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Growth in within graduate wage inequality: The role of subjects, cognitive skill dispersion and occupational concentration

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HIGHLIGHTS

- The growth in graduate wage inequality has occurred mostly within degree subjects.
- This is related to an increased variance in ability of students within subjects.
- It is also related to a wider range of jobs entered by graduates from each subject.
- The first effect is more strongly associated with increased wage inequality.
- Wider ability variance is due to increased participation of lower ability students.

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ABSTRACT

Increasing participation in Higher Education, and the rising number of graduates in the labour markets of most developed countries, are likely to alter graduate wage distributions. Increasing wage inequality amongst graduates has been observed in a number of countries. This paper takes as an example the UK, where the increase in inequality has been amongst the highest, to investigate any potential link between these two phenomena of participation and inequality. Dividing graduates by subject of degree to provide more variation, we show that most of the increase in graduate wage inequality has occurred within subjects. We investigate two potential explanations, specifically the increase in the variance of childhood cognitive test scores amongst graduates in the same subject, and the widening variety of jobs performed by graduates with degrees in the same subject. The paper 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 increased variance of test scores. The results also show that mean test scores are falling over time within every subject to a greater or lesser extent, suggesting that the widening variance of test scores is due to universities accepting individuals from lower in the ability distribution, as Higher Education participation has expanded.

1. Introduction

The wage inequality literature in Economics has typically focussed on wage differentials *between* education groups, often between college graduates and non-graduates. The literature revealed a growth in such differentials in the 1980s and early 1990s, since when they have been largely flat, despite large increases in Higher Education (HE) participation (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).

However, simple focus on average differences between groups can miss some of the overall change in inequality. Wages also vary *within* education categories, and 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) and Katz (1999) in the US or Gosling et al. (2000) in the UK. This paper therefore analyses within-group wage inequality, in particular focussing on the graduate group given that they are the fastest growing educational grouping and so of particular interest. Lemieux (2006) also shows that, of all the education levels in the US, within-group wage inequality has risen the fastest for graduates (Table 1). The context of the current paper is the UK, which is a particularly interesting country for which to investigate this issue, given both the relatively large rise in wage inequality generally (see OECD, 2013), and also the fast increase in Higher Education participation, faster than most OECD countries with the exception of the Eastern European newer entrants to the OECD (see OECD, 2014).

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Table 1
Trends in the variance of graduate log earnings, 1994–2011.

	1994	2000	2005	2011	2011–1994
Overall variance (graduates)	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
Overall variance (full population)	0.229	0.245	0.240	0.260	0.031

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.

In addition to documenting the growing wage inequality within this group, the original contribution of the paper will be to investigate *why* such wage inequality has grown. We will first show that most of the increase in graduate wage inequality has occurred within degree subjects, rather than between. This is the first paper in the literature, as far as we are aware, to consider changes in within-subject wage inequality. We then explore two possible explanations for this growing within-subject inequality, both linked to the expansion of the HE sector. Thus the fact that more individuals are now accepted onto degree courses may have altered selection onto different degree courses, whilst selection into occupations after graduating from a given subject may also be affected by the larger numbers graduating. Our results suggest that changing selection into subjects explains much of the growth in within-subject wage inequality, and hence also much of the growth in overall within-graduate wage inequality.

Subject of degree is therefore a key unit of observation in our analysis. Degree subject is a useful dimension along which to disaggregate graduates. Degree subject can determine both entry conditions into university and the occupational area after graduation, and thus is directly relevant to the two potential explanations of widening inequality mentioned above.[1] Students in the UK will typically go to university immediately after upper secondary education, at age 18. Entry to Higher Education is mostly determined by attainment in the examinations (Advanced Level qualifications, or ‘A levels’) taken at the end of the upper secondary education. Most students apply to the universities of their choice (up to a maximum of five) before taking these examinations, and receive an offer of the grades required to be accepted onto the course of their choice at that university. The grades required will typically vary both across and within universities, with the more prestigious universities and more popular courses requiring higher grades. Tuition fees were first introduced in 1998 at the level of £1000 per annum. There is currently a capped tuition fee regime, covered by student loans and repaid after graduation. The maximum fee chargeable was most recently increased to £9000 per annum in 2012. There can be variation in fees paid across universities, and within universities across subjects, though over half of all universities, including all of the most prestigious, charge the maximum amount for every subject. Most students apply for, and study a single subject throughout their time at university, though a minority will study two or more, usually related, subjects.[2] Student choices about subject to study will largely be based upon future employment and wage prospects, ability and interest in the subject, and the likely grade offer they will receive (with perhaps fees to be paid a consideration for those applying to the less prestigious universities).

Determining whether the growth in graduate wage inequality is between or within subjects is an important issue, since they point to different explanations of the rise in overall graduate wage inequality. If most of the increase was happening between subjects, this would point to changes in the relative wage returns to different subjects as being important, which in turn would suggest that relative demand and supply levels across subjects were changing. In fact, as mentioned above, our results show that most of the growth in graduate wage inequality has occurred within subjects, with relative wage returns to different degree subjects being largely flat over time. Hence, we look for causes of the increased within-subject inequality. There seem to be three possibilities in theory: (i) a widening inequality in the skills and abilities of students within each subject group, (ii) a growing variation in the quality of education provided within subject groups, or (iii) a greater variance in the occupations that graduates of each subject group select into. We do not consider institution quality (explanation (ii)) for a number of reasons. First, the subject groups analysed in this paper are at an aggregated level, and are likely to each be found in some form in every institution, so there has not been a widening in the distribution of institutional quality from new institutions providing a particular subject. Furthermore, though quality differences across institutions undoubtedly exist, there is no reason, or evidence, to suspect that such differences have grown wider. Previous evidence on subject of degree and institutional quality can be found in Chevalier (2011). Investigating the wage returns to degrees by subject, Chevalier finds that controlling for institutional quality[3] has virtually no effect on the estimated coefficients, suggesting a lack of correlation between institutional quality and subjects offered and thus negating the need to control for such quality in the present context. A final reason for not considering this explanation is that none of our data sets name the institution attended by respondents. Our analysis therefore focuses on wider dispersion in student ability and graduate occupations, within subjects (explanations (i) and (iii)).

Student ability will be measured by age 10 test scores. There is good reason to focus on test scores at this young age. First, previous work has suggested that early skills and abilities have important consequences for adult outcomes.[4] Second, the use of early test scores reduces any endogeneity issues. Later indicators, such as ‘A level’ public examinations taken at age 18 which qualify holders for entry to university, are likely to be co-determined along with university entry and wage outcomes, on the basis of motivation to succeed etc. Earlier test scores are much more likely to be exogenous to the university-entry decision. This paper is the first in the literature to empirically link early test scores to subject choice, to the best of our knowledge.

The diversity of jobs undertaken by graduates of a particular subject will be measured using an occupation concentration ratio, in particular the proportion of individuals with a degree in that subject working in one of the three most popular jobs for graduates of the degree subject.[5] The paper will show later that not working in one of the most popular jobs for a subject is associated with a wage penalty, on average. Thus, a degree subject that becomes occupationally less concentrated over time may experience growing wage inequality, as more graduates suffer the wage penalty.

A small but growing number of studies in the economics literature have considered degree subjects and labour market outcomes, usually estimating wage differentials by subject. In the UK, for example, O'Leary and Sloane (2005) consider degree subject in their analysis of changing returns over time. Their focus is therefore mostly on between-subject changes rather than within-subject changes as studied here. Their results suggest widening wage dispersion between subjects, with returns to Maths and engineering degrees rising between 1994 and 2002, and returns to arts-based degrees falling. Their quantile regression results are relevant to our within-subject story, however,

[1] Other dimensions along which graduates could be disaggregated include institution attended, and grade of degree achieved. However, neither directly influences the range of possible post-graduation occupations, whilst final grade is also unrelated to entry conditions. Furthermore, our data set does not contain any information on institution, and has information on grade for only a much shorter time period.

[2] These are the ‘Combined Degrees’ included in the analysis below.

[3] Chevalier (2011) measures institutional quality by scores on the UK's Research Assessment Exercise, and by indicators of teaching quality such as student–teacher ratios and expenditure per student.

[4] See for example Cunha and Heckman (2007), Heckman (2010) and Heckman et al. (2012).

[5] The results are robust to alternative measures of the concentration of occupations amongst graduates within the same subject group, as discussed in detail in Sections 4 and 5 below.

with the larger falls in returns to arts degrees in the lower quantiles being consistent with our results showing a widening in within-subject inequality, particularly at the lower end. 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. They show that the rates of return differ across subjects, and are typically highest for LEM (Law, Economics and Management) degrees. They also demonstrate variation in returns within subjects according to degree classification awarded, though they do not examine changes over time, to inform our discussion of changing within-subject wage inequality. Chevalier (2011) reveals the variation in graduate wages by subject, but shows there is still more variation in wages within subjects than between, consistent with the opening results of this paper. Using quantile regression, he finds the greatest within-subject wage inequality in Maths, IT, Architecture, Law, Business, Finance and Economics degrees, and the least in Linguistics, Education, Psychology and 'other' degrees. He does not study changes in such within-subject inequality over time. 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. They focus on between-subject variation in wages. They consider the occupation and ability stories that are the focus of this paper, but analyse them in levels as determinants of the between-subject wage variation, rather than the variation in occupations and ability within subjects as the cause of within-subject wage variation. A limitation of this study is that the data do not allow for the analysis of changes over time.

In terms of the story presented in this paper, elements have appeared in previous research, though never the full story offered here. The idea that an expansion of Higher Education might increase overall wage inequality is discussed in Budría and Moro-Egido (2008), who argue that given wage inequality is positively associated with the level of education, putting more people into Higher Education categories will therefore increase overall inequality. They show this is the case using Spanish data from the European Community Panel Survey. However, this does not explain why the within-graduate component of wage inequality has increased. Martins and Pereira (2004) turn to cross-sectional data sets for a range of European countries, and use quantile regression to show that within-group wage inequality is higher for graduates than for non-graduates. They speculate that this may be due to overeducation/mismatch (graduates doing jobs for which they are overqualified), to a positive interaction between ability and education so that the influence of ability is larger at higher levels of education, or due to quality differences across education institutions. These hypotheses are clearly related to the three potential causes of growing graduate wage inequality outlined above. However, they remain hypotheses for which the authors do not provide evidence, and furthermore they are seeking to explain the level, rather than the change in, graduate wage inequality. Perhaps the closest to our paper, in that they include analysis of subject of degree, and consider one of our explanations, that graduates are in the wrong job for their subject, are two papers by Robst (2007) and Nordin et al. (2010). These papers derive indicators of whether graduates are in inappropriate jobs for their degree subject, according to the graduates' subjective opinion, or the authors' subjective opinion respectively. Both papers find a wage penalty for working in an occupation that is not deemed appropriate for their degree subject, with this penalty observed overall, within subject and within occupations. Such mismatch can therefore explain some of the within-subject wage inequality. These papers do not consider the change in within-subject wage inequality, however, and neither do they present evidence on the ability story or assess the relative strengths of these explanations. We therefore consider this paper to be a more complete discussion of the role of degree subject and within-graduate wage inequality, than currently exists in the literature, by considering each of the possible explanations together in one place, and investigating which has been most closely associated with the rise in graduate wage inequality.

The rest of the paper is organised as follows. The next section provides the data on the extent of within-subject wage inequality, whilst Section 3 presents the trends in cognitive skills by subject. Section 4 investigates the extent to which changes in occupational concentration differ across subjects. Section 5 then estimates subject level inequality equations to explain growing graduate wage inequality through the potential drivers we consider. The final section concludes.

2. Trends in graduate wage inequality

We begin the results by documenting the changes in graduate wage inequality to be explained. For this we make use of the Labour Force Survey (LFS), between 1994 and 2011, the earlier year being the first year that the survey included information about subject of degree. The LFS is a quarterly survey of households but which provides us with an annual series.[6] We focus on full-time workers aged 23–45 so that our analysis is based on more recent graduates. 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.[7]

The first row of Table 1 shows the overall variance in the log of graduate wages, for selected years from 1994 to 2011. The data show a continuous rise in this variance throughout the period considered, by 0.044 points in total.[8] The following two rows decompose the variance of graduate log wages, $Var(lw_{ijt})$, into that which is within and that which is between subjects[9]:

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

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 1 shows most of the variance of log graduate wages is within subjects (for example at 0.228 of the total 0.241 in 2011), but most importantly for our purposes, that most of the *increase* in the variance has also occurred within subjects. The within-subject variance increased by 0.042 over the period, compared to an increase of only 0.002 for the between-subject variance.[10] Table 1 also makes clear that most of this increase in the overall and within subjects variance occurred in the

[6] 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).

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

[8] Other measures of dispersion show a similar increase, for example the ratio of the 90th/10th percentile of log graduate wages increased from 1.08 in 1994 to 1.23 in 2011.

[9] Degree subjects are divided into 12 groups, as listed in Table 2 below. Using broader groups, specifically 3 groups comprising STEM (Science, Technology, Engineering and Maths), LEM (Law, Economics and Management) and OSSAH (Other Social Sciences, Arts and Humanities), increased the proportion of the variance observed within subjects, but only by a very small amount. It was not possible to consistently identify narrower subject groups over time, due to changes in the relevant question in the LFS.

[10] Further evidence on the between-subjects component can be provided by estimated wage differentials to each degree subject in each year. When we do this, we find little variation in the estimated relative differences between subjects over time, again suggesting no role for the between-subjects components. Full details of these results are available from the authors on request.

Table 2
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
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	0.285
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.

early part of the period under consideration (mostly between 1994 and 2000).

The final row of Table 1 shows the variance of log earnings across the full age 23–45 full-time employed population, for comparative purposes. It is clear that graduate wage inequality has increased more than general wage inequality. In addition, the period of fastest growth in graduate inequality between 1994 and 2000 saw much less change in general inequality. The changes in graduate inequality to be investigated in this paper therefore do not simply reflect changes in the wider economy, but are particular to graduates and point to Higher Education being the source of the changes.

Table 2 therefore focuses on the within-subject variance, and how this has changed over time for each subject. Whether measured by the variance or the log 90th/10th percentile ratio,[11] wage inequality has increased over time within every subject group considered. The extent of this increase varies across subjects, with Engineering (0.074) and Economics (0.071) exhibiting particularly large growth in the variance of log 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 remaining subjects have still seen a positive, but statistically insignificant, increase. As with the overall changes in Table 1, the fastest growth in wage inequality is in the early part of the period between 1994 and 2000 for most, though not all, subjects. The growth in the 90th/10th percentile ratio shows a similar pattern, albeit with Economics now coming out on top (0.337), possibly as a consequence of increasing bonuses in the finance sector, to which many Economics graduates are attracted.[12]

The following sections analyse the determinants of the wage dispersion within subjects, and thus seek to address why inequality has increased more in some subjects than in others. 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 amongst 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 to match changing supply equally across all degree subjects. It is to these two potential explanations that we now turn.

3. 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 subjects using the National Child Development Study (NCDS), the British Cohort Study (BCS) and the Longitudinal Survey of Young People in England (LSYPE).[13] 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

[11] The 90th/10th log wage ratio is the log (ratio of the wage at the 90th percentile of the wage distribution to the wage at the 10th percentile of the wage distribution). Thus for example when this takes a value close to unity, as for many subjects in 1994 in Table 2, then the ratio of the 90th to the 10th percentile wage is around 2.7.

[12] For completeness, Table A1 in the Appendix presents the data on the mean and median log weekly real wage for each subject at each point in time. These data show rising average wages for graduates in all subjects from 1994 to 2005, but then falling real wages during the recession years for graduates in most subjects (with Economics proving to be an exception).

[13] The NCDS numeracy test scores are based on a 40 question test, involving numerical and geometric questions. One mark was awarded per correct answer. The test was devised by the National Foundation for Educational Research (NFER) in England and Wales, specifically for use in the NCDS survey. Across the full sample, the mean score was 16.63 with a standard deviation of 10.35 (see Shepherd, 2012). The NCDS literacy scores are based on a 35-question test of reading comprehension, requiring children to choose the correct word to complete a sentence. One mark was awarded per correct answer. The test was devised by the NFER specifically for use in the NCDS survey and was intended to parallel the existing Watts–Vernon test of reading ability. Across the full sample, the mean score was 15.98 with a standard deviation of 6.29 (see Shepherd, 2012). The BCS numeracy test scores are derived from the 'Friendly Maths Test', devised specifically for the BCS survey. It included 72 questions, covering arithmetic, fractions, measuring, algebra, geometry and statistics. Across the full sample, the mean score was 43.74 with a standard deviation of 12.24 (see Butler et al., 1980). Three respondents answered all items correctly. The BCS literacy test is a test of vocabulary, syntax, sequencing, comprehension and retention. It is based on a shortened version of the Edinburgh Reading Test, with 67 items chosen for inclusion. Across the full sample, the mean score was 32.11, with a standard deviation of 11.26 (see Butler et al., 1980). The LSYPE test scores are results from national mathematics and reading tests (Key Stage 2 tests) taken by every pupil in the country at the end of Year 6 (age 10/11). These are matched into LSYPE from the National Pupil Database by anonymous survey ID numbers. The Maths test involves calculations, problem-solving, measuring, shapes, and statistics. The maximum score was 36. The mean score in the full LSYPE sample was 26.34 with a standard deviation of 4.90. The reading test involves pupils reading a number of fiction and non-fiction short texts, and then answering questions on those texts that test their comprehension. The maximum score was 36. The mean score in the full LSYPE sample was 26.34 with a standard deviation of 4.44.

Table 3
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
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	216	486	561	270**	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
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.

2000 BCS and the 2010 LSYPE respectively. Unfortunately it now becomes necessary to combine economics with other social science degrees because of the categories that are provided in the LSYPE.

Table 3 reports the variance of the Maths and reading test scores assessed at age 10 in 1968, 1980 and 2000 from the three surveys, categorised by the degree subject that the children subsequently go on to obtain later in their life. 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.[14] 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 period 2000–2010). 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.

Overall, Table 3 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. Our hypothesis is that this increased variance of test scores is due to the increased participation in Higher Education that has occurred in the UK, meaning that those individuals from lower in the ability distribution, who would not have attended university at the start of the period, increasingly do participate as we move through the period. For a number of subjects, and particularly for the reading test scores, the increase in the variance is greater between the 1968 and 1980 cohorts than between the 1980 and 2000 cohorts. Remembering that the individuals were aged 10 at the time they took the test, those tested in 1980 were therefore attending university at the time of the fastest increase in participation, between 1988 and 1993.[15] The increase in the variance of test scores being due to increased participation is therefore consistent with these observed patterns between cohorts.

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 2) could potentially be partially driven by increases in the variance of their cognitive ability (as measured by age 10 test scores). This hypothesis will be tested in Section 5 below.

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 in line with supply equally across all degree subjects.

4. 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 the LFS, restricting the sample to 1994–2010 in order to obtain consistent occupation categories over time. In 1994, the LFS occupational categories were 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 and 2000 to the SOC2000 level.[16] This provides 102 consistently defined three-digit occupations. Given the large changes in the categories between the SOC2000 and SOC2010 classifications we did

[14] 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.

[15] Between 1988 and 1993, the proportion of 17–30 year olds who attended university doubled from 15% to 30% (see Chowdry et al. (2010)).

[16] 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.

Table 4
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
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
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.

not attempt to further extend the concordance to include respondents from 2011 onwards.

Table 4 documents the trends in occupational concentration indices by subject of degree, for a sample of workers aged 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% 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% of individuals), Science Professionals (5% of individuals) and Corporate Managers (3% of individuals) as shown in Table A3 of the Appendix A.[17] The 75% coverage rate is the number of different occupation titles undertaken by the 75% of individuals within each subject of degree in the most popular occupations. So for Medical degrees the 75% 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.

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 2) and consequently we return to this notion in the subsequent section. For growing occupational dispersion to be 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 needs 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

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

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 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 P_{it} is zero and the individual is not employed in one of the most popular occupations for that subject.[18]

The results in Table 5 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.[19]

5. 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

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

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 percentiles

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

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

[19] The fact that wages vary, on average, across subjects to the extent shown in Table 5, and yet the between subject proportion of the variance is relatively small in Table 1, implies the large extent of the variation in wages across graduates within subjects.

Table 5
Subject specific wage premium for workers in popular and less-popular occupations, 1994–2010.

	Subject (γ)	Interaction between subject and indicator that individual works in 1 of 3 most popular occupations (π)
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)
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 A. 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.

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 4. 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 3. Our approach is to firstly generate a Maths and reading test score variance for individuals with each year of birth between 1949 and 1989, calculated separately for every degree subject that the individuals subsequently acquire. We do this by interpolating between our three data points, for each subject. So for each subject we then have an estimate of the average test scores, separate for each year of birth. We then turn to the LFS dataset for 1994–2010, observe the birth years of graduates in work in each year, as well as their degree subject, and can therefore estimate the average test scores within each subject-year cell as a weighted average of the birth-year specific scores obtained in the first stage, with the weights based on the proportions with each birth year observed within that subject-year cell. 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 6 provides the results for Eq. (3), which includes fixed effects so that the results can be interpreted as within-subject changes. Given that the variances of the test scores are likely to be highly correlated, we use only literacy scores.[20] 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 0.067). The final two columns show that greater test score dispersion is associated with a lowering of the wage at the 10th percentile (−0.030) but an increase in the wage at the 90th percentile (0.0370) 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% significance level. 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 4) graduate wage inequality has increased, but this is only statistically significant for the 90–10 log wage ratio (−0.287). Looking at the final two columns suggests that this is working through decreasing the log wage at the 10th percentile (0.439) relative to the 90th percentile and thus increasing wage inequality.[21]

As expected, increasing the employment share into a subject should reduce the graduate wage, and this is exactly what we find for the 90th percentile wage (−0.854). Since the 90th percentile wage falls by more than the 10th percentile wage, this reduces inequality overall. Similarly, increasing the supply of women into a subject is associated with an increase in the 10th percentile wage (0.216) relative to the 90th percentile wage, thus reducing inequality overall. The effects of increasing the share of 23–28 year old workers largely offset each other at the 90th and 10th percentiles resulting in no effect on inequality. However, the share of workers aged 29–34 in a subject is associated with lower wage inequality, by reducing the wage at the 90th 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 6 firstly without any controls, 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 Fig. 1 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 2. 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 2). 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 6. 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.

Thus, the growing variation in childhood test scores amongst graduates within subject degrees is the more important determinant of the growing within-subject wage inequality. One question still to be answered is why there is an increasing variation in test scores within subjects over time. Our hypothesis at the start of the paper was that increasing variation in test scores was due to HE expansion leading universities to lower entry standards and accept students of lower ability than previously.[22] However, this was just conjecture, and the increasing variation could equally be caused by an influx of high ability students. Table 7 therefore reports the average ability (as opposed to the variance

[20] The results for the subject fixed effects regressions show a similar pattern when numeracy test scores are used, compared to the results with literacy test scores reported in Table 6. The statistical significance of some of the effects is however slightly lower with numeracy scores. It may be that literacy skills are important across all subjects, whereas numeracy skills are less relevant to some subjects.

[21] The demand side results are robust to the choice of occupation dispersion measure. In particular, we also tried using the 4-, 5- and 8-occupation concentration ratios. In addition, we also used the 75% coverage rate, as defined and tabulated in Table 4 above, as an alternative measure of occupation dispersion, treating the number of occupations covered by 75% of the subject's workforce as a grouped count variable. The pattern of results was consistently the same. Full details of these results are available on request.

[22] See Carneiro and Lee (2009) for a discussion of the effect of increased college enrolment on wage inequality, taking into account selection into college and a lowering of average ability levels when enrolment expands.

Table 6
Fixed effects 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	0.296** (0.091)	1.440** (0.275)	7.554** (0.202)	6.114** (0.182)
Variance 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 levels.

in ability reported earlier in Table 3), in each of the three youth cohorts, by subsequent degree subject, where ability is measured by the average percentile position in the age 10 Maths and reading distributions.

The results clearly show that every subject group is, to a greater or lesser extent, increasingly accepting students from lower in the ability distribution, and hence lowering the average ability score and widening the distribution of scores. Thus for example, students doing a medical degree came from the 90th percentile of the age 10 Maths score distribution on average amongst the 1958 cohort, but from the 84th percentile on average amongst the 1990 cohort. In actual fact, this fall in average position for medicine is not statistically significant, but for every other subject, the decline in the average position of graduates in the age 10 Maths score distribution is statistically significant in at least one of the periods, and in most cases both. The overall decline in average Maths ability is around 20 percentiles for each of the non-science subjects in the lower half of the table. Similarly for the reading test scores, each subject sees a statistically significant decline in the average position of its students in at least one of the periods, with the exception of

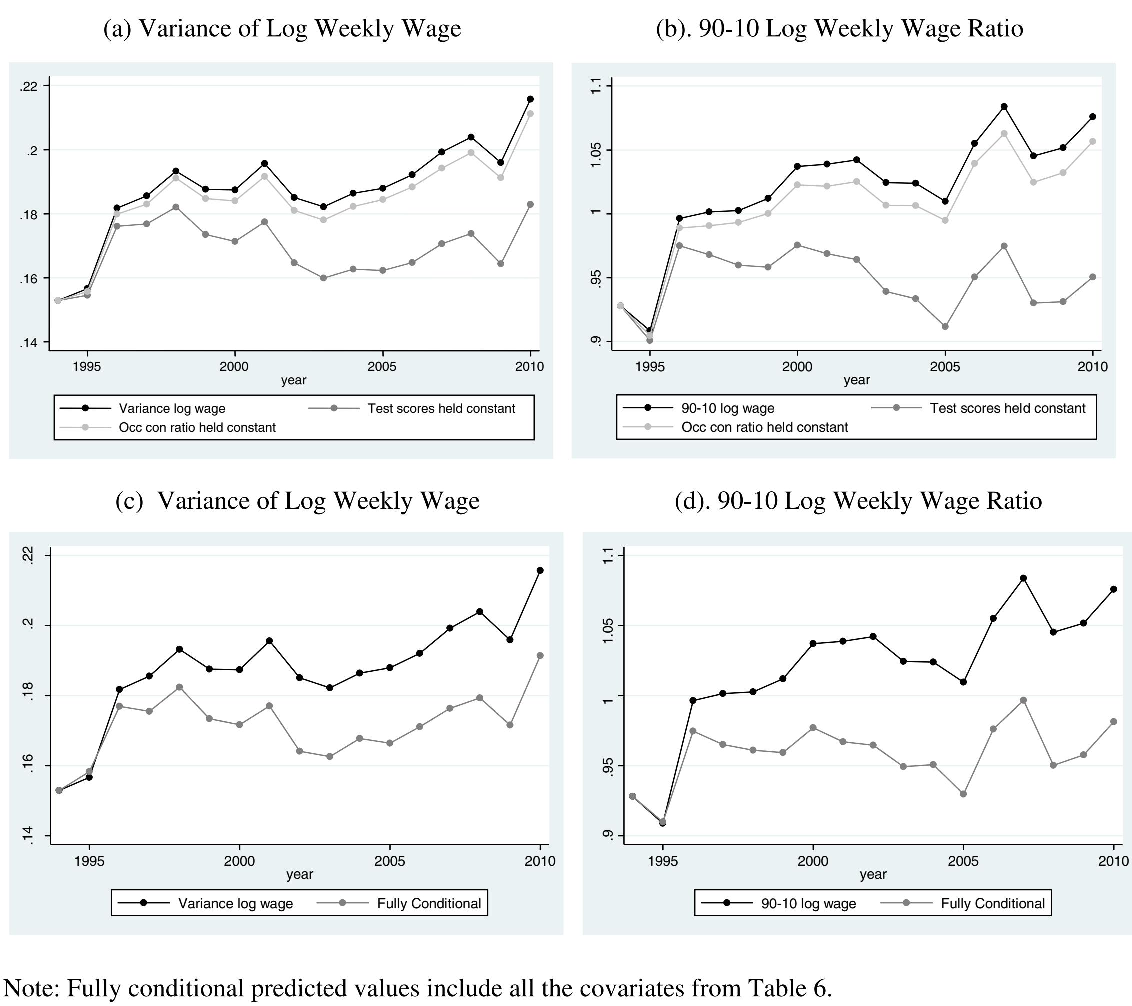

Fig. 1. Fixed effects estimates for predicted earnings inequality, 1994–2010. Note: Fully conditional predicted values include all the covariates from Table 6.

Table 7
Trends in the mean of Maths and reading percentile positions (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
Medical	89.5	86.6	84.3	−2.9	−2.3	88.9	82.5	82.6	−6.4	0.1
Medical Related	80.0	66.8	61.5	−13.1**	−5.3*	75.1	67.8	63.3	−7.2*	−4.6
Biological/Agricultural Sciences	81.9	72.6	69.0	−9.3**	−3.6	78.2	74.6	68.6	−3.5	−6.1**
Physical Sciences	83.8	79.3	75.5	−4.5*	−3.9	79.7	79.0	72.7	−0.7	−6.3**
Maths/Computer Science	87.2	78.4	70.7	−8.8**	−7.8**	82.1	73.4	63.3	−8.7**	−10.1**
Engineering/Technology	87.0	76.9	75.5	−10.1**	−1.5	77.7	66.1	64.2	−11.7**	−1.9
Law	83.1	76.7	63.9	−6.3*	−12.8**	84.4	80.7	67.7	−3.7	−13.0**
Management/Business	83.2	70.3	61.8	−12.9**	−8.5**	80.5	67.4	57.6	−13.1**	−9.8**
Economics & Social Sciences	84.1	67.2	62.7	−16.9**	−4.5*	83.7	68.2	65.2	−15.4**	−3.0
Arts/Humanities	79.8	71.8	63.2	−8.0**	−8.5**	80.9	75.4	68.7	−5.5**	−6.7**
Education	74.1	66.8	55.1	−7.3**	−11.7**	73.4	70.9	61.5	−2.5	−9.4**
Combined Degrees	78.6	75.0	57.1	−3.6	−17.9**	81.1	75.7	54.0	−5.4**	−21.7**

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

medicine. Timing also seems to be consistent, with for example the subjects that saw a later increase in test score variance (Table 3), such as Law and Combined Studies, also seeing a larger fall in mean scores in the second period. Furthermore, Table A2 in the Appendix A shows the percentile position within the full test score distribution of those at the 90th and 10th percentile positions within each subject at each point in time (so, for example, for the NCDS test of 10 year olds in 1968, of those who went on to study medicine, the individual at the 90th percentile scores more highly on the Maths test than 99% of the full population, whilst the individual at just the 10th percentile within medicine still scores more highly than 78% of the general population). The results in the table make clear that the most able individuals within each degree subject remain very close to the top of the full distribution over time. The big change is at the 10th percentile, where we see the lower ability students within each degree subject being located at increasingly lower points of the overall test score distribution. Thus, the increase in the variance of ability within subjects is due to acceptance of students from lower in the ability distribution.

6. Concluding comments

Graduate wage inequality has risen in many developed countries. This paper has searched for explanations, using the context of the UK as an example, where both graduate wage inequality and Higher Education participation have increased rapidly. The paper uses, as a unit of observation, subject of degree, in order to provide some variation across graduates. The idea is that if inequality has increased more within some subjects than others, and if such variation can be systematically related to the characteristics of graduates in those subjects, then this will provide information as to the causes of the growth in graduate wage inequality.

The results of the analysis using UK data from the period 1994–2011 show that the growth in graduate wage inequality has not occurred between degree subjects, as might have been hypothesised if it was supposed that the supply of and demand for graduates were changing differently across subjects over time. In fact, the relative wages differentials for most subjects have changed very little over this period, and it is within subjects that virtually all of the increase in graduate wage inequality has occurred. The extent of this increase has differed across subjects, however, with the largest and most significant increases observed amongst graduates of Engineering/Technology, Economics, Management/Business, Arts/Humanities, Education and Combined Degrees (Table 2).

The main contribution of the paper is then the consideration of 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, though more so for some subjects (Law, Combined Degrees, Maths/Computer Science, Education and Arts/Humanities) than others. This increased dispersion is due to rising acceptance of students from lower in the ability distribution. We also found that subjects increasingly produce graduates who work in jobs that are more occupationally diverse (less concentrated) than others, and that those who work in the less common occupations for that subject earn less, on average. Again some subjects (for example, Arts/Humanities, Law and Engineering/Technology) have changed more than others in terms of falling occupational concentration. We then linked these changes to the growing within-subject wage inequality, and found that even after conditioning on changes in the supply and composition of graduates, the greater dispersion of cognitive skills and occupational dispersion are associated with 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.

In conclusion, then, we can say that 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, and that those subjects which have accepted a wider ability range onto university courses, and whose graduates perform a wider range of jobs (which typically pay less than the most popular jobs) have seen the largest increase in wage inequality, which in turn can explain a large part of the overall increase in graduate wage inequality. This would suggest that individual ability does remain important, and acquiring a university education does not automatically compensate for a lower initial ability level, and that the matching of graduates to appropriate jobs remains important for successful labour market outcomes.

In terms of policy implications, there is a trade-off for policy makers, between widening graduate wage inequality on the one side and increased participation by more young people in Higher Education on the other. The results presented here suggest that those of lower ability who enter university will on average earn lower wages after graduation than their higher ability peers, widening the graduate wage distribution at the bottom end. The decision over the policy trade-off then depends on the extent to which the widening participation is making the additional participants better off than they otherwise would be, thus justifying the additional inequality. It will therefore be important to continue to monitor graduate wage differentials, and not just at the mean but throughout the distribution.

Acknowledgements

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Appendix A

Table A1
Trends in earnings means and medians by subject of degree, 1994–2011.

	Means					Medians				
	1994	2000	2005	2011	2011–1994	1994	2000	2005	2011	2011–1994
Medical	6.864	6.837	7.014	6.800	−0.064	6.825	6.837	6.982	6.773	−0.052
Medical Related	6.511	6.482	6.499	6.345	−0.165**	6.521	6.471	6.439	6.348	−0.173
Biological/Agricultural Sciences	6.415	6.422	6.455	6.417	0.002	6.423	6.435	6.477	6.432	0.009
Physical Sciences	6.525	6.549	6.597	6.521	−0.004	6.505	6.527	6.527	6.508	0.003
Maths/Computer Science	6.561	6.685	6.663	6.554	−0.007	6.551	6.656	6.638	6.554	0.003
Engineering/Technology	6.557	6.623	6.656	6.623	0.066**	6.547	6.588	6.659	6.620	0.073
Law	6.538	6.614	6.684	6.507	−0.031	6.543	6.623	6.655	6.443	−0.100
Economics	6.624	6.689	6.684	6.726	0.102	6.596	6.672	6.662	6.708	0.113
Management/Business	6.565	6.633	6.627	6.477	−0.089**	6.558	6.566	6.575	6.450	−0.108
Other Social Sciences	6.376	6.406	6.647	6.386	0.010	6.398	6.391	6.440	6.385	−0.013
Arts/Humanities	6.773	6.371	6.383	6.327	−0.446	6.395	6.379	6.382	6.324	−0.017
Education	6.459	6.415	6.479	6.389	−0.071**	6.499	6.445	6.489	6.642	0.143
Combined Degrees	6.391	6.471	6.515	6.449	0.058**	6.402	6.453	6.497	6.456	0.055

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 a t test between two means.

Table A2
Trends in the 90th and 10th percentile Maths and reading percentile positions (age 10/11 in 1968, 1980 and 2000) by subsequent subject of degree.

	Maths						Reading					
	90th percentile			10th percentile			90th percentile			10th percentile		
	1968	1980	2000	1968	1980	2000	1968	1980	2000	1968	1980	2000
Medical	99	99	99	78	67	57	99	97	100	71	49	59
Medical Related	98	91	91	55	30	25	96	93	96	47	33	30
Biological/Agricult. Sciences	98	98	96	63	39	32	97	97	95	47	30	34
Physical Sciences	99	98	99	66	46	39	97	99	96	60	55	38
Maths/Computer Science	99	99	98	73	43	27	98	99	95	60	28	27
Engineering/Technology	100	97	98	66	36	39	97	97	92	44	28	27
Law	98	97	95	63	43	22	97	99	97	71	56	27
Management/Business	98	97	93	58	33	26	98	95	89	60	33	24
Economics & Social Sciences	99	97	95	63	33	25	99	95	95	60	33	30
Arts/Humanities	98	96	95	53	36	25	99	97	97	53	41	30
Education	96	96	91	50	28	19	96	95	92	47	38	24
Combined Degrees	98	96	90	55	46	18	98	97	91	60	49	16

Notes: Source is the NCDS, BCS and LSYPE.

Table A3
The percentage in the 3 most frequent jobs by subject and year.

	Percent	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),

Table A3 (*continued*)

	Percent	Top three jobs (percent)
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.

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