wages and the second term is the between subject variance. Table 6 shows that the within subject variance is larger at 0.228 of the total 0.241 in 2011, and has increased by 0.042 over the period compared to an increase of only 0.002 for the between subject variance. As a consequence, we compare inequality indices separately by subject. Table 7 shows that Engineering (0.074) and Economics (0.071) exhibit particularly large growth in the variance of wages between 1994 and 2011. This is smaller for Arts/Humanities (0.054), Combined (0.051), Management and Business (0.043) and Education (0.037) degrees. The remainder seem to have remained relatively constant. The increased wage inequality is therefore more noticeable within non-STEM subjects than within STEM subjects. The growth in the 90-10 ratio shows a similar pattern, albeit with Economics now coming out on top (0.337) which is probably a consequence of increasing bonuses in the finance sector.

To summarise the results so far, the mean wage for Economics, Engineering and Combined degrees has increased vis-à-vis non-graduates but the `within-subject' variance has also increased. For Management/Business, Arts/Humanities and Education the variance of wages has increased more so than for other degree subjects, but average wage returns have remained fairly flat. So in the subsequent sections we investigate why the dispersion of wages within some degree subjects is increasing more than others. In particular we focus on two potential explanations. Firstly, as the Higher Education sector has expanded, more individuals have been accepted onto degree courses. This could potentially lead to a wider range of cognitive skills being observed amongst graduates, if those attending before the expansion were from the top of the ability distribution. This in turn could partly explain the variation in the increasing wage dispersion across subjects if the distribution of cognitive skills has changed differently across subjects. One could think of this as a supply side explanation for increasing graduate wage inequality. Secondly, the increase in the supply of graduates is likely to have led to greater competition amongt them for the available graduate jobs, and so to employment in a wider range of jobs, if demand cannot keep pace with this increasing supply. This in turn may also have increased the variance of graduate wages in some subjects. One could think of this as a demand side explanation for increasing graduate wage inequality, since employers are not expanding graduate jobs equally across all degree subjects. It is to these two potential explanations that we now turn.

5. Cognitive Skill Differences of Graduates by Subject of Degree

In this section we want to assess whether the variance of childhood mathematics and literacy test scores is higher for graduates of some subjects, but more importantly whether subjects have *increased* their variance in test scores to the same extent, given the increase in the supply of graduates overall. To do this we compare the cognitive skills of children assessed around age 10 across their subsequent degree subject using the National Child Development Study (NCDS), the British Cohort Study (BCS) and the Longitudinal Survey of Young People in England (LSYPE). The NCDS assesses children born in 1958, the BCS assesses children born in 1970 and the LSYPE assesses children born in 1990, all at approximately age 10. We then look at their subsequent degree subjects measured at age 23, 30 and 20 from the 1981 NCDS, the 2000 BCS and the 2010 LSYPE respectively. Unfortunately it is necessary to combine economics with other social science degrees because of the categories that are provided in the LSYPE.

Table 8 reports the variance of the maths and reading test scores assessed at age 10 in 1968, 1980 and 2000 by subsequent degree subject from the three surveys. To take account of the fact that these surveys assess maths and reading scores differently (there are a different number of questions in the tests), test scores are measured using the percentile of the distribution at which each individual appears.[6] For graduates observed in 1981, the variance of the maths test scores that they obtained as age 10 children in 1968 was the highest for

Medical Related graduates (389), with Arts/Humanities close behind (388). Perhaps not surprisingly given their high entry requirements, it was Medical (126) and Law (182) graduates that exhibited the smallest variance in childhood maths test scores. A similar pattern holds for literacy test scores, with the highest being for Medical Related (397) and Arts/Humanities (365) graduates and the smallest being for Law (147) and Medical (184) graduates. These results also show how highly correlated across individuals the numeracy and literacy test scores are with each other.

In terms of changes over time, for most subjects the variance of maths and reading test scores increased over the first period (graduates observed in 1981-2000, tests taken at age 10 in 1968 to 1980) with smaller increases more recently (between those aged 10 in 1980 and 2000) when graduates' subjects were observed in the large higher education expansion period of 2000 to 2010. Law and Combined degrees are particularly interesting cases, since the variance of maths and reading test scores for these two subjects increased quite dramatically in the second period. Other smaller but statistically significant increases for the variance in both maths and reading scores were observed only in Arts and Humanities. Maths/computing and Management/Business graduates exhibited an increase in the variance of maths test scores (but not reading test scores), whilst Education graduates demonstrated an increase only in the reading test score variance.

There also appears to be a STEM/non-STEM difference in the changes, particularly with respect to reading scores and the second period. The variance of reading scores in this period actually falls amongst many of those who go on to obtain a STEM degree, while those who obtain a non-STEM degree in this period come from an increasingly wide range of reading ability.

Overall, Table 8 clearly shows that the variance of test scores has increased more so in some subjects than in others, with increases being particularly large for Law and Combined Degree graduates. So for graduates with degrees in Combined Studies, Management/Business, Arts/Humanities and Education, the large increase in the variance of wages (found in Table

7) could potentially be partially driven by increases in the variance of their cognitive ability (as measured by age 10 test scores).

A wider variance in cognitive ability cannot be the only cause of growing within-subject wage inequality, however. For example for Engineering/Technology graduates, the wage distribution is widening, but there has actually been a fall in the variance of both maths and reading scores between graduates observed in 2000 and 2010. . In the next section we therefore consider another determinant of rising wage inequality, looking at the demand side to see whether employers have expanded graduate jobs equally across all degree subjects.

6. Occupational Dispersion of Graduate Jobs by Subject of Degree

In this section we look at the occupational distribution of subjects. In particular we look at how the occupational dispersion of graduates within subjects has changed over time. To do this we go back to using the LFS restricting the sample to 1994-2010 in order to obtain consistent occupation categories over time. In 1994, the LFS occupational categories are defined using the 1990 Standard Occupational Classification (SOC90), changing in 2001 to use the 2000 Standard Occupational Classification (SOC2000). This was changed again to the 2010 Standard Occupational Classification (SOC2010) in 2011. Using guidance provided by the Office for National Statistics, we concorded the SOC90 data between 1994-2000 to the SOC2000 level.[7] This provides 102 consistently defined three digit occupations. Given the large changes in the categories between the SOC2000 and SOC2010 classifications we did not attempt to further extend the concordance to include respondents from 2011 onwards.

Table 9 documents trends in occupational concentration indices by subject of degree, for a sample of workers age 23-45. The first concentration measure we report is the three-occupation concentration ratio. This is the proportion of individuals within each degree subject who are covered by the three most popular jobs for that subject. For example, 89 percent of individuals with Medical degrees in 1994 were employed in the top three most popular occupations for people with that degree. These occupations are Health Professionals (81 percent of individuals), Science Professionals (5 percent of individuals) and Corporate

Managers (3 percent of individuals) as shown in Table A1 of the Appendix.[8] The 75 percent coverage rate is the number of different occupation titles undertaken by the 75 percent of individuals within each subject of degree in the most popular occupations. So for Medical degrees the 75 percent of the workers in the most popular jobs are employed in just one occupation (Health professionals).

As expected, the subjects that lead to the traditional graduate professions have a more concentrated selection of jobs, for example Education, Medicine, Law, and Medical Related. With the exception of Law these subjects typically lead to public sector jobs. The least concentrated are Management/Business, Physical Sciences and Combined Degrees, which are much less likely to lead to a specific profession.

Overall, all subjects have become less concentrated, with Law (-0.312) seeing the largest fall in the three-occupation concentration ratio, followed by Arts/Humanities (-0.152) and Engineering (-0.117) also demonstrating a relatively large fall. The largest changes therefore again mostly occur for the non-STEM subjects, in terms of reduced occupational concentration.

So for graduates of Arts/Humanities, Engineering/Technology and Combined Degree subjects, increases in occupational dispersion could be a potential driver of the increases in the variance of wages (found in Table 7) and consequently we return to this notion in the subsequent section. For growing occupational dispersion to be a a possible cause of growing wage inequality, though, it has to be the case that less popular jobs pay less well than the more popular jobs for a degree subject, as the graduates diversify into a wider range of less popular jobs. In principle, there is no reason why this need be the case, if those in the less popular occupations are performing specialised, and so well-rewarded, jobs for example. We therefore estimate a standard wage equation

$$lw_{it} = X_{it}\beta + S_{it}\gamma + (S_{it} \cdot P_{it})\pi + \varepsilon_{it} \qquad (2)$$

where X_{it} is a vector of controls for age and its square, gender, race and region of residence, whilst S_{it} is a vector of binary dummies for each subject of degree and P_{it} is a vector of binary dummy capturing whether the graduate i works in one of the top three most popular occupations for their subject at time t (as defined in Table A1). The π terms therefore capture the additional wage return for working in one of the top three most popular jobs for a given subject, over and above the log wage returns (γ) to each degree subject when not employed in one of the most popular occupations for that subject. [9]

The results in table 10 show that for every degree subject, the estimated wage return is significantly higher when the graduate works in one of the three most popular occupations for that subject. This differential is highest for medical degrees (i.e. the wage return to a medical degree is much greater when the holder works as a medical practitioner). We would therefore expect that if individuals are increasingly having to work in non-popular occupations for their degree subject, then we will observe lower wages for such individuals and hence a wider distribution of wages within that degree subject. This is tested in the next section.

7. Graduate Inequality Equations by Subject of Degree

So far we have found evidence to support the existence of two potential drivers of increasing within-subject wage inequality. In this section we therefore estimate subject-level inequality equations to compare these drivers and thus look for correlations between growing graduate wage inequality and increasing dispersion in the cognitive skills and occupational distribution. We also condition on subject specific changes in the supply of graduates and the composition of graduates. To do this we create a subject-level panel for 1994-2010. Altogether we have 12 subjects observed over 17 years which provides 204 observations. We therefore estimate

$$I_{jt} = X_{jt}\beta + OC_{jt} + \delta Var(A)_{jt} + \alpha_j + \omega_t + \varepsilon_{jt} \qquad (3)$$

where X_{jt} is a vector of controls including the employment share, female share and the age share of subject j at time t. The α_j and the ω_t are the subject and time fixed effects respectively, which we capture by including 12 subject dummies and 17 year dummies. We measure the age share using three groups (23-28, 29-34 and 35-40) relative to the omitted category of 41-45. We use two dependent variables for measuring earnings inequality I_{jt} within subject j at time t. These are the variance of log weekly wages and the 90-10 log weekly wage ratio. We also look separately at the log weekly wage at the 90th and 10th percentile to help us to understand where in the earnings distribution the changes are occurring.

Our measure for occupational concentration OC_{jt}, is straightforward since we simply use the Three-Occupation Concentration Ratios from Table 9. Measuring cognitive skill dispersion $Var(A)_{jt}$, is a little more complicated since we require a subject level panel for 1994 to 2010 using the three data points (for people born in 1958, 1970 and 1990) observed in Table 8. Our approach is to firstly generate a maths and reading test score variance for every year of birth between 1949 and 1989, calculated separately for every degree subject that individuals subsequently acquire. We do this by interpolating between our three data points, for each subject. In the main LFS data set for each year, we observe the birth years of each graduate, and can therefore estimate the variance of age 10 maths and reading scores for the observed adults with each degree subject, as a weighted average of these subject-specific and birth year-specific test score variances, with the weights based on the proportions with each observed birth year actually observed within that subject category. Our measures of cognitive skill can therefore take account of the changing levels of childhood ability amongst graduates over time, the changing relative popularity of different degree subjects over time, and any changes in the selection into different subjects by individuals with different levels of ability.

Table 11 provides the results for equation (3) which include fixed effects and thus provide within-subject changes. Given that the variances of the test scores are likely to be highly correlated, we use only literacy scores. The first column shows that as the variance of literacy scores increases, a subject's log wage variance also increases, thus increasing wage inequality. The same can also be said for the 90-10 log wage ratio (increasing the ratio by 0.0669). The final two columns show that greater test score dispersion is lowering the wage at the 10th percentile (-0.0299) but increasing the wage at the 90th percentile (0.0369) by slightly more, suggesting that increased dispersion in test scores is increasing wages at the top end of the earnings distribution (relative to the bottom), although these are just outside the 10 percent significance level.[10] Of course any measurement error would lead to our underestimating these effects and since our cognitive measures are interpolated one should bear that in mind.

On the demand side, as subjects have become less occupationally concentrated (as we found in Table 9) graduate wage inequality has increased, but this is only statistically significant for the 90-10 log wage ratio (-0.2867). Looking at the final two columns shows that this is working through decreasing the log wage at the 10^{th} percentile (0.4393) relative to the 90^{th} percentile and thus increasing wage inequality.

As expected, increasing the employment share into a subject should reduce the graduate wage, and this is exactly what we find for the 90^{th} percentile wage (-0.8541). Since the 90^{th} percentile wage falls by more than the 10^{th} percentile wage, this reduces inequality overall. Similarly, increasing the supply of women into a subject increases the 10^{th} percentile wage (0.2159) relative to the 90^{th} percentile wage, thus reducing inequality overall. The effects of increasing the share of 23-28 year old workers largely offset each other at the 90^{th} and 10^{th} percentile resulting in no effect on inequality. But the share of workers aged 29-34 in a subject reduces wage inequality by reducing the wage at the 90^{th} percentile.

What if there had been no change in the dispersion of cognitive skills or the occupational distribution of subjects? What would have happened to graduate earnings inequality? To answer this question we plot predicted inequality estimates alongside counterfactual estimates. We do this by plotting the year dummies from Table 11 firstly without any controls and then secondly controlling for the variance in literacy scores and then thirdly controlling for the three-occupation concentration ratios. In effect, we are holding the test scores constant at the 1994 level and showing what would have happened to inequality over time. Then we are holding the occupational concentration ratios constant to see what would have happened to inequality patterns.

Panels (a) and (b) in Figure 2 present these graphs for both the variance and 90-10 ratio of wages. The first thing to note is that the inequality measures presented here are averaged over

12 subjects in the panel regression (even though they are calculated for individuals) and so they are not the same as those found in Table 3. In panel b the average predicted 90-10 log wage ratio increased from 0.928 in 1994 to 1.076 in 2010 (an increase of 0.148 compared to 0.16 between 1994 and 2011 in Table 3). Holding the occupational concentration ratios constant reduces inequality, and the growth in inequality over time, but not by nearly as much as holding test scores constant. In fact, panel b shows the average 90-10 log wage ratio would have stayed fairly flat (0.951 in 2010) if test scores had remained at the 1994 level. Panels (c) and (d) include the full set of covariates from Table 11. Even after conditioning on labour supply and composition effects, wage inequality would have remained constant if both the variance of test scores and the occupational distribution had remained at the 1994 level.

8. Concluding Comments

Graduate wage inequality has increased over time, but this paper has shown that the growth in the supply of UK graduates has not been evenly distributed across all subjects. The largest increases in supply have been in non-STEM subjects such as Business/Management, and Arts and Humanities. Amongst the STEM subjects, the biggest increases were seen in Medical Related and Maths/Computing degrees. In terms of the best-paying subjects, these are Medical, Economics, Engineering/Technology, Maths/Computer Science and Management/Business, with Arts/Humanities paying the least on average. The time series element revealed that the only subjects to have seen an increase in their relative wage differentials since 1994 are Engineering/Technology, Economics, Other Social Science and Combined Degrees. We have found overall that changes in the relative returns to different subjects have not been the main driver of rising within-graduate wage inequality.

Most of the growth in graduate wage inequality has occurred within subjects rather than between them. The variance of wages has increased for graduates of Engineering/Technology, Economics, Management/Business, Arts/Humanities, Education and Combined Degrees, but not for other graduates.

The paper then considered potential reasons why this growth in inequality might be happening. We found evidence that the variance of childhood maths and reading scores has increased for all subjects, but more so for some subjects (Law, Combined Degrees, Maths/Computer Science, Education and Arts/Humanities) than others. We also found that some subjects are more occupationally diverse (less concentrated) than others but also that all subjects have become less concentrated over time. Again some have changed more than others (Arts/Humanities, Law and Engineering/Technology). Finally we found that even after conditioning on changes in the supply and composition of graduates, increased cognitive skills and occupational dispersion have increased graduate earnings inequality over time. In fact, graduate wage inequality would have remained relatively flat if the dispersion of cognitive skills had remained at the 1994 level.

The growing inequality in wage outcomes that we can observe amongst graduates can therefore be linked in part to the expansion of Higher Education that has occurred in the UK, which has resulted in a wider ability range being accepted into universities, and a wider range of jobs (which typically pay less than the most popular jobs) being performed by graduates. These processes have occurred particularly in non-STEM subjects, which have seen, on average, larger increases in within-subject wage inequality, and also on average larger increases in ability variation and also an increasingly less concentrated occupation distribution, both in turn linked to the greater expansion of provision in these subjects. Thus, the non-STEM subjects typically produce a wider distribution of wages.

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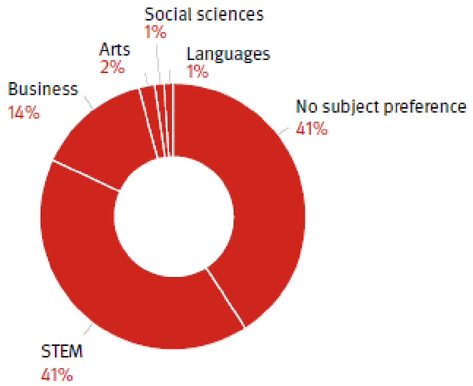
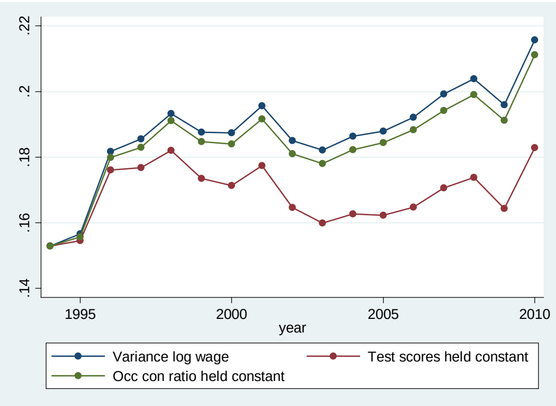
Figure 1 Degree Subjects Preferred by UK Employers



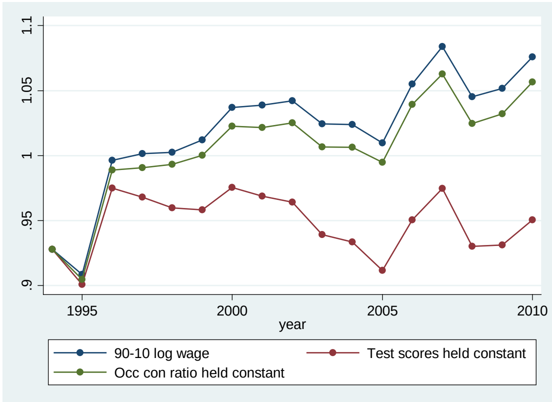
Source: The CBI Education and Skills Survey 2011, CBI (2011).

Figure 2: Fixed Effects Estimates for Predicted Earnings Inequality, 1994-2010

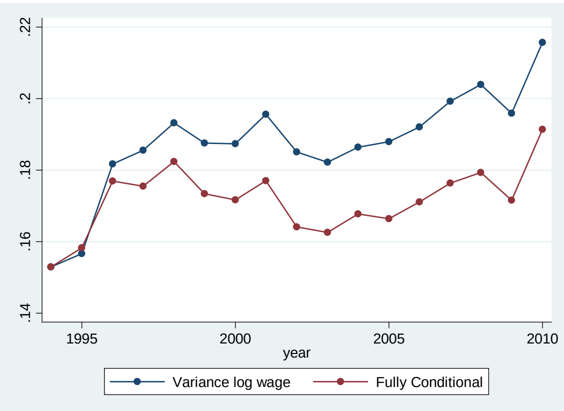
(a) Variance of Log Weekly Wage



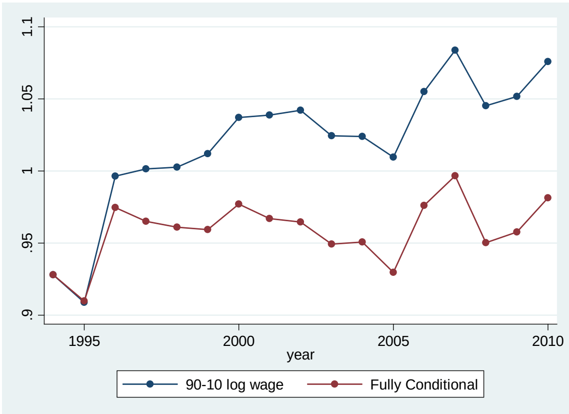
(b). 90-10 Log Weekly Wage Ratio



(c) Variance of Log Weekly Wage



(d). 90-10 Log Weekly Wage Ratio



Note: Fully conditional predicted values include all the covariates from Table 11.

Table 1. Change in Employment Shares by Education Group and Gender, 1994-2011

	1994	2000	2005	2011	2011-1994
Men					
No Qualifications	0.09	0.07	0.07	0.05	-0.04* (0.002)
Less than 2 A Levels	0.58	0.57	0.53	0.51	-0.07* (0.003)
2 Plus A Levels	0.05	0.05	0.05	0.05	0.01* (0.001)
Higher (Below Degree)	0.11	0.12	0.12	0.10	-0.01* (0.002)
Graduates	0.16	0.18	0.23	0.28	0.12* (0.002)
N	65115	60143	50585	36834	
Women					
No Qualifications	0.14	0.08	0.05	0.03	-0.159* (0.002)
Less than 2 A Levels	0.53	0.55	0.53	0.49	0.039* (0.002)
2 Plus A Levels	0.04	0.05	0.05	0.05	0.012* (0.001)
Higher (Below Degree)	0.16	0.15	0.14	0.12	-0.043* (0.002)
Graduates	0.13	0.17	0.23	0.30	0.151* (0.002)
N	62832	59576	52019	38782	

Notes: Source is the 1994-2011 Labour Force Surveys. Employment shares are defined for people in work age 23 to 45. * denotes statistically significant at the 5 percent level

Table 2. Change in Log Weekly Wage Differentials by Education Group and Gender, 1994-2011

	1994	2000	2005	2011	2011-1994
			Men		
No Qualifications	-0.305* (0.015)	-0.314* (0.014)	-0.276* (0.017)	-0.300* (0.024)	0.004 (0.028)
Higher (Below Degree)	0.005 (0.013)	0.040* (0.011)	0.047* (0.012)	0.054* (0.016)	-0.059* (0.021)
Graduates	0.322* (0.011)	0.359* (0.009)	0.359* (0.010)	0.364* (0.010)	0.042** (0.016)
N	9943	17063	13300	9361	
			Women		
No Qualifications	-0.274* (0.017)	-0.294* (0.018)	-0.287* (0.024)	-0.278* (0.035)	-0.004 (0.037)
Higher (Below Degree)	0.215* (0.014)	0.215* (0.011)	0.177* (0.013)	0.152* (0.017)	-0.063* (0.024)
Graduates	0.451* (0.013)	0.432* (0.010)	0.430* (0.010)	0.461* (0.011)	0.010 (0.019)
N	6121	10525	8972	6435	

Notes: Source is the 1994-2011 Labour Force Surveys. Log weekly wages are deflated using the Retail Price Index and are bottom coded. These are for full time employees age 23 to 45. The differentials are relative to intermediate qualifications and condition on race, region of residence, age and age squared. Standard errors are in parentheses. * (**) denotes statistically significant at the 5 (10) percent level

Table 3. Trends in Earnings Inequality Indices, 1994-2011

	1994	2000	2005	2011	2011-1994
Variance					
All Workers	0.228	0.246	0.241	0.261	0.033*
Graduate Workers	0.197	0.234	0.238	0.241	0.044*
90-10 Ratio:					
All Workers	1.18	1.23	1.23	1.27	0.09
Graduate Workers	1.08	1.18	1.21	1.23	0.16
90-50 Ratio:					
All Workers	0.59	0.66	0.66	0.65	0.06
Graduate Workers	0.54	0.62	0.63	0.63	0.09
50-10 Ratio:					
All Workers	0.58	0.57	0.57	0.62	0.03
Graduate Workers	0.54	0.56	0.57	0.60	0.07

Notes: Source is the 1994-2011 Labour Force Surveys. Log weekly wages are deflated using the Retail Price Index and are bottom coded. These are for full time employees age 23 to 45. * (**) denotes statistically significant at the 5 (10) percent level in an F test between two variances.

Table 4. Change in Employment Shares of College Graduates by Subject of Degree, 1994-2011

	1994	2000	2005	2011	2011-1994
STEM Subjects					
Medical	0.026	0.021	0.018	0.024	-0.002 (0.002)
Medical Related	0.020	0.050	0.058	0.072	0.053* (0.002)
Biological/Agricultural Sciences	0.067	0.057	0.082	0.083	0.015* (0.003)
Physical Sciences	0.071	0.063	0.062	0.055	-0.015* (0.002)
Maths/Computer Science	0.057	0.064	0.072	0.078	0.020* (0.003)
Engineering/Technology	0.106	0.098	0.080	0.074	-0.032* (0.003)
Non-STEM Subjects					
Law	0.037	0.028	0.039	0.042	0.005* (0.002)
Economics	0.029	0.019	0.023	0.019	0.010* (0.002)
Management/Business	0.086	0.105	0.139	0.149	0.064* (0.003)
Other Social Sciences	0.065	0.074	0.060	0.059	-0.006* (0.002)
Arts/Humanities	0.137	0.182	0.195	0.201	0.044* (0.004)
Education	0.070	0.091	0.072	0.086	0.015* (0.003)
Combined Degrees	0.207	0.147	0.099	0.055	-0.153* (0.003)
N	18290	20231	22418	21395	

Notes: Source for the United Kingdom is the 1994-2011 Labour Force Surveys. Employment shares are defined for graduates in work age 23 to 45. * (**) denotes statistically significant at the 5 (10) percent level.

Table 5. Change in Graduate Wage Premium by Subject of Degree, 1994-2011

	1994	2000	2005	2011	2011-1994
STEM Subjects					
Medical	0.729*	0.749*	0.910*	0.820*	0.091
	(0.045)	(0.039)	(0.035)	(0.037)	(0.063)
Medical Related	0.474*	0.461*	0.443*	0.392*	-0.082
	(0.059)	(0.027)	(0.023)	(0.024)	(0.074)
Biological/Agricultural Sciences	0.327*	0.303*	0.328*	0.383*	0.056
	(0.031)	(0.025)	(0.019)	(0.020)	(0.042)
Physical Sciences	0.388*	0.372*	0.368*	0.408*	0.020
	(0.029)	(0.022)	(0.020)	(0.023)	(0.041)
Maths/Computer Science	0.417*	0.510*	0.442*	0.442*	0.025
	(0.030)	(0.021)	(0.020)	(0.020)	(0.041)
Engineering/Technology	0.372*	0.404*	0.405*	0.480*	0.108*
	(0.023)	(0.017)	(0.018)	(0.020)	(0.033)
Non-STEM Subjects					
Law	0.461*	0.496*	0.525*	0.509*	0.048
	(0.047)	(0.035)	(0.029)	(0.029)	(0.063)
Economics	0.489*	0.502*	0.489*	0.628*	0.139*
	(0.044)	(0.040)	(0.036)	(0.039)	(0.063)
Management/Business	0.471*	0.503*	0.480*	0.427*	-0.044
	(0.026)	(0.017)	(0.015)	(0.016)	(0.034)
Other Social Sciences	0.279*	0.313*	0.328*	0.353*	0.074*
	(0.032)	(0.021)	(0.023)	(0.024)	(0.044)
Arts/Humanities	0.289*	0.268*	0.252*	0.281*	-0.007
	(0.021)	(0.014)	(0.013)	(0.014)	(0.028)
Education	0.388*	0.349*	0.387*	0.378*	-0.010
	(0.029)	(0.019)	(0.021)	(0.021)	(0.040)
Combined Degrees	0.311*	0.368*	0.381*	0.397*	0.086*
	(0.016)	(0.015)	(0.018)	(0.025)	(0.029)
N	16064	27588	22272	15796	

Notes: Source is the 1994-2011 Labour Force Surveys. For all working men and women age 23 to 45. The differentials are relative to intermediate qualifications and condition on race, region of residence, age and age squared. Standard errors are in parentheses. * (**) denotes statistically significant at the 5 (10) percent level.

Table 6. Trends in the Variance of Graduate Log Earnings, 1994-2011

	1994	2000	2005	2011	2011-1994
Overall Variance	0.197	0.234	0.238	0.241	0.044
Between Subjects	0.011	0.014	0.015	0.013	0.002
Within Subjects	0.186	0.220	0.223	0.228	0.042

Notes: Source is the 1994-2011 Labour Force Surveys. Log weekly wages are deflated using the Retail Price Index and are bottom coded. These are for full time employees age 23 to 45.

Table 7. Trends in Earnings Inequality Indices by Subject of Degree, 1994-2011

	Variance of Log Wage					90-10 Log Wage Ratio				
	1994	**2000**	**2005**	**2011**	**2011-1994**	**1994**	**2000**	**2005**	**2011**	**2011-1994**
STEM Subjects										
Medical	0.167	0.161	0.152	0.180	0.012	1.020	0.986	0.935	1.104	0.083
Medical Related	0.125	0.156	0.160	0.126	0.001	0.934	0.978	0.968	0.761	-0.173
Biological/Agricultural Sciences	0.169	0.218	0.203	0.210	0.041	0.993	1.164	1.135	1.196	0.202
Physical Sciences	0.186	0.249	0.228	0.220	0.034	1.033	1.198	1.132	1.181	0.148
Maths/Computer Science	0.219	0.256	0.317	0.235	0.016	1.153	1.154	1.381	1.174	0.021
Engineering/Technology	0.148	0.228	0.188	0.223	0.074*	0.861	1.156	1.014	1.146	0.245
Non-STEM Subjects										
Law	0.264	0.297	0.288	0.317	0.053	1.373	1.495	1.338	1.500	0.128
Economics	0.219	0.328	0.380	0.290	0.071**	1.142	1.486	1.470	1.479	0.337
Management/Business	0.275	0.318	0.319	0.318	0.043*	1.313	1.484	1.375	1.471	0.158
Other Social Sciences	0.202	0.183	0.207	0.240	0.038	1.040	1.029	1.203	1.300	0.260
Arts/Humanities	0.189	0.207	0.203	0.243	0.054*	0.994	1.119	1.097	1.204	0.210
Education	0.089	0.091	0.096	0.126	0.037*	0.671	0.722	0.751	0.784	0.112
Combined Degrees	0.194	0.254	0.248	0.245	0.051*	1.065	1.215	1.164	1.217	0.152

Notes: Source is the 1994-2011 Labour Force Surveys. Log weekly wages are deflated using the Retail Price Index and are bottom coded.
These are for full time employees age 23 to 45. * (**) denotes statistically significant at the 5 (10) percent level for an F test between two variances.

Table 8. Trends in the Variance of Maths and Reading Test Scores (Age 10/11 in 1968, 1980 and 2000) by Subsequent Subject of Degree

	Maths					**Reading**				
	1968	**1980**	**2000**	**1980-1968**	**2000-1980**	**1968**	**1980**	**2000**	**1980-1968**	**2000-1980**
STEM Subjects										
Medical	126	166	313	40	147	184	399	282	215*	-117
Medical Related	389	522	629	133	107*	397	546	619	149	73
Biological/Agricultural Sciences	218	486	561	268*	75	325	598	528	273*	-70
Physical Sciences	195	419	517	224*	98	268	374	468	105	94
Maths/Computer Science	225	513	714	288*	201*	302	654	637	352*	-16
Engineering/Technology	211	538	513	326*	-24	435	696	590	261*	-106
Non-STEM Subjects										
Law	182	384	687	202*	303*	147	357	660	210*	303*
Management/Business	250	511	609	260*	99**	230	576	590	346*	13
Economics & Social Sciences	188	593	688	405*	95	227	532	603	305*	71
Arts/Humanities	388	518	660	129*	142*	365	479	626	114*	147*
Education	356	683	593	327*	-89	325	410	587	86	177*
Combined Degrees	337	406	711	69	305*	278	413	722	134*	310*

Notes: Source is the NCDS, BCS and LSYPE. * (**) denotes statistically significant at the 5 (10) percent level in an F test between two variances.

Table 9. Trends in Occupational Concentration by Subject of Degree, 1994-2010

	Three-Occupation Concentration Ratio					**75% Coverage Rate**				
	1994	**2000**	**2005**	**2010**	**2010-1994**	**1994**	**2000**	**2005**	**2010**	**2010-1994**
STEM Subjects										
Medical	0.893	0.845	0.938	0.891	-0.002	1	1	1	1	0
Medical Related	0.745	0.646	0.702	0.712	-0.033	4	6	4	5	1
Biological/Agricultural Sciences	0.435	0.384	0.344	0.367	-0.068	11	16	18	20	9
Physical Sciences	0.398	0.366	0.392	0.346	-0.052	11	13	14	15	4
Maths/Computer Science	0.655	0.681	0.625	0.628	-0.027	5	4	6	6	1
Engineering/Technology	0.612	0.564	0.529	0.495	-0.117	6	8	9	11	5
Non-STEM Subjects										
Law	0.821	0.571	0.547	0.509	-0.312	2	9	10	10	8
Management/Business	0.395	0.445	0.428	0.388	-0.007	13	11	12	15	2
Economics & Social Sciences	0.407	0.313	0.337	0.316	-0.091	13	14	14	16	3
Arts/Humanities	0.497	0.374	0.328	0.345	-0.152	11	17	20	20	9
Education	0.925	0.861	0.875	0.871	-0.054	1	1	1	1	0
Combined Degrees	0.402	0.389	0.374	0.327	-0.075	16	16	19	21	5

Notes: Source is the 1994-2010 Labour Force Surveys. The three-occupation concentration ratio is the proportion of individuals within each subject of degree who are covered by the three most popular jobs for that subject. The 75% coverage rate is the number of different occupation titles undertaken by the 75% of individuals with each subject of degree in the most popular jobs for that subject. These are for full time employees age 23 to 45.

Table 10. Subject Specific Wage Premium for Workers in Popular and Less-Popular Occupations, 1994-2010

	Subject (γ)	**Interaction Between Subject and Works in 1 of 3 most popular occupations (π)**
STEM Subjects		
Medical	0.350* (0.029)	0.410* (0.027)
Medical Related	0.237* (0.017)	0.040* (0.013)
Biological/Agric. Sciences	0.159* (0.015)	0.117* (0.011)
Physical Sciences	0.265* (0.015)	0.094* (0.011)
Maths/Computer Science	0.321* (0.016)	0.112* (0.010)
Engineering/Technology	0.325* (0.015)	0.115* (0.009)
Non-STEM Subjects		
Law	0.262* (0.018)	0.283* (0.015)
Management/Business	0.244* (0.014)	0.310* (0.008)
Economics & Social Sciences	0.227* (0.015)	0.108* (0.010)
Arts/Humanities	0.080* (0.014)	0.194* (0.010)
Education	-	0.216* (0.014)
Combined Degrees	0.207* (0.014)	0.131* (0.008)

Notes: Source is the 1994-2010 Labour Force Surveys. The three most popular occupations for each subject in 1994 and 2010 are detailed in Table A1 of the appendix. These are for full time employees age 23 to 45. The differentials are relative to Education graduates and condition on race, region of residence, age and age squared.* (**) denotes statistically significant at the 5 (10) percent level.

Table 11. Fixed Effects Estimates Explaining Inequality Measures by Subject of Degree, 1994-2010.

N = 204	Log Wage Variance	90-10 Log Wage Ratio	90^{Th} Percentile Log Wage	10^{Th} Percentile Log Wage
Constant	0.296* (0.091)	1.440* (0.275)	7.554* (0.202)	6.114* (0.182)
Variance of Age 10 Literacy Scores/100	0.018** (0.011)	0.067* (0.034)	0.037 (0.025)	-0.030 (0.022)
Three Occupation Concentration Ratio	-0.064 (0.055)	-0.287** (0.165)	0.153 (0.121)	0.439* (0.109)
Subject Employment Share	-0.236* (0.106)	-0.728* (0.320)	-0.854* (0.235)	-0.126 (0.212)
Female Share	-0.099** (0.058)	-0.402* (0.176)	-0.186 (0.129)	0.216** (0.116)
Age 23-28 Share	0.004 (0.084)	0.017 (0.255)	-0.560* (0.188)	-0.577* (0.169)
Age 29-34 Share	-0.176* (0.081)	-0.536* (0.245)	-0.325** (0.180)	0.211 (0.162)
Age 35-40 Share	-0.111 (0.096)	-0.235 (0.292)	-0.381** (0.215)	-0.146 (0.193)
Year Dummies	Yes	Yes	Yes	Yes
Subject Dummies	Yes	Yes	Yes	Yes
R Squared	0.868	0.882	0.926	0.896

Notes: All regressions include a full set of year and subject dummies. * (**) denotes statistically significant at the 5 and 10 percent level.

Appendix.

Table A1 . The Percentage in the 3 Most Frequent Jobs by Subject and Year

	Prop	Top Three Jobs (percent)
1994		
Medical	89	Health professionals (81), Science professionals (5), Corporate Managers (3)
Medical Related	74	Health professionals (45), Teaching professionals (17), Health associate professionals (13)
Biological/Agric. Sciences	44	Science professionals (18), Teaching professionals (16), Functional managers (10)
Physical Sciences	40	Functional managers (14), Teaching professionals (13), Science professionals (13)
Maths/Computer Science	66	ICT professionals (32), Teaching professionals (20), Functional managers (13)
Engineering/Technology	61	Engineering professionals (43), Production managers (10), ICT professionals (8)
Law	82	Legal professionals (73), Functional managers (4), Administrative occupations: finance (4)
Economics	56	Functional managers (25), Teaching professionals (18), Business and statistical professionals (14)
Management/Business	39	Functional managers (22), Business and statistical professionals (11), Administrative occupations: finance (6)
Other Social Sciences	40	Teaching professionals (21), Public service professionals (10), Functional managers (9)
Arts/Humanities	50	Teaching professionals (34), Architects, town planners, surveyors (9), Functional managers (7)
Education	92	Teaching professionals (89), Corporate managers (2), Functional managers (2)
Combined Degrees	40	Teaching professionals (23), Functional managers (13), Engineering professionals (5)
2010		
Medical	89	Health professionals (85), Health and social service managers (2), Teaching professionals (2)
Medical Related	71	Health associate professionals (44), Therapists (16), Health professionals (12)
Biological/Agric. Sciences	37	Teaching professionals (15), Functional managers (12), Science professionals (11)
Physical Sciences	36	Science professionals (15), Functional managers (10), Teaching professionals (10)
Maths/Computer Science	63	ICT professionals (32), Functional managers (19), Teaching professionals (12),
Engineering/Technology	50	Engineering professionals (27), Production managers (13), Functional managers (10)
Law	51	Legal professionals (39), Functional managers (6), Legal associate professionals (6)
Economics	50	Business and statistical professionals (20), Functional managers (18), Business and finance associate professionals (13)
Management/Business	39	Functional managers (23), Business and statistical professionals (10), Sales and related associate professionals (6)
Other Social Sciences	35	Public service professionals (13), Teaching professionals (12), Functional managers (10)
Arts/Humanities	35	Teaching professionals (17), Functional managers (10), Architects, town planners, surveyors (7)
Education	87	Teaching professionals (81), Childcare and related personal services (4), Social welfare associate professionals (2)
Combined Degrees	33	Teaching professionals (16), Functional managers (12), ICT professionals (5)

Notes: The sample consists of workers age 23-45.

Table A2. OLS Estimates Explaining Inequality Measures by Subject of Degree, 1994-2010.

N = 204	Log Wage Variance	90-10 Log Wage Ratio	90Th Percentile Log Wage	10Th Percentile Log Wage
Constant	0.035 (0.092)	0.536** (0.280)	6.318* (0.246)	5.782* (0.171)
Variance of Age 10 Literacy Scores/100	-0.014* (0.004)	-0.046* (0.013)	-0.071* (0.012)	-0.025* (0.008)
Three Occupation Concentration Ratio	-0.144* (0.021)	-0.534* (0.066)	0.044 (0.058)	0.578* (0.040)
Subject Employment Share	-0.260* (0.091)	-0.999* (0.274)	-1.352* (0.243)	-0.353* (0.168)
Female Share	-0.131* (0.024)	-0.383* (0.073)	-0.639* (0.064)	-0.257* (0.045)
Age 23-28 Share	0.745* (0.099)	2.417* (0.298)	1.847* (0.264)	-0.571* (0.183)
Age 29-34 Share	0.228* (0.114)	0.823* (0.345)	1.445* (0.306)	0.623* (0.212)
Age 35-40 Share	0.318* (0.149)	1.169* (0.451)	1.466* (0.400)	0.296 (0.277)
Year Dummies	Yes	Yes	Yes	Yes
Subject Dummies	No	No	No	No
R Squared	0.563	0.610	0.644	0.754

Notes: All regressions include a full set of year dummies. * (**) denotes statistically significant at the 5 and 10 percent level.

[1] Each household remains in the sample for five consecutive quarters, before dropping out to be replaced by a new incoming cohort of households. The survey design is therefore of a rolling panel. Around 45,000 households are surveyed in each quarter, with each individual in the participating household included. Data from the LFS quarters were merged to form annual data sets, covering the period 1994 to 2011. Each year has on average around 150,000 observations. For further information see Office for National Statistics (2011).

[2] For an analysis of the returns to specifically postgraduate study, see Lindley and Machin (2011).

[3] These are estimated from log weekly wage equations estimated separately by year and gender, whilst conditioning on race, region of residence and a quadratic in age using a sample of full time workers aged between 23 and 45. When estimating UK graduate wage differentials the usual approach is to use 2+ A levels as the comparative group but given that Table 1 shows the proportion of this group to be relatively small (around 5 percent) we focus on graduate wage differentials with respect to all those with less than higher education (hence we combine those with less than A-levels and 2+ A levels) which we call `intermediate' qualifications.

[4] See also Lindley and Machin (2012) who find similar patterns for women. When Lindley and Machin (2012) look at a younger 26-35 age group they find a fall over time in the undergraduate differential (standard error) of -0.035 (0.025) for men and -0.037 (0.029) for women. Also O'Leary and Sloane (2005) report a falling wage differential to an undergraduate degree for younger women.

[5] We estimate log weekly wage equations including subject specific binary dummies, separately by year and gender, conditioning on race, region of residence and a quadratic in age using a sample of full time workers aged between 23 and 45. Again these differentials are relative to workers with `intermediate' qualifications.

[6] For robustness purposes we also used two alternative measures of test scores. Firstly, we standardised the test scores to have mean zero and standard deviation 1, and assumed that the test score distributions are normal. Secondly, we used principal component analysis to extract a single ability measure from the various childhood tests (see the discussion on pages 6-8 of Galindo-Rueda and Vignoles (2005)). Overall our results are qualitatively robust to the choice of using any of these test score measures but we prefer the percentile approach over the standardised measures because the latter are relative measures amongst graduates within a degree subject relative to the overall population (for whom the standard deviation by construction is unity, so whether the standardised variance for graduates within a subject group is greater than or less than one indicates the relative variance for this group compared to the full population). The percentile scores, on the other hand, capture the absolute value of the variance for graduates within each subject category.

[7] The relationship between SOC1990 and SOC2000 can be downloaded from the Office for National Statistics website: http://www.ons.gov.uk/ons/guide-method/classifications/archived-standard-classifications/standard-occupational-classification-2000/index.html

[8] We also calculated five-occupation and eight-occupation concentration ratios, but the results were qualitatively similar.

[9] The estimated returns are all relative to the omitted category, which is education degrees used in non-popular occupations.

[10] For completeness the OLS estimates are provided in Table A2 of the Appendix. This shows that the correlation between the variance of literacy test scores and wage inequality is negative which is all working through a negative correlation with the 90^{th} percentile wage. Thus subjects with a relatively higher test score variance pay lower wages at the 90^{th} percentile. It is only within-subjects that this correlation is positive, as shown in Table 11.