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# Executive Summary

- Each year more than 350,000 students start Higher Education (HE) degrees in England at a total cost of around £17 billion paid by graduates in repayments on student loans and the taxpayer (Belfield et al., 2017). This represents a significant investment and has the potential to have considerable implications for the students' later-life outcomes. Students typically make the decision about where and what to study at university at an early age. This decision is influenced by many things, reflecting the various expected benefits associated with a higher education, but a key one will be the potential impact on their future employment prospects. However, currently there is little evidence about the differential impact different degrees might have on their medium term earnings or employment prospects. Accurate and timely estimates of the relative value of different degree courses are vital to ensure degrees represent value for money for both students and the government.

- This report is the first in a series of reports seeking to improve the information available to stakeholders on the value of different degree courses. The reports are making use of the new Longitudinal Education Outcomes (LEO) administrative dataset developed by the UK Department for Education (DfE), which tracks English students through school, college, university and into the labour market. The current report will provide estimates of the labour market return - measured by earnings and employment 5 years after graduation - to different subjects, institutions and degree courses relative to the average degree.

- Graduates' earnings and employment prospects are affected both by their pre-university characteristics, such as their ability level or social background, and by the impact of studying a particular degree. As a result, subjects may have very high average graduate earnings simply because they take high-ability students rather than because of the impact of the degree itself. Raw differences between courses can therefore be misleading as to the actual return from doing a given degree.

- This report tries to disentangle the impact of a degree on earnings and employment outcomes from that of student characteristics, providing estimates of the impact of different degrees on graduate earnings. The LEO dataset provides a unique opportunity to do so by allowing us to account for differences in background and prior attainment between graduates who take different degrees.

## Findings

- The labour market returns to different degrees vary considerably even after accounting for the considerable differences in student composition. Both the subject of degree and institution attended make a considerable difference to graduates' earnings. All these estimates refer to differences in earnings 5 years after graduation (or expected graduation for dropouts).

- We know there is wide variation in the earnings between graduates from different degrees. Medicine, maths and economics graduates all typically earn at least 30% more than the average graduate, while creative arts graduates earn around 25% less on average. A large proportion of these differences in raw earnings can be explained by differences in the characteristics of students taking these degrees. However, after accounting for these, significant differences in the relative returns to different subjects remain. Once these differences have been controlled for, medicine and economics degrees have returns around 20% greater than the average degree, and business, computing and architecture degrees all offer relative earnings premia in excess of 10% above the average earnings for graduates. Creative arts - which enrols more than 10% of all students - still has very low returns: around 15% less than the average degree.

- These differences in returns are large. By comparison, after conditioning on all other characteristics, degree subject and institution, graduates from independent schools and the top quintile earn around 7% to 9% more than those graduates from the lowest SES backgrounds. Similarly, adding an extra A at A-level increases earnings by around 3%.

- These figures represent the average returns based on the students who take these subjects. There is no reason to expect the returns will be the same for all students; for example, lower ability students would be unlikely to be able to achieve the high returns that we observe for medical degrees (even if they were able to gain access to the course). Indeed we do find evidence that degrees have a different impact on different types of students. Medicine, pharmacology and English have relatively higher returns for females than males. Computer science by contrast is more beneficial for males. Medicine and education have higher returns for students from lower socio-economic backgrounds, while economics and history have higher returns for students from higher socio-economic backgrounds. Social care and creative arts have a relatively higher return for students with lower levels of ability, as measured by their prior achievement.

- There is also considerable variation in raw earnings across institutions. High-status universities, such as the Russell Group and universities established before 1992, typically have higher-earning graduates. These universities however also typically take the highest-ability students. Once differences in the student composition between universities have been accounted for, the variation in returns is considerably reduced, but significant differences remain. Even after controlling for these differences, the traditionally high-status universities such as the Russell Group still provide the highest returns. This analysis cannot distinguish whether these differences result from the differences in the economic value of the skills provided by the universities or the signalling value of having attended a prestigious university. However, recent evidence on the issue of signalling vs. human capital effects of university education has suggested that the latter is important (Arteaga, 2018). Further, from a student choice perspective, this distinction might be less important.

- One of the key contributions of the LEO data including the full population of students is that we are able to estimate the returns to specific courses (a specific subject at a given university). Some of the estimates are imprecise due to small sample sizes. Nonetheless, the variation across courses is striking. The top-earning courses attract a 100% premium over average graduate earnings, whilst the lowest-earning courses attract earnings that are around 40% below average graduate earnings.

- These findings imply that studying the same subject at a different institution can yield a very different earnings premium. For example, the best business studies degrees have returns in excess of 50% more than the average degree while the worst business degrees have below average returns. These are considerable differences in graduate earnings.

- There is also considerable variation in the impact of different subject choices on the probability of being in employment. The differences do not highly correlate with the differences in earnings. Some subjects appear to increase the probability of being in work and others increase graduates' earnings conditional on being in work. For women, studying pharmacology, medicine, maths, architecture, nursing and subjects allied to medicine increases the probability of being employed by around 2-3 percentage points over the average graduate. For men, studying social care and medicine increases the probability of being employed by up to 6-7 percentage points over the average graduate.

- There are also significant differences in the impact on employment between different institutions. However, once again, the earnings and employment estimates look quite different; unlike the earnings estimates, it is not the high-status universities which have the largest effects on employment. In fact, institutions in the 'Other' university group appear to improve employment prospects more than Russell Group institutions. However, it should be noted that employment information on graduates who move abroad is not recorded and so these individuals count as not being in employment. This may well be more common amongst graduates from Russell Group institutions, for example.

### Main implications

- Our results suggest that a student may end up with very different earnings as a result of making different decisions about which university to attend and what to study. These findings are likely to provide useful additional information for a student who is perhaps considering a set of institutions or choosing between two different subjects for which they are qualified to study.

- These results also highlight significant differences in returns between institutions and this information could be used to evaluate universities. If these differences are the result of certain teaching practices which improve labour market outcomes then these could be applied in other universities to the benefit of graduates.

### Caveats

- Differences in graduates' earnings may reflect differences in the demand for different skills in the labour market or differences in the quality of HE provision, or both. A course might be higher quality but produce skills not valued by the labour market and vice versa. Hence earnings cannot be used by themselves as a proxy for quality of provision, but would need to be used alongside other factors and with the appropriate context. In addition, since our estimates are based on degrees taken 5-10 years ago they may not reflect the returns individuals are likely to face in the future.

- Our findings significantly expand understanding of the variation in graduate earnings, but caution should be exercised in their interpretation; specifically, the findings should not be interpreted as the true causal effect of taking different subjects or attending different institutions. We use new exciting data and apply sophisticated methodologies to control for the selection into different HE courses, and in so doing move beyond the existing literature in the UK. However, selecting an institution and subject to study is an inherently non-random process. It reflects the skills and preferences of young people, and may be affected by unobservable traits, such as confidence or other soft skills that also determine labour market outcomes.

- We do not observe identical people in every institution or studying different subjects and the impact of a specific course may be different for different types of people. We estimate the average effect of a course based on the people that take that course. We are not claiming that all individuals would have higher earnings if they studied medicine, regardless of their prior attainment and A-level subject choices. It also has to be kept in mind that the universities with the highest returns may not be accessible to all individuals due to entry requirements.

- This analysis explicitly focuses on the labour market value of HE for the individual student. However, this is a clearly only one of many potential gains from HE. There are non-monetary benefits for individuals, such as job satisfaction, which we do not observe in these data. There are also significant social benefits from HE, such as the impact on the productivity of other workers or the level of political participation, which again are beyond the scope of this report.

## Acknowledgements

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# 1 Introduction

Accurate and timely estimates of the relative value of different higher education (HE) courses are vital: the provision of HE is very costly to both graduates and the taxpayer and at an early age individuals make life-changing decisions about where and what to study at university. Currently, the evidence base underpinning these important decisions is weak. In this work, we exploit the new Longitudinal Education Outcomes (LEO) administrative data developed by DfE[1] which tracks individuals through school, university and into the labour market to produce precise and robust estimates of the impact of different HE courses on individuals' labour market employment and earnings.

It is well known that attending higher education has a significant pay-off in terms of higher earnings and higher employment rates on average (Walker and Zhu, 2011) and that this pay-off has held up through the rapid expansion in the number of Higher Education students since the 1990s, potentially due to technological changes putting a greater premium on the skills possessed by graduates (Blundell et al., 2016). Recent evidence has uncovered a high level of variation in the earnings of graduates who study different subjects or who attend different higher education institutions (Britton et al., 2016; Walker and Zhu, 2017). From this evidence, we know that students who studied economics and medicine tend to have the highest earnings, whilst those who studied English, history or creative arts tend to have the lowest earnings. Similarly, graduates from higher-status universities, such as the Russell Group, tend to have the highest earnings, on average. Such variation by subject of study and institution can also be seen in other countries, such as the US (Altonji et al., 2012) or Norway (Kirkeboen et al., 2016). With the exception of the Norwegian case, however, there is little understanding as to whether these differences in graduate earnings are causal or not. This is a critical question for policymakers.

On the one hand, it could be that the variation in graduate earnings is primarily causal and the result of differences in the quality of higher education institutions or differences in the labour market value of the knowledge accrued in different degrees. If this is the case, then policymakers might be well advised to focus on understanding what is driving the high returns at some universities. If there are teaching styles or other practices which are driving high returns then it might be possible to improve the quality of low-performing institutions and therefore increase the earnings of their graduates by replicating these practices. Such variation may also suggest that differences in young people's subject choices, such as gender differences in taking science, technology, engineering and maths (STEM) subjects, are a direct cause of labour market inequalities. This might be addressed by increasing the information available to students while making these important decisions or by incentivising students to take higher-earning subjects.

On the other hand, it could be that differences in graduate earnings by subject and institution are mainly down to differences in the characteristics of young people taking these courses, particularly their prior attainment and skills on entry to higher education. If this is the case, then differences in graduate earnings are mostly the result of differences in the skills young people possess before they attend HE and policymakers would be better advised to focus on earlier stages of

[1]See the DfE website for more details on the LEO dataset and a range of publications, for example: https://www.gov.uk/government/statistics/graduate-outcomes-longitudinal-education-outcomes-leo-data

education if they are concerned by the level of variation in graduate earnings. Furthermore, to be valid and useful, measures of the quality of different higher education institutions would need to account for the prior attainment and characteristics of young people on entry into higher education. Without doing so, any measure of institutional quality would be biased and potentially misleading.

In reality, differences in graduate earnings by subject and institution are likely to be the joint result of causal impacts and the characteristics of young people on entry to higher education. How much each explanation matters is then an empirical question. To answer this question requires researchers to fully account for characteristics and traits that determine both later life earnings and the subject/institution choice made at higher education. If they do not then differences in graduate earnings by subject/institution could still reflect traits and characteristics of young people, rather than true causal estimates. To date, however, attempts to extend the evidence base in the UK have been heavily limited by the available data. Datasets have either been relatively small, preventing researchers from looking at earnings by subject and institution, and/or there have been doubts about the quality of data, such as self-reported earnings measures.

In this regard the LEO data represents a significant leap forward. The National Pupil Database (school records) contains detailed information on pupil attainment histories and backgrounds for individuals that went to school in England. The data includes the full population of students attending HE institutions across the UK[2] enabling precise estimates of the returns to specific subjects, institutions and even courses (a given subject at a specific institution). This is linked to HMRC earnings and employment data, as well as Department for Work and Pensions (DWP) data on receipt of means-tested benefits, providing high-quality and reliable measures of earnings.

Using this new data, we make use of a sophisticated methodological technique that takes account of how young people's characteristics affect their subject and institution choices to measure the impact of HE degrees in specific subjects and institutions on later life earnings. Moreover, we are able to look in detail at how these returns vary by individual characteristics, such as gender, socio-economic background and prior attainment. As the NPD data only contains the school records of those that went to school in England, our analysis is limited to English students. This implies that the estimated returns for institutions with a significant proportion of non-English students, such as institutions in Wales, Scotland or Northern Ireland, may not be representative of the average return for their students.

Our findings significantly expand understanding of the variation in graduate earnings; however, we cannot argue that our findings can definitely be interpreted as the true causal effect of different subjects and institutions. We use new exciting data and apply sophisticated methodologies to control for the selection into HE courses, and in so doing move beyond the existing literature in UK. However, selecting an institution and subject to study is an inherently non-random process. It reflects the skills and preferences of young people, and may be affected by unobservable traits, such as confidence or other soft skills, that also determine labour market outcomes. Research from Norway has been able to get round this problem by using quirks of the admissions system and further data. Future work may thus be able to improve on our estimates if the LEO data is further linked to data on soft skills in surveys or to UCAS data on young people's preferences.

[2] The data does not include HE students at some alternative providers that did not return data to the Higher Education Statistics Agency (HESA).

Furthermore, we do not observe identical people (even on observable characteristics) at multiple different institutions and the impact of a specific course may be different for different types of people. We estimate the average effect based on the people that take that course. For example, we are not claiming that all individuals would have higher earnings if they studied medicine.

This analysis explicitly focuses on the private pecuniary returns to Higher Education. This is a clearly only a subset of the overall returns. There are private non-pecuniary returns in terms of the impact on job satisfaction or work-life balance. This data does not allow us to explore any of these additional private returns to HE. There are also significant social returns to HE. Some of these social returns are intrinsically linked to the private returns. The more graduates earn over their lifetime the more they pay in tax and the less they receive in benefit income. High-earning graduates also repay more of their student loans which reduces the implicit government subsidy to HE. We will provide some evidence on these pecuniary social returns in a following paper. However, we will not be able to provide any evidence on the non-pecuniary social returns such as the impact of HE on the productivity of other workers or the crime rate or level of political participation.

In what follows, we start in Section 2 by describing findings and methodologies from the existing literature in more detail. Section 3 describes the various datasets that we have used and how they are linked together, how the final sample and key variables are determined, and data quality issues. Section 4 summarises the main methodology we use in our estimates and how the results can be interpreted. Section 5 shows the main empirical results by subject of study and Section 6 by institution of study. Section 7 then looks at variation by course, which we define as a subject/institution combination. This allows us in Section 8 to examine, for instance, the variation in the average earnings of maths graduates depending on which institution they attended. Section 9 investigates employment returns, while Section 10 concludes.

## 2 Existing literature and approaches

There is an extensive and convincing literature that suggests that the causal effect of higher education (HE) on wages (and earnings and incomes) is large (Card, 1999; Blundell et al., 2005). Specifically, human capital theory suggests that HE adds to the productivity of those that have HE compared to those who do not have HE - and it is this that is reflected in the higher wages paid to HE graduates relative to non-graduates (Becker, 1964). This would also imply that different degrees add differing amounts of productivity and therefore will differ in their impact on employment and wages.

There are alternative explanations for the positive correlation between earnings and higher education, specifically that there is a signalling effect in the labour market (for example, see arguments in Chevalier et al. (2004)). High-productivity individuals may signal their superior productivity by acquiring more education than individuals who are less productive. Empirical evidence on whether the signalling or the human capital effect dominates is limited, but there is recent international evidence that the latter effect can be important (Arteaga, 2018). That said, there are major selection issues whereby individuals with higher levels of prior academic achievement (and hence potential productivity) enrol on certain degree courses and not others. A major focus of this study is, in the absence of experimental or quasi-experimental data, to use the comprehensive data that we have to control for these selection effects.

Much of the literature on wage returns has explored how the effect of education varies over time and there is now a broad consensus that the magnitude of the return to HE has risen over the last half century, although it appears to be stabilising in some countries now. There is further consensus that this phenomenon of strong returns to HE can be substantially attributed to "skill-biased technical change" - the world of work has become more and more complex because of technological advances and this has led to a rise in the demand for workers with the complementary skills to manage and exploit such changes, at the expense of workers whose skills substitute for such changes (Goldin and Katz, 2009; Goos et al., 2009; Michaels et al., 2014). These rising returns to skills have occurred even though there has also been a dramatic rise in the supply of highly skilled labour to the market. This is because, up to now at least, the demand for skills, driven by technological change, has kept pace with or outstripped the supply of skills. The race between technology and education supply is being won by the demand side and the gap in real wages between the highly skilled and the rest of the labour force has continued to rise in many countries. Certainly the UK literature is clear that the value of a degree is still substantial, despite an expansion in the numbers taking degrees over recent decades (Blundell et al., 2005; Walker and Zhu, 2011, 2013; Blundell et al., 2016).

However, the overall average returns to HE do not tell us much about the particular types of higher education that are valued by the labour market. There is literature that explores variation in the return to HE across subjects studied but far less work on variation by institution. We discuss the relevant literature that investigates these margins below.

### 2.1 Relative returns by subject

There is a large and long-standing literature for the US which has focused on the variation in graduate earnings by degree subject (college major). A review by Altonji et al. (2012) suggested substantial variation in earnings by subject of degree but also noted that there is significant sorting into different subjects on the basis of student ability, preferences and students' views of their comparative advantage in that subject. The latter issue would imply that students who expect to earn more from a particular subject are more likely to take it, making it difficult to determine the causal impact of subject per se on earnings. With these caveats in mind, Altonji's summary of the evidence for the US suggested that engineering, business and science degrees attract a higher premium than social science, education and humanities degrees. The authors then used the American Communities Survey (ACS) to revisit the question and confirmed that the (relative) return to different degree subjects still varied substantially, despite the fact that US students concentrate their studies on a single subject area rather late in their studies. This variation in earnings by degree subject is sizeable compared to the absolute return on average across all subjects, i.e. the difference between graduates, on average, and non-graduates.

The US literature, which has gone to great lengths to try to account for the selectivity of degree subject choice, and indeed selectivity in response to surveys, has still found substantial returns across degree subject (Arcidiacono, 2004; Hamermesh and Donald, 2008). One might conclude from this evidence therefore that the nature of the skills and knowledge acquired at university does impact on students' subsequent wages, as human capital theory would predict.

For the UK, there is a body of evidence that also suggests that the returns to a degree vary substantially by subject (O'Leary and Sloane, 2005; Chevalier, 2011; Walker and Zhu, 2013; Britton et al., 2016). For example, Walker and Zhu (2013) in their report for the Department for Business, Innovation and Skills (BIS) examine variation by subject and find large earnings differences - with medicine and economics having particularly large returns relative to the counterfactual non-graduate group (who might have conceivably gained entry to HE at the margin). Chevalier (2011) also highlights the substantial variation in earnings within subject, though his data does not enable him to explain this. It is worth highlighting the fact that much of this UK literature on the returns by subject has not been able to control for institutional differences in earnings and hence identifying the distinct effect of subject is problematic.

Using administrative data, Student Loans Company data and tax records, Britton et al. (2016) find large differences in earnings across subjects for UK graduates. They also explore the relative wage returns across 'courses' (i.e. subjects and institutions) whilst attempting to allow for the fact that different types of student enrol in different courses and therefore some students may be more able and earn more irrespective of the specific degree they take. They find similar results to Walker and Zhu (2013) in terms of the variation in earnings by subject, with creative arts degrees being an outlier attracting particularly low returns, while medicine and economics are outliers at the opposite extreme.

Walker and Zhu (2017) use UK Labour Force Survey (LFS) data, which has recently included both subject of study and HE institution attended, to conduct a similar analysis to Britton et al. (2016). Their dataset is obviously somewhat smaller but they produce similar findings of large variation in earnings by subject.

## 2.2 Relative returns by institution

The literature on the extent to which the wage return to a degree varies by institution attended is much more limited due to lack of data availability and the results, for the US at least, are mixed. Much of the early literature examined the correlation between institutional characteristics, rather than attendance at specific institutions, and earnings. Monks (2000), for example, documented how graduates' earnings varied across different types of US college and found that the wage premium from attending a selective college was significantly greater. Further, the return to a degree was higher for those graduating from an institution which offered postgraduate degrees, was research intensive and/or a private institution. Witteveen and Attewell (2017) more recently continue to find a large return to attending a more selective college in the US. Yet alongside this, many studies have found significant but modest variation in earnings by institution (see Zhang (2012), for a summary of some of this literature). Dale and (2014) conclude that whilst the variation in earnings by college characteristics is very large, much of this can be explained by sorting of students into institutions. In their study, institution characteristics became small and statistically insignificant determinants of graduates' wages, after controlling for selectivity.

There is a limited literature from the UK which has also explored how earnings vary by institution characteristics. Chevalier and Conlon (2003) and Hussain et al. (2009) use an aggregate indicator of university quality, which contains various data including research intensity and selectivity of student intake. Both papers suggest that there is a positive wage return to attending a higher-quality institution, particularly at the top end of the earnings distribution. Both papers also suggest that selective sorting of students into different institutions is substantial and has increased over time. They also present some evidence that the return to university quality/selectivity has increased over time.

The above literature has tried to establish the wage return to particular college characteristics, rather than explore how graduates' earnings vary according to the specific institution that they attended, as we do here. A study that is more similar in spirit to the analysis presented in this report is Cunha and Miller (2014) who use administrative data records from Texas to estimate the 'value added' by different institutions, as measured by earnings. They find very large differences in earnings across institutions but these differences become markedly smaller (more than halved in many cases) when they control for student characteristics. Despite the different context, this paper is important as it rehearses many of the arguments about whether value added models, so commonly used with test score data to measure the quality of schools, can be adapted for use in higher education. Their study has the advantage that it includes data on applicants' choices of colleges and which colleges accepted each applicant. This allows the authors to compare the earnings of students who expressed similar preferences and had a similar acceptance profile, and hence arguably control for factors (inclinations, attitudes etc.) that are unobserved in our data. They conclude that whilst there is variation in value added across institutions, estimates are both sensitive to comparator groups (i.e. what controls are included in the model) and institutional estimates of value added are imprecise. The latter issue suggests that distinguishing institutional performance in a statistically significant sense may be problematic. They urge caution with the use of such data and that it be used as part of a basket of measures of institutional performance.

Another closely related study is Kirkeboen et al. (2016) who use Norwegian administrative data and try to address the problem of selectivity. Their data contains, like LEO, the tariff scores of every individual and, unlike LEO, also information about the preferred course and the next best alternative to it. Admission to a Norwegian course requires that the student apply and that her high school Grade Point Average (GPA) exceed some (ex ante unknown) critical value - the highest-GPA applicant to a particular course gets a place on this, her most preferred course, while the next highest applicant to the same course gets a place if one is available and, if not, gets a place at her second most preferred course (up to 15 choices are possible in the Norwegian application system), and so on until the marginal student is admitted to each and every course. Thus, it is possible to identify which individuals were only just admitted to an institution and compare them with individuals who just failed to get admitted. It is this ranking that allows these researchers to use the resulting discontinuities in the admission probability as instrumental variables. Their study found substantial variation in earnings by subject of degree whilst the return to a more selective institution was relatively small, after controlling for subject choice. They also concluded that individuals choose fields in which they have a comparative advantage, confirming the need to account for selectivity in both institution and choice of subject.

For the UK, the only study to our knowledge that has been able to estimate institution effects is

Britton et al. (2016) who analysed the variation in graduate earnings by higher education institution attended using linked administrative tax data. They found considerable variation in earnings both within and across different institutions. However, much of this variation was explained by student background and subject mix. The study also lacked good individual-level controls for students' prior achievement and hence potentially could not account fully for sorting across different subjects and institutions. Given this rather mixed literature, the contribution of this report to the UK evidence base is to use more comprehensive and arguably higher-quality data to develop better comparison groups against which to compare the students taking one degree as opposed to another. The data, with the more sophisticated methodology, will enable us to be more confident that the estimates represent the additional value of the degree rather than the type of students who take it.

## 3 Data

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

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

The NPD contains the school records of everyone who studied in England. This provides a full set of background characteristics for all students who took their GCSE (age 16) examinations in 2002 or later. The dataset includes information on gender, ethnicity, region, school type and exam scores at ages 7, 11, 16 and 18, as well as an indicator of socio-economic status (SES) based on Free School Meal eligibility and a set of population statistics based on the individual's postcode. People who attended school in Scotland, Wales and Northern Ireland are not included.

HESA is the administrative higher education records. It is a census, including all individuals in a higher education institution in the UK each year. Some alternative providers may be excluded from the data if they did not return data to HESA in the relevant year; this accounts for a very small proportion of the total population of students at higher education institutions. The LEO data includes everyone who graduated from HE between 2003-04 and 2013-14. The HESA data includes information on institution, subject studied and degree outcomes. We link individuals across records to identify individuals who drop out from university, switch course or move between institutions.[3]

The HMRC data is Pay As You Earn (PAYE) individual tax records. The LEO data currently includes all tax records between 2005-06 and 2015-16. PAYE records are the employer-filed records which show taxable earnings in a given year. This includes all taxable income, but excludes both

[3] The HESA data also includes UCAS tariff upon entry to university for some individuals. This is a single score that equivalises English A-Levels with (e.g.) Scottish Highers and with non-academic equivalents. We do not use this in our analysis.

employer and employee pension contributions. This data is also used to define employment spells which allows us to identify the period of time for which an individual has been employed and hence enables us to use a measure of sustained employment in our employment estimates, defined as working in 5 of the last 6 months of a tax year.

The data also include Self Assessed (SA) tax records, which record self-employment income, for the tax years between 2013-14 and 2015-16. Table 3 later shows that around 6% of graduates in their late 20s file self-assessed tax forms (with a slightly higher prevalence of filing for men than for women), the majority of whom are self-employed. As discussed in Section 4, we do not include the SA data in our main estimates, but we do check the robustness of our results to its inclusion in the Appendix to this paper. Due to the rise of SA filing with age as found in Britton et al. (2018), the importance of including the SA data in estimates such as these will increase as more years of data are added to LEO.[4]

Table 1: Sample sizes for LEO dataset by cohort

| Year of graduation | Base sample (1) | Valid sample (2) | Earnings sample (3) | Employment sample (4) |
|---|---|---|---|---|
| 2003-04 | 243,000 | - | - | - |
| 2004-05 | 260,000 | - | - | - |
| 2005-06 | 269,000 | - | - | - |
| 2006-07 | 269,000 | - | - | - |
| 2007-08 | 305,000 | 134,000 | 111,000 | 134,000 |
| 2008-09 | 302,000 | 156,000 | 128,000 | 156,000 |
| 2009-10 | 318,000 | 173,000 | 137,000 | 173,000 |
| 2010-11 | 328,000 | 181,000 | 136,000 | - |
| 2011-12 | 354,000 | 194,000 | 131,000 | - |
| 2012-13 | 320,000 | - | - | - |
| 2013-14 | 336,000 | - | - | - |
| Total | 3,303,000 | 838,000 | 642,000 | 463,000 |

Notes: The table gives the sample size in the LEO data by year of graduation, including dropouts classified by their expected year of graduation. Base sample is students of valid first degree in the HESA record. Valid sample includes those who entered university at ages 18 to 20, for whom we have an NPD record with sufficient information and who have been out of university for 3 full tax years in our data. We also remove those with the top 5% estimated IPWRA weights (see Section 4 on how these are constructed), so as not to make the results depend disproportionately on very few individuals. The earnings sample includes the individuals from the valid sample who, in any of the periods considered (3 to 7 years after graduation), have non-zero earnings and are in sustained employment. The employment sample includes all individuals from the valid sample who have been out of university for 5 full tax years.

Table 1 outlines the sample sizes in the linked data. As the baseline sample we take those individuals who graduate (or expected to graduate and dropped out) from a valid first degree in the HESA records who have been linked to DWP's Customer Information System (CIS).[5] Our

[4]Finally, the WPLS data records spells of benefit receipt for a number of means-tested benefits. We do not yet use this data in our analysis.

[5]Appendix Table D1 shows the distribution of valid courses for the 2011-12 graduation cohort. The vast majority of students are taking first honours degrees, but we also include integrated masters and degrees at the same level as

sample therefore includes all individuals to enter university (dropouts and graduates). Results for only graduates are shown in an Online Appendix. If an individual switches course during their degree they are included for the course in which they graduate. Individuals who take joint honours are included for both subjects and weighted according to their percentage full-time equivalence.

The Table shows the sample by year of graduation. The number of individuals grows from around 240,000 in 2003-04 to around 340,000 in 2013-14 reflecting the expansion of HE during this period. The second column displays the number of individuals in this sample that are matched to a KS5 NPD record[6] and who have been out of university for at least 3 full tax years. The NPD data only includes individuals who took their GCSEs in England since 2001-02. This means that there are very few successful matches for those who graduate before 2006-07 as they typically took their GCSEs too early to appear in our data. In practice we do not use the 2006-07 cohort in our analysis, because these individuals only have NPD records if they went to university at age 18 and so are a select sample of the full 2006-07 cohort. In the later cohorts, the people who do not match to the NPD are a combination of mature students and students who went to school outside of England. We define individuals as having a valid NPD record if they have an NPD record containing sufficient data to be included in our estimation (this includes being observed at A-levels or Key Stage 5, meaning we exclude individuals who enter HE but do not go to sixth form).[7] This also includes individuals who were educated in independent (private) schools in England. For these individuals we typically lack some background characteristics and some of the academic records. In the analysis (described in Section 4), we include an independent school dummy which will also reflect the average difference in the characteristics of independent school students.

Column (3) shows the number of individuals that are included in our sample in the main earnings regressions. We include from the valid sample the individuals who are in sustained employment and have positive earnings in any of the periods considered in our earnings regression (see Section 4 for more details). The final column shows the individuals included in the employment regression. We include all individuals from the valid sample who have been out of university for at least 5 years, as our outcome variable will be being in employment 5 years after graduation. This leaves us with 3 cohorts on which to run the employment analysis.

Table 2 compares some of the background characteristics of our sample of HE participants to the NPD population. HE participants are considerably more likely than average to be from high SES backgrounds or privately educated and they typically have higher prior attainment.

first honours degree

[6]This excludes individuals who attend FE colleges that are not included in the NPD, but includes any students studying for vocational qualifications in sixth forms that are in the NPD

[7]We drop some individuals who are missing background characteristics or exam data which we need for our analysis. Those missing Key Stage 2 attainment variables are included with missing dummies as is standard in the academic literature.

Table 2: Background characteristics of matched and NPD samples

| | Women | | Men | |
|---|---|---|---|---|
| | NPD | HE sample | NPD | HE sample |
| *Background* | | | | |
| FSM | 0.12 | 0.05 | 0.12 | 0.05 |
| EAL | 0.08 | 0.11 | 0.09 | 0.11 |
| SEN | 0.09 | 0.02 | 0.15 | 0.03 |
| State school | 0.93 | 0.86 | 0.92 | 0.83 |
| *of which:* | | | | |
| SES Q1 - least deprived | 0.20 | 0.33 | 0.21 | 0.36 |
| SES Q2 | 0.20 | 0.25 | 0.21 | 0.25 |
| SES Q3 | 0.20 | 0.19 | 0.20 | 0.19 |
| SES Q4 | 0.20 | 0.13 | 0.20 | 0.12 |
| SES Q5 - most deprived | 0.20 | 0.09 | 0.19 | 0.08 |
| *Ethnicity* | | | | |
| White | 0.83 | 0.79 | 0.83 | 0.80 |
| Black | 0.03 | 0.04 | 0.03 | 0.03 |
| Asian | 0.06 | 0.09 | 0.06 | 0.10 |
| Other | 0.07 | 0.08 | 0.07 | 0.08 |
| *Prior attainment* | | | | |
| KS2 maths level 5+ | 0.19 | 0.36 | 0.23 | 0.46 |
| KS2 English level 5+ | 0.26 | 0.47 | 0.17 | 0.35 |
| KS4 maths A*/A | 0.13 | 0.32 | 0.14 | 0.39 |
| KS4 English A*/A | 0.22 | 0.50 | 0.13 | 0.39 |
| UCAS tariff score | 226 | 270 | 214 | 265 |
| Maths A- or AS-level | 0.06 | 0.16 | 0.10 | 0.30 |
| Science A- or AS-level | 0.11 | 0.28 | 0.14 | 0.39 |
| N | 1,150,000 | 256,000 | 1,142,000 | 208,000 |

Notes: The HE sample includes all individuals from the employment sample, and hence aligns with the last column in Table 1. The NPD sample includes all those with non-missing NPD information that took their GCSEs in the same years as our employment sample (2002-03 to 2005-06). EAL = English as an additional language, FSM = free school meals, SEN = non-statemented special educational needs. All numbers are proportions over the respective sample, except UCAS scores, which is the average score, and SES quintiles, ethnicity and KS4 scores, which are only defined for state school pupils.

Table 3 shows how the HE participants are distributed across degree subjects, using the Higher Education Classification of Subjects (HECoS) CAH2 definitions.[8] The Table shows that for both genders, business and creative arts are the two biggest subject areas. English, sociology, subjects allied to medicine, education and psychology are considerably bigger subjects for women than for men, while the opposite is true for physics, engineering, computing and economics.

[8]Celtic studies, humanities and 'combined' are not shown due to small sample sizes. The complete set of subject classifications are provided in an accompanying Online Appendix.

Table 3: Subject sizes, dropout rates and self-employment rates

| | Women | | | | Men | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Share of pop (%) | Dropout rate (%) | SA (%) | N | Share of pop (%) | Dropout rate (%) | SA (%) |
| Agriculture | 2,000 | 0.8 | 9.5 | 6.3 | 900 | 0.5 | 13.5 | 7.8 |
| Allied to med | 11,900 | 4.6 | 4.9 | 6.7 | 4,400 | 2.1 | 6.4 | 7.8 |
| Architecture | 2,600 | 1.0 | 10.3 | 5.0 | 7,000 | 3.4 | 14.4 | 6.9 |
| Biosciences | 12,100 | 4.7 | 5.4 | 2.7 | 10,800 | 5.2 | 10.6 | 3.1 |
| Business | 24,800 | 9.7 | 10.6 | 2.4 | 28,900 | 13.9 | 13.6 | 3.7 |
| Comms | 10,500 | 4.1 | 10.9 | 4.9 | 8,000 | 3.8 | 13.9 | 8.3 |
| Computing | 2,900 | 1.1 | 14.9 | 2.1 | 14,900 | 7.2 | 19.0 | 4.7 |
| Creative arts | 35,600 | 13.9 | 9.9 | 13.9 | 20,600 | 9.9 | 12.6 | 19.0 |
| Economics | 2,700 | 1.0 | 5.0 | 1.8 | 7,400 | 3.5 | 7.2 | 2.7 |
| Education | 15,300 | 6.0 | 8.5 | 1.9 | 2,500 | 1.2 | 13.7 | 4.0 |
| Engineering | 2,500 | 1.0 | 10.0 | 2.5 | 15,500 | 7.5 | 15.7 | 3.9 |
| English | 17,200 | 6.7 | 5.9 | 5.1 | 6,600 | 3.2 | 8.8 | 8.1 |
| Geography | 7,000 | 2.8 | 3.4 | 2.4 | 7,100 | 3.4 | 6.8 | 3.7 |
| History | 11,900 | 4.7 | 4.3 | 4.1 | 11,500 | 5.5 | 7.0 | 4.4 |
| Languages | 11,000 | 4.3 | 6.0 | 4.7 | 5,200 | 2.5 | 10.4 | 5.8 |
| Law | 14,900 | 5.8 | 7.2 | 3.0 | 8,500 | 4.1 | 10.7 | 4.5 |
| Maths | 4,200 | 1.6 | 5.8 | 2.6 | 6,600 | 3.2 | 9.7 | 3.0 |
| Medicine | 3,400 | 1.3 | - | 17.6 | 2,300 | 1.1 | - | 18.6 |
| Nursing | 5,100 | 2.0 | 16.5 | 1.1 | 200 | 0.1 | 22.5 | - |
| Pharmacology | 2,300 | 0.9 | 2.4 | 10.3 | 1,700 | 0.8 | 6.4 | 15.4 |
| Philosophy | 4,100 | 1.6 | 7.0 | 4.6 | 3,500 | 1.7 | 7.4 | 6.2 |
| Physics | 1,000 | 0.4 | 4.4 | 3.4 | 4,100 | 2.0 | 9.0 | 3.5 |
| Physsci | 3,100 | 1.2 | 10.7 | 1.9 | 3,300 | 1.6 | 15.2 | 3.0 |
| Politics | 4,000 | 1.6 | 6.2 | 2.7 | 5,900 | 2.8 | 8.0 | 3.8 |
| Psychology | 18,800 | 7.4 | 6.4 | 2.5 | 4,000 | 1.9 | 11.2 | 3.8 |
| Social care | 3,900 | 1.5 | 13.8 | 2.4 | 300 | 0.2 | 25.5 | - |
| Sociology | 12,600 | 4.9 | 9.3 | 2.4 | 4,100 | 2.0 | 13.6 | 3.9 |
| Sportsci | 6,300 | 2.5 | 9.4 | 6.4 | 9,700 | 4.6 | 15.3 | 7.8 |
| Technology | 1,300 | 0.5 | 13.0 | 4.7 | 2,200 | 1.1 | 17.1 | 9.1 |
| Vetsci | 600 | 0.2 | - | 6.5 | 100 | 0.1 | - | - |
| Total | 256,000 | 100 | 8.0 | 5.1 | 208,000 | 100 | 12.0 | 6.4 |

Notes: The sample includes all individuals from the employment sample, and hence aligns with the last column in Table 1. Individuals are only classified as dropouts if they do not switch to another course during the observation period. The SA column contains the percentage of individuals that filed a Self Assessed record 5 years after graduation. Due to the length of medicine and veterinary science degrees, some of the students in the cohorts here will not have NPD records, and hence will not be included in the final estimates. Consequently, the sample of medicine and veterinary science students here included will therefore be smaller. "-" indicates the result has been suppressed due to small sample sizes. Here, and throughout the report, Biosciences refers to a combination of Biological Sciences and Chemistry for sample size reasons.

The Table also shows dropout rates by subject and the proportion of students that have a Self Assessment record 5 years after graduation (for the cohorts graduating between 2007-08 and 2009-10 only). Overall, these dropout rates are similar to official published non-continuation rates from HESA.[9] The dropout rates vary widely across subject areas.[10] Pharmacology, geography and subjects allied to medicine have the lowest dropout rates for both genders, ranging from 2% to 7% of graduates not finishing the degree. Computing and nursing are some of the subjects with the highest dropouts rates, of around 15% or more for both men and women. Figures A3 and A4 in the Appendix show the impact on our results of excluding dropouts. This does not change any of the main conclusions.

Overall the proportion of graduates having self-employment earnings 5 years after graduation is very low, particularly for women, with just over 5% of female and 6% of male graduates having a self-employment record. Medicine and creative arts however are outliers with around 15-20% of graduates of both genders having a self-employment record. If some individuals are in 'sustained employment' and have some self-assessment income this part of their income will be excluded from our main estimates and will bias the estimates for these degrees downwards. Alternatively, if individuals who are self-employed have very different earnings profiles to those with PAYE records this will be missed by our estimates. Figures A1 and A2 in the Appendix re-estimate our results including the self-assessment income. We find that including self-assessment data does not significantly change the estimates deduced using only PAYE data.

### 3.1 Data descriptives

In this subsection, we provide some descriptive statistics from the LEO dataset. In doing so, we set out the importance of accounting for various background characteristics when attempting to identify the impact of degrees on students' earnings.[11]

Figures 1 and 2 show real average earnings of the various graduation cohorts conditional on being in sustained employment by tax year and years after graduation, respectively.[12] There is clear earnings growth as graduates age. Male real earnings increase by around 75% in the first 7 years after graduation. Female earnings growth is slower but still significant. Strikingly, there is very little - if any - real earnings growth between the different cohorts. After accounting for age effects and inflation, individuals who graduated in 2012 earn very similar amounts on average to those who graduated in 2008. Overall, male graduates earn more than female graduates and the gap grows over time, as shown in Figure 3. Seven years after graduation men earn £7,000 more than women on average.

[9] See https://www.hesa.ac.uk/data-and-analysis/performance-indicators/non-continuation.

[10] Some of the courses are very small for specific genders and we do not place too much weight on the overall variation in dropout rates.

[11] The sample used for all figures in this subsection is all individuals with a valid NPD record graduating between 2007-08 and 2011-12 who have positive earnings and are in 'sustained employment' in the relevant year. Equivalent to column (3) of Table 1.

[12] As in the later analysis, earnings are top and bottom coded at the 1st and 99th percentile.

Figure 1: Real earnings by graduation cohort (conditional on sustained employment)

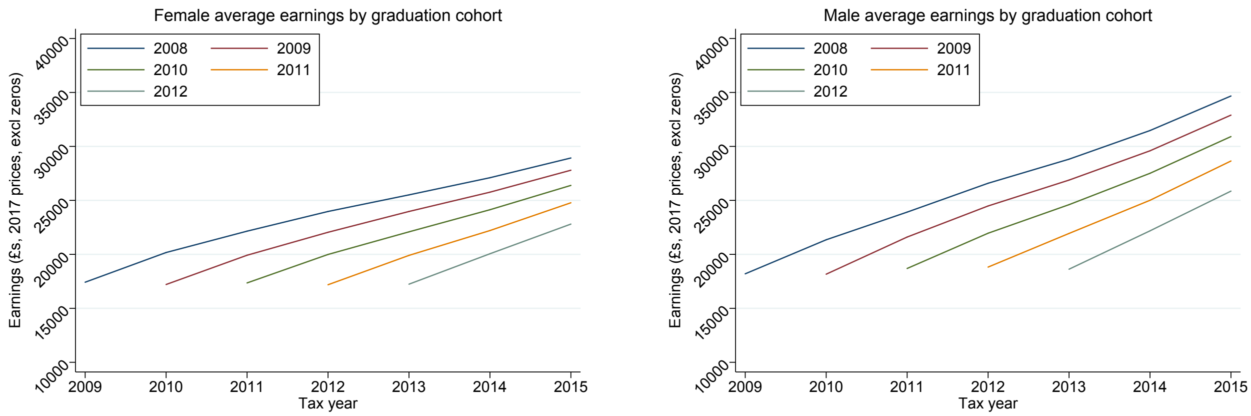



Figure 2: Real earnings by time after graduation (conditional on sustained employment)

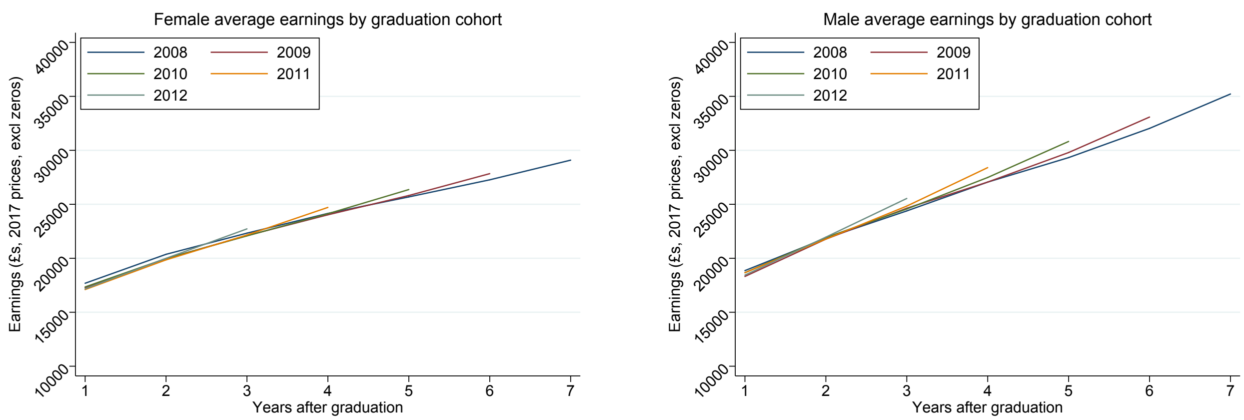



Figure 3: Real earnings by gender (conditional on sustained employment)

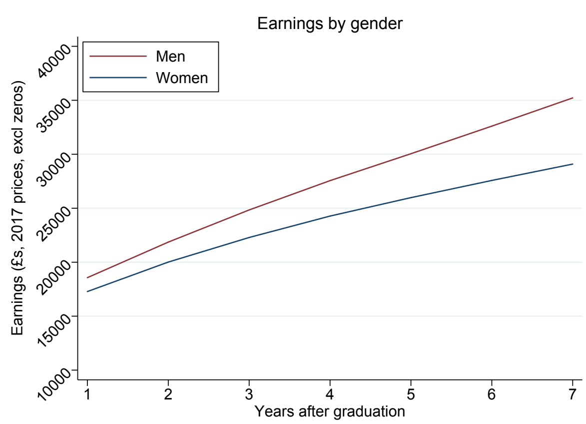



Figure 4 shows the average earnings of men and women by their GCSE maths grade. All groups experienced earnings growth following graduation, but there are considerable gaps between the grades, both in initial earnings and in earnings growth. The starkest difference is between the A and A* grades. Seven years after graduation, men with an A* in GCSE maths earn around

£7,000 more than men with an A in GCSE maths, with a similar gap for women. These differences are purely descriptive and should not be interpreted as causal, but they do highlight the potential importance of accounting for ability when investigating differences in graduate earnings.

Figure 4: Real earnings by GCSE maths grade (conditional on sustained employment)

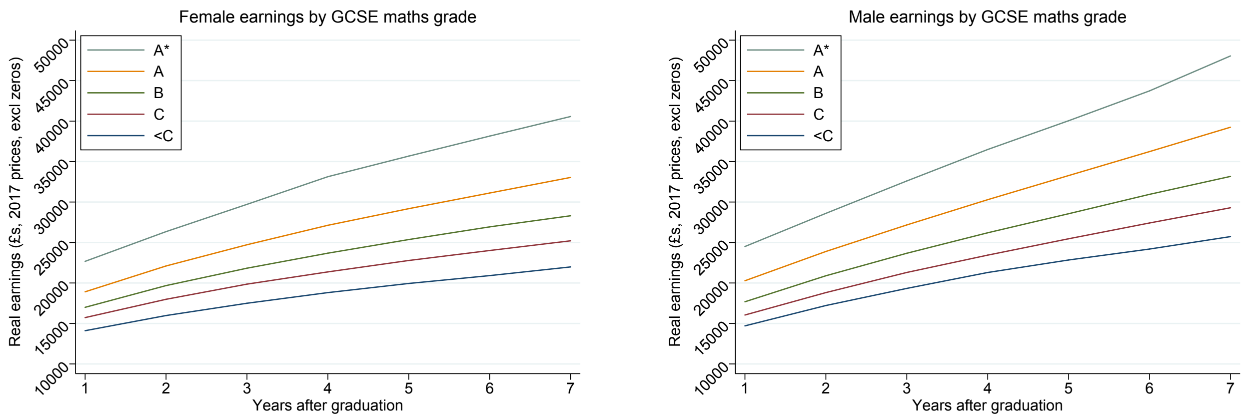



Figure 5 shows average earnings for men and women by socio-economic status. State school students are divided into SES quintiles and privately educated students are shown separately. There is a clear pattern in earnings differences between the SES groups, with those from better-off backgrounds typically earning more. This is in line with the literature on social mobility (e.g. Belfield et al. (2017)). However, there is still a considerable difference between the top quintile of state-schooled people and graduates who went to independent schools. The gap grows with age so that 7 years after graduation privately educated women earn £5,000 more than the top quintile of state-educated women and privately educated men earn £7,000 more than state-educated men. As with the previous figures in this subsection, these differences are not causal, but they do highlight the potential importance of some of the background characteristics of graduates when investigating their earnings.

Figure 5: Real earnings by socio-economic status (conditional on sustained employment)

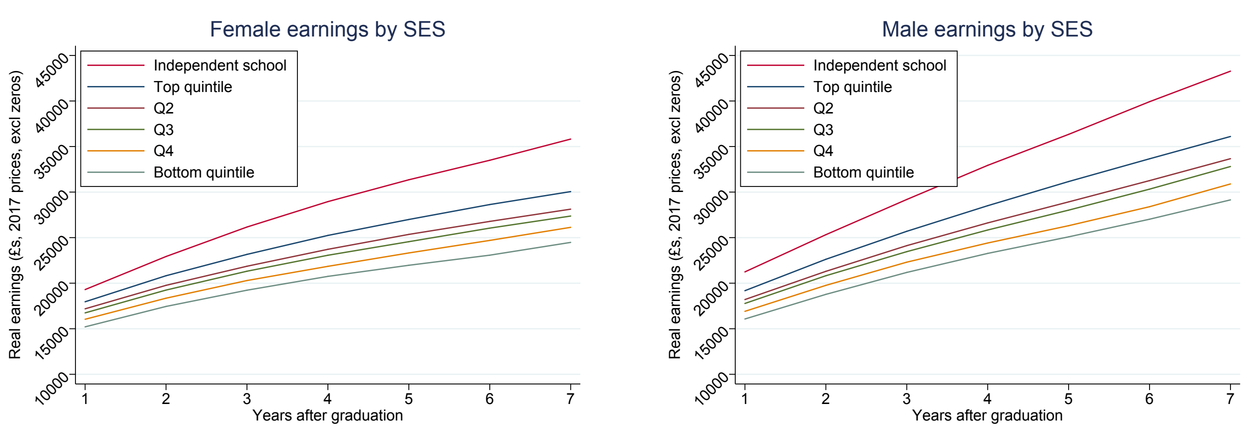
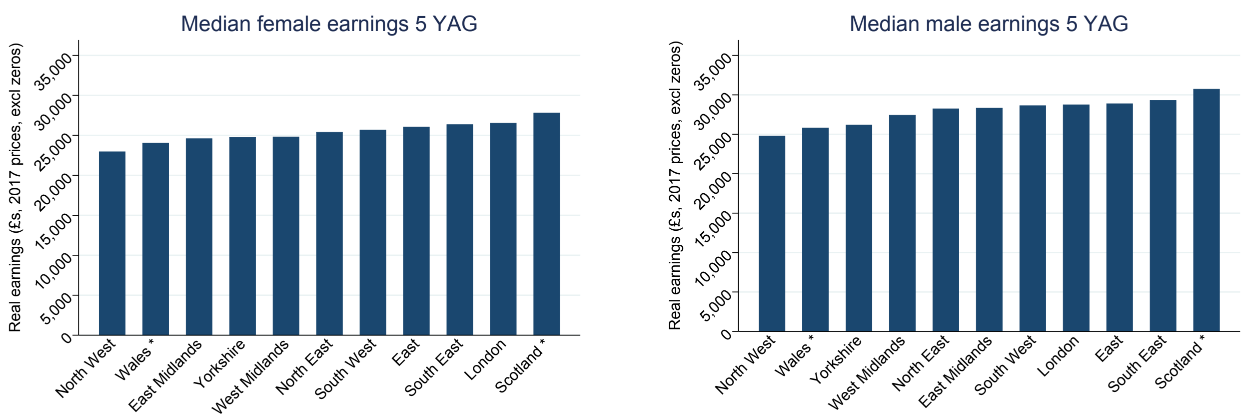



Figure 6 shows average earnings 5 years after graduation (YAG) by geographic region of the institution graduates went to. Overall, graduates from institutions in different parts of the country earn similar amounts, but there is some variation. Graduates from universities in and around London typically have higher earnings than those from the North West of England and Wales. It is worth noting however that this data only includes the earnings of graduates from Scottish and Welsh institutions who went to school in England. This may not be representative of the average graduate at those institutions. These differences between earnings of graduates from institutions in different regions could be due to graduates getting access to certain labour markets as a result of the location of study. We can never observe the same institution in multiple locations and so in our main specification we do not control for institution region. It is worth bearing in mind that some of the institutional returns may be a result of the institution location.

Figure 6: Real earnings by institution region (conditional on sustained employment)




Note: Average earnings for institutions in Wales and Scotland only reflect the students from English schools (as they have to have valid NPD records to appear in the sample). This is to be consistent with later results.

## 3.2 Earnings differences by subject and institution

We now look at some descriptive earnings differences by subject and higher education institution. Figures 7 and 8 show the average earnings 5 years after graduation by degree subject for women and men, respectively. In line with previous literature, we see large differences in average earnings across the degree subjects (Britton et al., 2016). Medicine and economics graduates have average earnings in excess of £40,000 per year 5 years after graduation, while the average creative arts graduate only earns around £20,000.

Figure 7: Mean earnings 5 years after graduation by subject for women in sustained employment

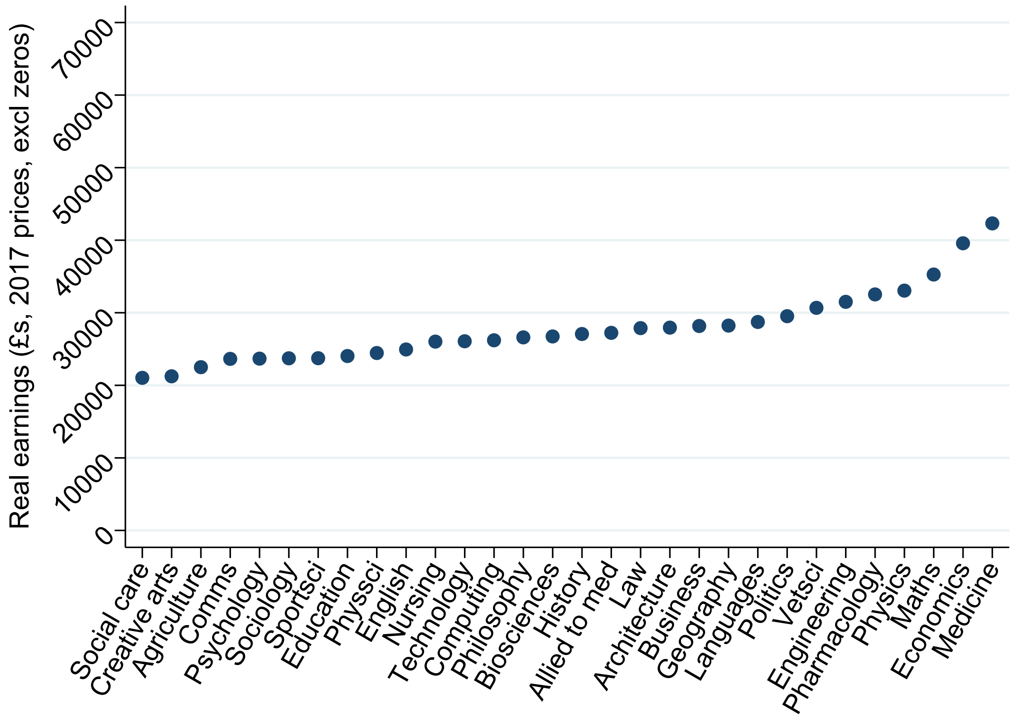
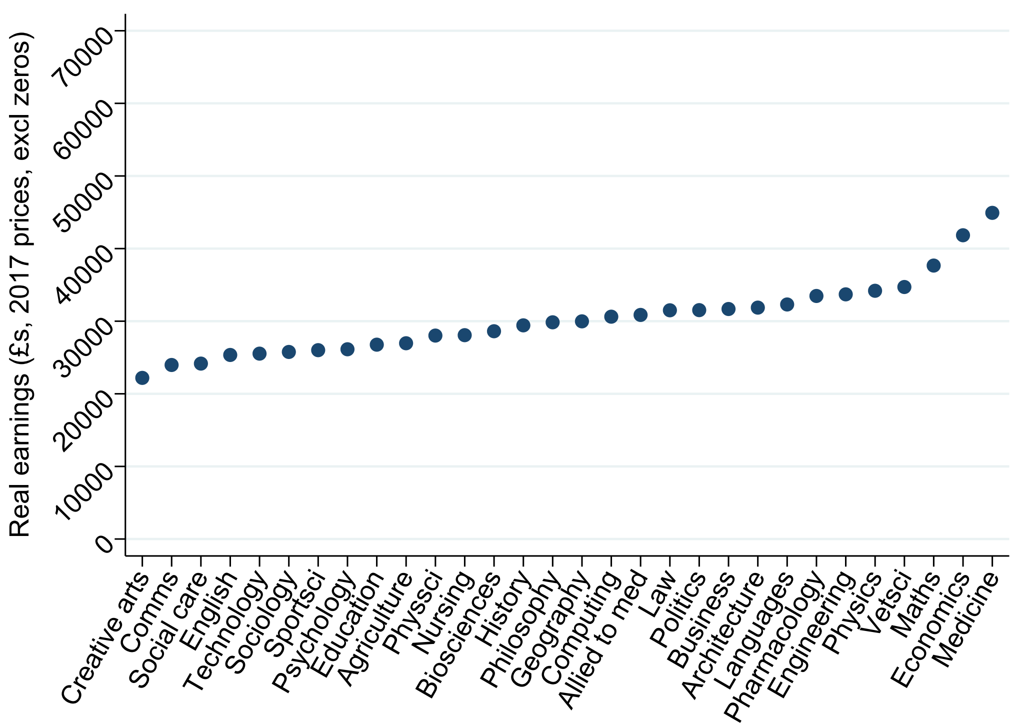


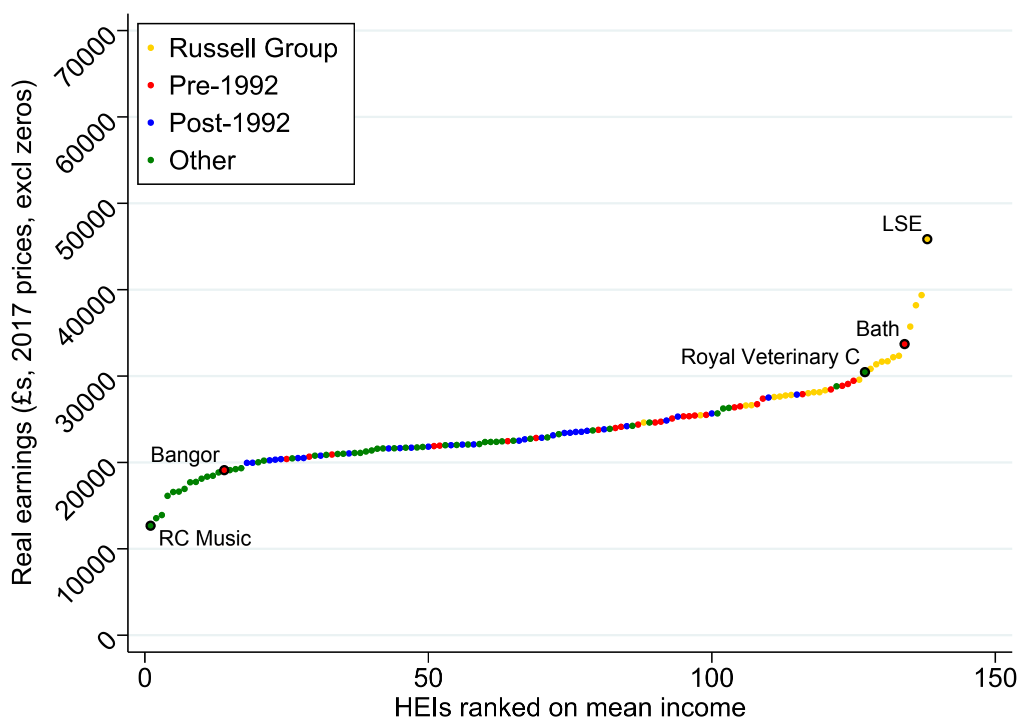

Figure 8: Mean earnings 5 years after graduation by subject for men in sustained employment




There are also considerable differences in the average earnings between the graduates of different institutions, as shown in Figures 9 and 10. Graduates of the London School of Economics on average have the highest earnings by quite some distance, with the average female LSE graduate earning around £45,000 and the average male earning more than £60,000. Institutions such as Trinity College and the Royal College have the lowest average earnings, at around £13,000 5 years after graduation. These figures do not include self-employment earnings, which may potentially be more important for those institutions, given the much larger share of self-employment records we see for creative arts graduates in Table 3. Overall, traditionally high-status universities such as the Russell Group and those established before 1992 tend to have the highest earnings.[13]

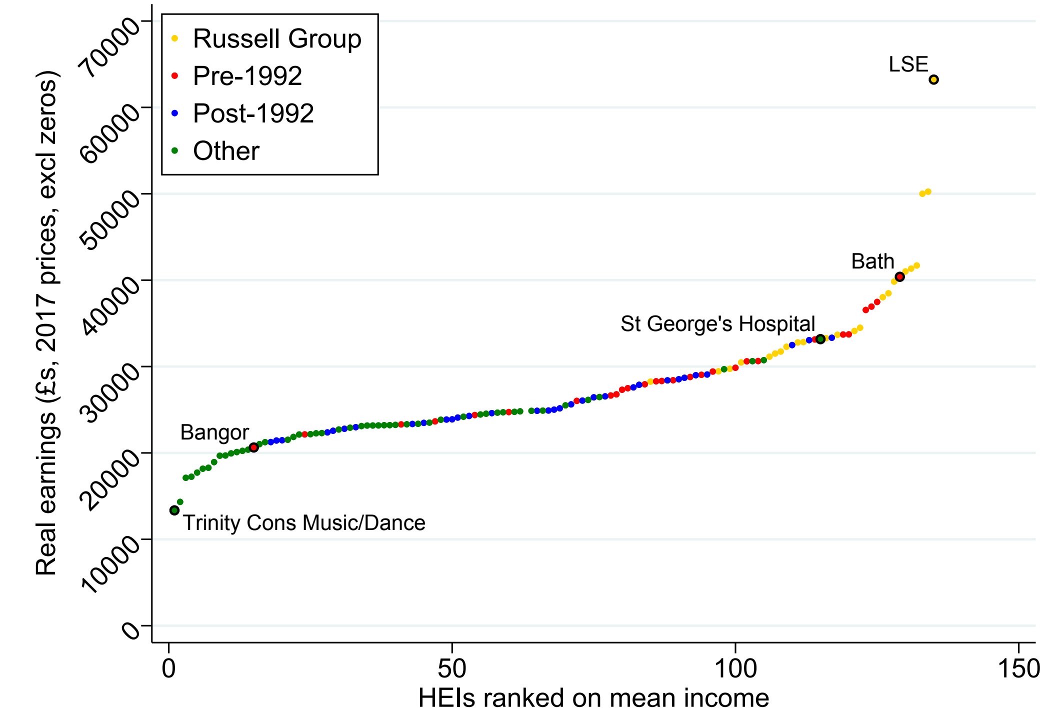
These differences in average earnings between subjects and institutions could be the result of differences between the types of students each of these degrees take or the direct impact of attaining the qualification itself. The primary contribution of this report is to separate these two effects, by taking account of differences in observable student characteristics.

Figure 9: Mean earnings 5 years after graduation by HEI for women in sustained employment




[13]In this report we divide institutions into four groups: "Russell Group" which is a self-selected association of elite research institutions; "Pre-1992" institutions which are traditional universities that obtained university status prior to the '1992 Further and Higher Education Act'; "Post-1992" institutions with polytechnic or central institution roots; and "Other"institutions which are post-1992 institutions without polytechnic or central institution roots. See the Online Appendix for a list of the institutions in each group.

Figure 10: Mean earnings 5 years after graduation by HEI for men in sustained employment




# 4 Methodology

The objective of this report is to identify the *causal* impact of studying a specific subject or at a given institution on later life earnings. However, many characteristics, in addition to university degrees, impact individuals' earnings, and different courses typically take students with different characteristics. The methodological challenge is to account for all the differences between students studying different courses that might affect earnings or employment prospects to isolate the true impact of the university course. In this section, we set out our method for controlling for these differences along with the assumptions that this implies, and detail our model of graduates' earnings and the interpretation of the estimated parameters.

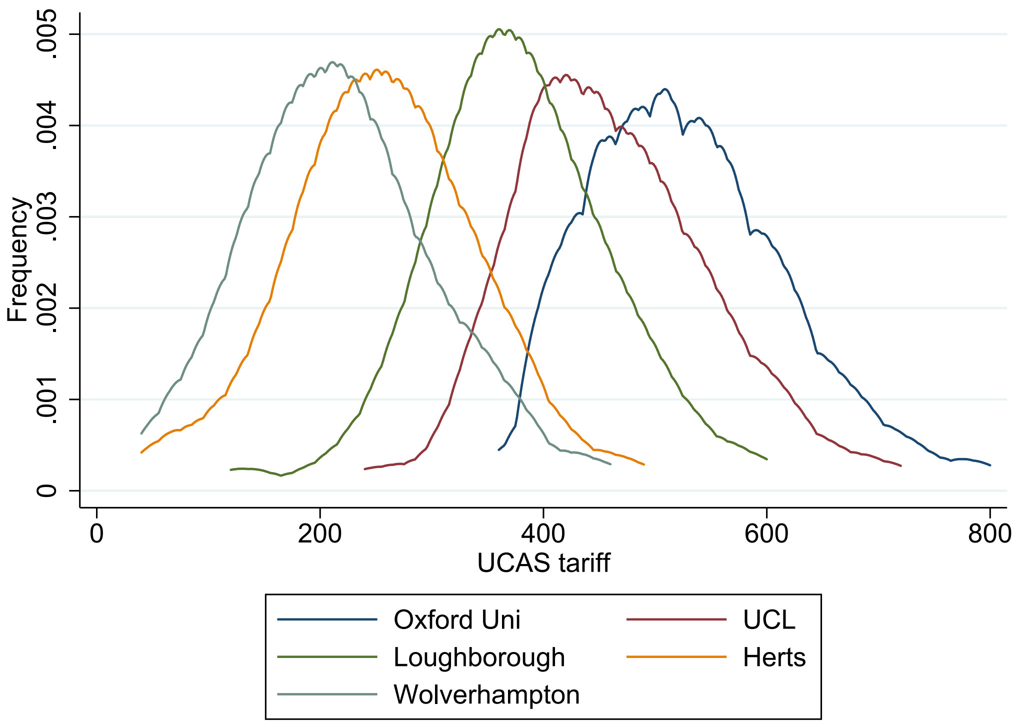
## 4.1 Controlling for selection into courses

There are clear differences between students studying different subjects or at different institutions. Figure 11 shows the extent of sorting of students into institutions based on ability. Clearly, students with high ability (measured here by UCAS points tariff) typically attend a higher-status university such as the University of Oxford or University College London. If underlying ability has a direct impact on earnings over and above university degrees then failure to control for these differences would bias our results.

Similarly, there are considerable differences between students who study different subjects. As shown in Figure 12, almost all men studying for maths and physics degrees have a maths A- or AS-level compared to only around 5% of students studying communications and sociology. Figure

13 shows the differences in the proportion of men who have a science A- or AS-level by university subjects. Again, there are significant differences across courses: medical and biological sciences students almost all have an A- or AS-level in a science subject compared to less than 15% of creative arts and communications students.[14]

Figure 11: Distribution of UCAS points by university




[14] Equivalent Figures for women are in the Appendix.

Figure 12: Share of students studying each subject with a maths A- or AS-level, men

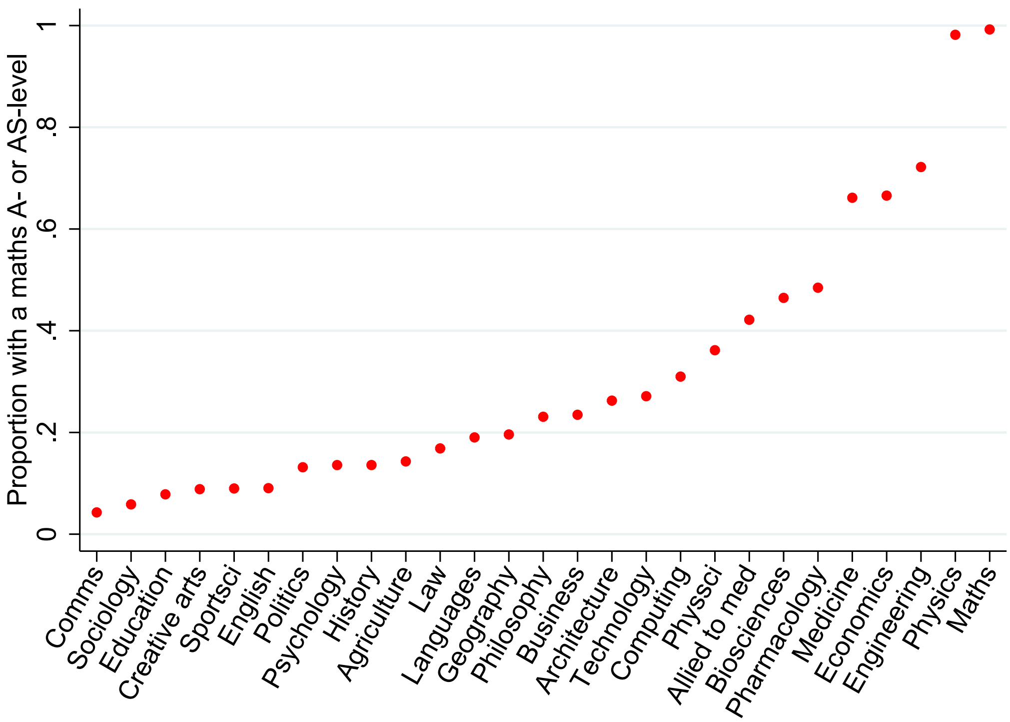
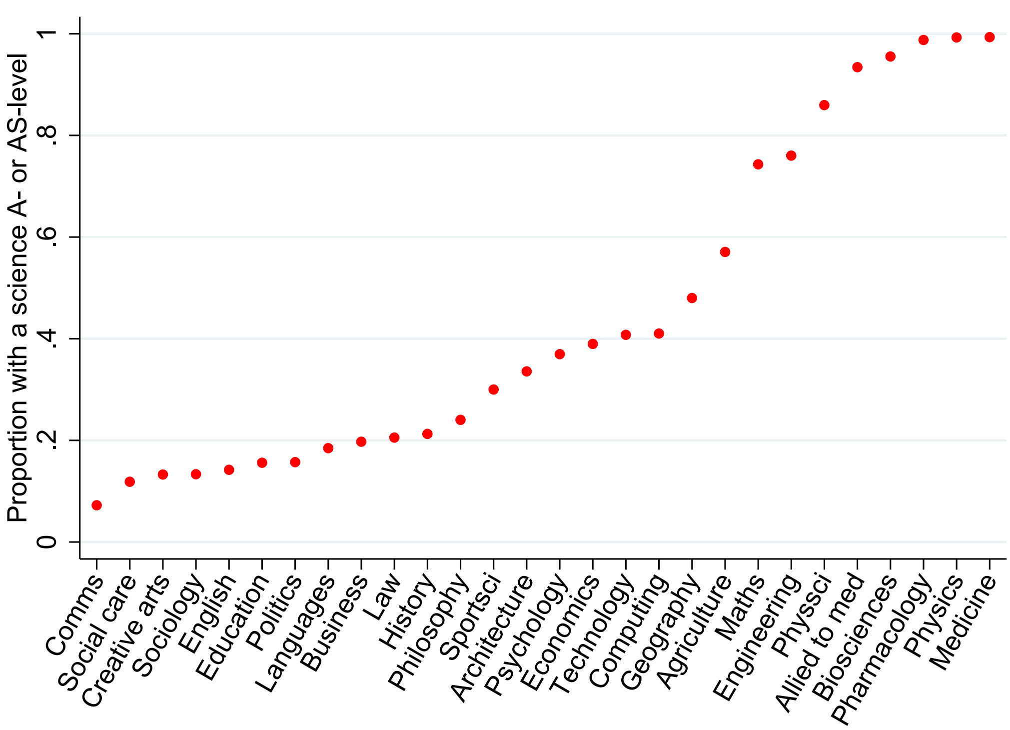



Figure 13: Share of students studying each subject with a science A- or AS-level, men




Importantly, these differences between students are observable in the data, and because there is considerable overlap between different subjects and institutions (i.e. having a high UCAS tariff does not entirely determine which institution a student attends or having a Maths A or AS-level does not perfectly identify a given subject studied) it is possible to separately estimate the effect of these additional characteristics on earnings and isolate the impact of university courses. This highlights the value of the rich background characteristics observed in the NPD and HESA data as described in the previous section.

The simplest approach for controlling for observed differences between students taking different subjects would be to control for observable characteristics using a linear functional form using an Ordinary Least Squares (OLS) estimation, as in the following:[15]

$$Y_i = X_i'\gamma + Subject_i'\beta + \epsilon_{it} \tag{1}$$

where $Y_i$ is the outcome measure of earnings, $Subject_i'$ is a vector of indicators for the subject studied and $X_i'$ is a vector of observable characteristics. In our estimation, $X_i'$ includes:

- Prior attainment - measured by GCSE and A-level points score;
- Subject mix of age 18 qualifications;
- School type (independent or state school);
- SES background;
- Ethnicity;
- Region of applicant;
- Cohort of graduation;
- Age started university;
- "Living at home".[16]

$X_i'\gamma$ gives the impact of these background characteristics on earnings and the vector of coefficients $\beta$ shows the impact of degree subjects on graduates' earnings. Note that we intentionally do not include degree classification in the $X$ variables, as this is on the causal path. That is, an individual might be more likely to get a first class degree if they chose one university over another, and that should be reflected in our outcomes, rather than adjusted for.

This methodology makes a number of important assumptions. First, there is a strong functional form assumption. The model implies that the characteristics in $X_i'$ have a linear impact on earnings. In practice, this may not be the case. Characteristics may have non-linear impacts or interactions between some characteristics may be important. This is always an issue when comparing groups which are observationally disparate.

Second, not all of the differences between students that can affect earnings are observed in the data. For example, non-cognitive skills and preferences for different types of work are not observed

[15] Example is shown for a subject estimation although similar specifications could apply to HEI or course effect estimation.

[16] As proxied by whether the graduate goes to university in the same region as they went to school.

but do have the potential to impact earnings. For example, students who go to the London School of Economics might have a preference for working in finance jobs. If these characteristics differ systematically between institutions or subjects then they might bias our estimates. To the extent that this occurs our estimates reflect the impact of the specific course combined with the effect of systematic differences in unobservable characteristics.

Third, this proposed methodology has implicitly assumed that the returns to specific courses are homogeneous - that is, that all types of student, on average, could be expected to receive the same return from studying a given course (even if the levels of earnings differ due to differences in background characteristics). This is a strong assumption.[17] For example, we might consider that a student with lower prior ability or without a science A-level might get less benefit out of a medicine or physics degree if they understand less of the material. We explore the extent of heterogeneity of our estimates by SES background and prior attainment in the results section.

A possible solution to the first of these issues is to use a matching methodology which only compares individuals in each group who look similar on observable characteristics. However, this is clearly impractical when considering a large number of treatment groups as in this analysis. Instead, we improve on the standard OLS estimation by using an Inverse Probability Weighted Regression Adjustment (IPWRA) - following Wooldridge (2007). This process weights individuals in each treatment group (university-subject combination) who look more similar to individuals not in that treatment group more heavily. Hence, the final weighted sample has treatment groups that are more similar on observable characteristics and so less weight is placed on the functional form assumption. This is done by explicitly modelling the probability each individual studies the course they take using observable characteristics and weighting individuals with the inverse of this probability. We elaborate further on this methodology in the following subsection. We note carefully that this approach does not resolve the remaining two issues of unobservable student differences and the assumption of homogeneity, which should be kept in mind when making conclusions based on our results.

## 4.2 Inverse Probability Weighting first stage

To model the probability an individual studies a specific subject at a given institution we use a three-step nested multinomial logit.[18] We estimate the probability an individual studies each subject as a function of observable characteristics $Z'$.[19] Then, conditional on the subject they study we estimate the probability they attend one of four types of institution (Russell Group, Pre-1992, Post-1992, Other). Finally, conditional on the subject studied and type of university we estimate the probability of attending each specific university. This estimation process is given by the following equations:

[17] If the effects of degrees are heterogeneous across students our estimates will be some weighted average of the different effects. This will not necessarily be the overall Average Treatment Effect (effect across the whole population) or the Treatment Effect on the Treated (effect for those doing the specific degree).

[18] Typically in the existing applications of the method, the IPWRA first stage is modelled using a single multinomial logit first stage; with more than 1,600 possible courses, this is impractical.

[19] The set of observable characteristics varies slightly between the steps of the nested logit. For Steps 1 and 2 $Z_1'$ includes: KS4 and KS5 attainment and subject choices; SES; gender; ethnicity; and school type. For Step 3 $Z_2'$ excludes subject choices as these are unlikely to be an important determinant of university conditional on subject and university type.

$$Pr(Sub = s_j) = \frac{exp(Z_1'\beta_j^S)}{\sum_k exp(Z_1'\beta_k^S)} \forall k \neq j, k \in Sub \tag{2}$$

$$Pr(UniType = UT_h) = \frac{exp(Z_1'\beta_h^T)}{\sum_i exp(Z_1'\beta_i^T)} \forall i \neq h, i \in UniType\, if\, Sub = s_j \tag{3}$$

$$Pr(Uni = U_q) = \frac{exp(Z_2'\beta_q^U)}{\sum_p exp(Z_2'\beta_p^U)} \forall p \neq q, p \in Uni\, if\, Sub = s_j\, and\, UniType = UT_h \tag{4}$$

Multiplying the predicted probabilities from these three equations gives the probability each individual studies the course they do. The weights are then calculated as the inverse of this probability. As a result, an individual who looks more similar to those who do not take the same course is weighted more heavily. We drop any individuals with very extreme weight[20] (i.e. very small probability of doing the course they study) to avoid placing a heavy weight on a small number of students, particularly given that these individuals are highly unusual.

Table 4 shows the impact of applying these weights on the summary statistics of our sample for men. There is very little impact on the overall summary statistics. However, the weighting does change the average characteristics at specific institutions or specific courses (Imperial College London and business studies are shown as illustrations with some example characteristics). Students at Imperial are, on average, higher ability, more likely to have a maths or science A- or AS-level, more likely to be from London and less likely to be white than the average HE entrant. Applying the IPWRA weights results in a sample of Imperial students who look more similar to the average student. However, the differences are not entirely eliminated. The treatment group of students studying for business degrees is also distinct from the average HE participant in observable characteristics, but the differences are considerably smaller than for the Imperial group. Here the IPWRA does almost eliminate the difference between the subgroup and the overall sample. This highlights the value, and limitations, of the IPWRA approach.

Table 4: Raw and IPWRA-weighted sample statistics for men used in the final sample

| | All | | Imperial | | Business | |
|---|---|---|---|---|---|---|
| | Raw | Weighted | Raw | Weighted | Raw | Weighted |
| FSM | 0.05 | 0.04 | 0.03 | 0.03 | 0.07 | 0.05 |
| Ind school | 0.17 | 0.15 | 0.37 | 0.30 | 0.15 | 0.16 |
| London | 0.18 | 0.17 | 0.22 | 0.22 | 0.17 | 0.17 |
| Maths A- or AS-level | 0.31 | 0.25 | 0.90 | 0.84 | 0.23 | 0.25 |
| Science A- or AS-level | 0.39 | 0.37 | 0.97 | 0.92 | 0.20 | 0.30 |
| UCAS tariff | 270 | 260 | 430 | 390 | 230 | 240 |

### 4.3 Model of earnings

We model the impact of university subjects, institutions and specific courses (institution-subject combinations) on earnings 5 years after graduation (or expected date of graduation) for HE en-

[20] Those above the 95th percentile.

trants.[21] This estimation focuses on those who are in 'sustained employment'.[22] In the following subsection, we detail a separate model which explores the impact of HE on employment prospects. We exclude the first two years of earnings after graduation as these are likely to be noisy and not informative of the returns to subjects or institutions. This means the final sample for our earnings model includes all those who enter university and graduate (or expected to graduate) between 2007 and 2013.

To model earnings we use a pooled cross-sectional model. This extends the model given by Equation 1 to include multiple earnings observations per individual. In doing so, we increase the efficiency of our estimates by reducing the randomness resulting from the transitory component of earnings. Our outcome is real log earnings between 3 and 7 years after graduation.[23] We only have Self Assessment data between 2013-14 and 2015-16; hence including self-assessment earnings would mean that we would be unable to use earnings information from earlier years. This would severely reduce our sample size and hence reduce the reliability and precision of our estimates. As a result, our main estimates will exclude self-employment income. In Appendix Figures A1 and A2 we show results on the subset of years for which we have self-assessment income. The inclusion of self-employment income for those years does not seem to significantly impact our results.[24]

We model log real earnings as a function of observable characteristics, $X_i'$, the treatment of interest (subjects, $Subject_i'$, institutions, $HEI_i'$ or courses, $Course_i'$) and a treatment-specific time trend ($Subject_i' * t$, $HEI_i' * t$ or $Course_i' * t$). This is to allow different courses to have different age-earnings profiles.[25] When modelling the returns to institutions we control for the subject studied (and subject-specific time trends) to prevent differences in subject mix affecting our results (e.g. preventing an institution estimate purely being driven by the institution only offering high-return subjects) and vice versa.

Hence, we estimate the following equations:

$$Y_{it} = X_i'\gamma + Subject_i'\delta_1 + (Subject_i * t)'\delta_2 + HEI_i'\rho_1 + (HEI_i * t)'\rho_2 + \epsilon_{it} \tag{5}$$

$$Y_{it} = X_i'\gamma + Course_i'\beta_1 + (Course_i * t)'\beta_2 + \epsilon_{it} \tag{6}$$

where both the subject and institution returns are derived from Equation (5) and the course returns are derived from Equation (6). Our main outcome of interest is earnings 5 years after graduation to avoid results being masked by the early-career volatility in earnings without limiting our sample size too much. From the above equations our outcomes of interest are given by the following:[26]

[21] Figures in this report include all entrants to HE courses and hence include those who drop out from university. We define dropouts as individuals who drop out and do not start another degree during the time period for which we observe them. Those that switch course are counted as the course in which they graduate (or the last course they study). Figures A3 and A4 in the Appendix compare the results including and excluding dropouts and show that this does not have a significant impact on the results. Subject, institution and course returns for graduates only are shown in an Online Appendix.

[22] This is defined by the Department for Education as being in employment (with a PAYE record) in at least 5 out of the last 6 months of the financial year.

[23] Earnings are capped at the 1st and 99th percentile to reduce the sensitivity to outliers.

[24] Self Assessment filing rates increase with age, and consequently the importance of including self-employment income may increase as more years of data become available and we can look at earnings at older ages.

[25] A linear time trend is appropriate for the short time period we are modelling. As more years of outcome data are added it may be sensible to move to a higher-order polynomial.

[26] Note that the time trend is set to zero 3 years after graduation.

- **Subject returns** are given by $\delta_1 + 2\delta_2$
- **HEI returns** are given by $\rho_1 + 2\rho_2$
- **Course returns** are given by $\beta_1 + 2\beta_2$

All results are estimated separately by gender. All variables are demeaned (and there is no constant) and so estimates show the impact of subject/institution/course relative to the average earnings of a man/woman who enters higher education.

### 4.4 Model of employment

We also model the impact of subjects and institutions on the employment rate of their students. In the earnings model the lack of self-employment data (for much of the sample period) was not a considerable issue because we focus only on individuals who have PAYE records (and test the effect of this constraint in our robustness checks). However, when looking at the impact on employment this is not possible. If we focused on the impact of different courses on the probability individuals are in PAYE employment we would be penalising any courses which led to a higher rate of self-employment.

Instead, we restrict our sample to only the years for which we have PAYE and Self Assessment (SA) data (2013-14 to 2015-16). We model the impact of subject and institution on the probability of being in sustained employment, self-employment or further study. By restricting our sample to this shorter period we are not able to estimate the impact of specific courses (subject-institution combinations) due to the sample size. Our model for employment outcome is a pure cross-sectional model of employment outcomes 5 years after graduation on individual characteristics, subject studied and institution attend, given by the following equation:

$$Y_i = X_i'\gamma + Subject_i'\delta + HEI_i'\rho + \epsilon_i \tag{7}$$

Again, subject and institution effects are included in the same equation to control for difference in subject mix between institutions. This equation is estimated using a Linear Probability Model estimation run separately by gender and all variables are demeaned.[27] As a result, the vectors $\delta$ and $\rho$ give impacts of subjects and institutions on employment prospects relative to the average HE entrant respectively.

## 5 Subject estimates

We start by investigating the relative returns to different degree subjects. Table 5 shows the subject-level estimates, split by gender. Columns (1) and (6) present the raw earnings percentage differences by subject compared to the gender-specific average, for women and men respectively. Note that the earnings data is for HE participants and includes both graduates and dropouts. The

[27] An alternative approach would be to estimate a non-linear model such as a Probit or Logit estimation. These models have some preferable features including non-linear marginal effects preventing prediction outside the unit interval. However, estimating the average marginal effect of many parameters in a large dataset such as this one is very computationally intensive.

highest-earning subject is medicine for both women and men. Female and male medical graduates earn 74% and 63% more than the average graduate 5 years after graduation, respectively.[28] Creative arts has the lowest earnings, with female and male students earning 21% and 29% less than the average student 5 years after graduation.

Columns (2) and (7) add controls for the prior attainment of students. This includes the set of A-level courses taken (usually at 18), the total point score achieved on those A-levels, the total point score achieved on GCSEs taken at age 16 and test scores in maths, English and science at age 11. This clearly has a significant impact on the estimates. The estimated return to a medical degree falls to 37% for women and 24% for men. This is because typically high-ability individuals earn more in the labour market regardless of the degree they study and medical students are higher ability than the average student.

Columns (3) and (8) add further controls for the background characteristics of the students, including ethnicity, socio-economic status, school type and a measure of special educational needs. Overall, including those characteristics has limited impact on our estimates over and above the impact of including prior attainment. That is not to say these characteristics do not affect future earnings. As shown in Appendix Table C1 graduates from independent schools and the top quintile earn around 7% to 9% more than those graduates from the lowest SES backgrounds, even after conditioning on all other characteristics, degree subject and institution. Similarly, adding an extra A at A-level (120 UCAS) increases earnings of graduates by around 3%. The Online Appendix shows that differences persist between ethnicities, with Bangladeshi, Chinese and black African students earning around 10% less on average.

Columns (4) and (9) then add controls for the institution the student attends. This is to remove the confounding effect of institutional quality which may be related to the subjects offered by different types of institution. For example, sports science courses may disproportionately be offered by institutions with below-average returns. We want to remove the effect of these institutions with below-average returns from our estimate of the returns to sport science. Including institutional controls also has limited impact on the estimates, over and above the controls that are already included. The coefficients on the control variables included in these regressions are shown in the Appendix Table C1 broadly follow the expected patterns: high-ability students, those who take maths A-level, students from rich backgrounds and those who attend private schools all earn more.[29]

Finally, in columns (5) and (10) we move to our preferred IPWRA specification, weighting individuals in each treatment group who look more similar to the non-treated group more heavily. This does not significantly impact our results, suggesting that in general our estimates are not overly sensitive to the treatment or weighting of any specific individuals. The only real exceptions are veterinary sciences for women and nursing for men, for which the IPWRA estimates are considerably different to the OLS estimates in columns (4) and (9). This is likely driven by veterinary sciences being a small, unusual course, and by very few men studying nursing.

[28] This ordering of subjects is slightly different to the data in Figures 7 and 8 because these are model-based estimates of log earnings rather than raw averages.

[29] A full list is provided in the Online Appendix.

Table 5: Subject estimates for men and women (in %)

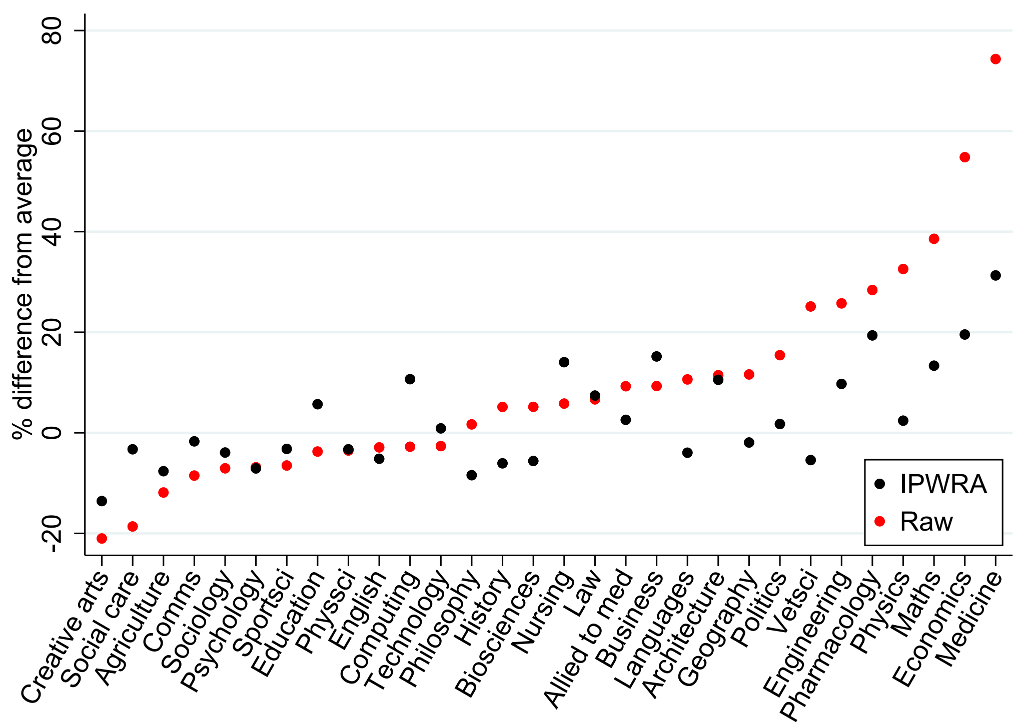
| | Women | | | | | Men | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | | | | IPWRA | OLS | | | | IPWRA |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Agriculture | -11.9 | -9.1 | -9.6 | -10.8 | -7.6 | -6.2 | -2.7 | -3.2 | -5.8 | -4.7 |
| Allied to med | 9.3 | 4.8 | 5.7 | 5.6 | 2.6 | 7.2 | -0.7 | 1.2 | 2.1 | 1.6 |
| Architecture | 11.5 | 5.0 | 5.4 | 4.7 | 10.5 | 6.3 | 8.9 | 9.1 | 9.3 | 11.0 |
| Biosciences | 5.2 | -2.5 | -1.3 | -3.2 | -5.6 | -2.5 | -8.4 | -6.9 | -8.9 | -8.4 |
| Business | 9.3 | 13.8 | 13.5 | 13.6 | 15.2 | 6.6 | 10.6 | 11.5 | 12.0 | 14.8 |
| Comms | -8.5 | -1.0 | -1.2 | -0.6 | -1.7 | -20.1 | -9.0 | -8.4 | -7.1 | -5.9 |
| Computing | -2.8 | 6.7 | 8.9 | 8.7 | 10.7 | 3.3 | 10.5 | 12.3 | 12.6 | 14.4 |
| Creative arts | -21.0 | -16.0 | -15.9 | -13.7 | -13.6 | -29.2 | -21.1 | -20.9 | -17.8 | -17.9 |
| Economics | 54.8 | 30.4 | 28.8 | 25.7 | 19.5 | 40.9 | 21.2 | 21.5 | 20.1 | 18.6 |
| Education | -3.7 | 3.7 | 4.3 | 6.1 | 5.7 | -5.1 | 5.8 | 6.7 | 7.8 | 7.1 |
| Engineering | 25.7 | 14.7 | 15.0 | 11.8 | 9.7 | 16.1 | 9.9 | 10.2 | 8.1 | 8.8 |
| English | -2.9 | -6.0 | -5.4 | -5.3 | -5.2 | -16.6 | -17.7 | -16.7 | -16.0 | -13.0 |
| Geography | 11.6 | 2.5 | 1.9 | 0.2 | -1.9 | 2.1 | -3.5 | -3.2 | -4.2 | -3.5 |
| History | 5.2 | -1.8 | -2.3 | -3.9 | -6.1 | -2.7 | -7.0 | -6.6 | -7.3 | -7.2 |
| Languages | 10.6 | -0.3 | -1.4 | -4.4 | -4.0 | 4.9 | -6.6 | -8.0 | -10.3 | -10.2 |
| Law | 6.7 | 4.1 | 6.3 | 6.9 | 7.4 | 4.9 | 1.2 | 4.5 | 6.0 | 7.9 |
| Maths | 38.6 | 15.7 | 17.0 | 14.4 | 13.4 | 26.8 | 7.2 | 8.8 | 6.2 | 7.3 |
| Medicine | 74.3 | 37.0 | 36.2 | 33.0 | 31.3 | 62.7 | 23.7 | 22.4 | 20.8 | 24.8 |
| Nursing | 5.8 | 14.4 | 14.8 | 13.5 | 14.1 | 0.0 | 11.0 | 10.3 | 4.2 | 12.8 |
| Pharmacology | 28.4 | 18.1 | 20.9 | 20.3 | 19.4 | 11.4 | 4.8 | 8.9 | 10.0 | 8.3 |
| Philosophy | 1.7 | -4.7 | -5.1 | -7.7 | -8.4 | -0.8 | -9.2 | -9.4 | -11.6 | -10.1 |
| Physics | 32.6 | 8.1 | 8.1 | 4.3 | 2.4 | 16.4 | -1.8 | -1.2 | -4.9 | -3.3 |
| Physsci | -3.5 | -4.8 | -3.7 | -2.9 | -3.3 | -3.7 | -5.1 | -4.0 | -4.9 | -4.2 |
| Politics | 15.4 | 7.3 | 6.7 | 3.8 | 1.8 | 4.9 | -0.4 | -0.4 | -1.5 | -1.1 |
| Psychology | -6.8 | -8.2 | -7.4 | -6.5 | -7.1 | -10.3 | -10.4 | -8.8 | -7.2 | -6.3 |
| Social care | -18.6 | -6.5 | -4.3 | -3.7 | -3.3 | -16.5 | -2.3 | 2.4 | 0.6 | -0.6 |
| Sociology | -7.1 | -2.8 | -2.3 | -3.8 | -3.9 | -11.8 | -6.2 | -5.0 | -6.2 | -5.1 |
| Sportsci | -6.5 | -0.3 | -2.1 | -2.1 | -3.2 | -11.0 | -1.9 | -2.8 | -2.7 | -4.1 |
| Technology | -2.6 | 0.6 | 1.9 | 2.4 | 0.9 | -16.7 | -9.6 | -9.0 | -7.8 | -2.8 |
| Vetsci | 25.1 | 7.7 | 5.6 | 2.0 | -5.4 | 33.0 | 5.2 | 1.5 | 0.8 | 0.9 |
| N individuals | 358,300 | 358,300 | 358,300 | 358,300 | 358,300 | 283,500 | 283,500 | 283,500 | 283,500 | 283,500 |
| N observations | 1,088,300 | 1,088,300 | 1,088,300 | 1,088,300 | 1,088,300 | 846,700 | 846,700 | 846,700 | 846,700 | 846,700 |
| Prior attainment | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Background chars | | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ |
| HE controls | | | | ✓ | ✓ | | | | ✓ | ✓ |
| IPWRA weights | | | | | ✓ | | | | | ✓ |

Notes: Coefficients shown in the table have been transformed into percentage points. See Appendix Table C1 and the Online Appendix for the coefficients on the control variables. Prior attainment controls include the set of A-level courses taken (usually at 18), the total point score achieved on those A-levels, the total point score achieved on GCSEs taken at age 16 and test scores in maths, English and science at age 11. Background characteristics include ethnicity, socio-economic status, school type and a measure of special educational needs. HE controls control for the institution the graduate attended. The IPWRA specification includes all the above controls and includes the IPWRA weights which weight individuals in each treatment group who look more similar to the non-treated group more heavily. Here, and throughout the report, Biosciences refers to a combination of Biological Sciences and Chemistry for sample size reasons.

The overall impact of controlling for the institution attended and the prior attainment and background characteristics of students doing different subjects is considerable. For example, the earnings difference between a creative arts graduate and an average graduate is reduced from -21% to -14% for women and from -29% to -18% for men. Similarly, returns to medicine for women fall by more than half from 75% to 31%.[30] This highlights that much - but not all - of the very large gap in earnings between medicine and creative arts students can be explained by differences in student intake and, in particular, prior attainment. For a direct comparison Figures 14 and 15 display the raw and IPWRA coefficients for each subject. There is a clear pattern that controlling for background characteristics tends to reduce the estimated return to high-earning subjects and increase the estimated returns to low-earning subjects, reflecting the fact that typically higher-earning subjects attract students with higher earnings potential. When we control for these differences the variation in returns is considerably reduced.

Controlling for differences in student intake also changes the order of estimated subject returns. For example, the returns to computer science, nursing and business studies degrees all increase considerably. Conversely, the estimated return to physics, languages and philosophy all decline significantly.

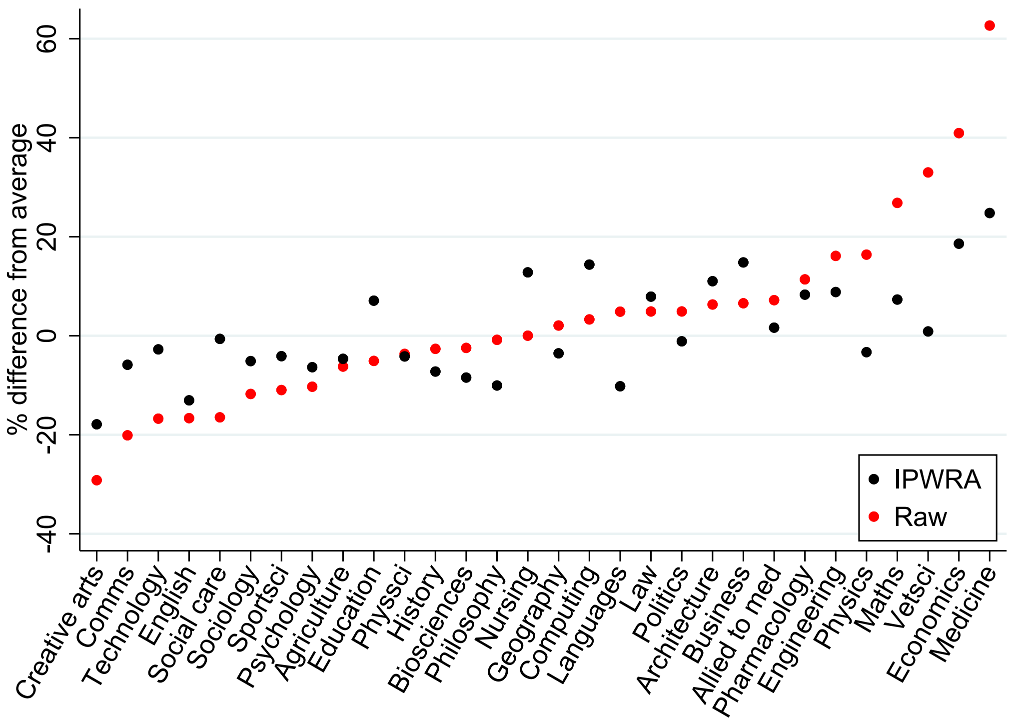
Figure 14: Subject raw and IPWRA coefficients for women




Note: Data behind this figure comes from Table 5.

[30] Although note that this effect differs across subjects depending on the selectivity of the course.

Figure 15: Subject raw and IPWRA coefficients for men




Note: Data behind this figure comes from Table 5.

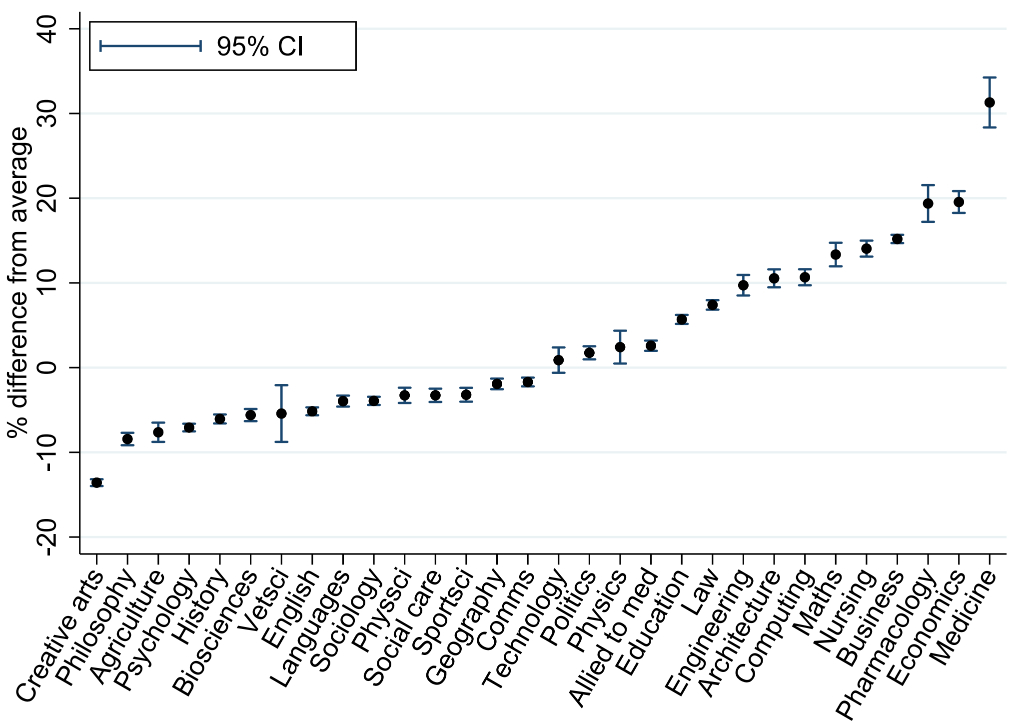
Figures 16 and 17 reorder the subjects based on the IPWRA estimates of returns and show 95% confidence intervals.[31] Medicine remains the highest returns subject and creative arts still has the lowest estimated returns. However, there is considerable reordering amongst the other subject groups. Social care, communication, nursing, computer science and business studies all rise, while physics, languages, history and philosophy all fall. The effects are not insignificant. The rank of business studies increases from only 12th for women and 9th for men in terms of raw graduate earnings to 4th and 3rd, respectively. Veterinary sciences falls dramatically, moving from seventh highest in terms of raw estimates for women to seventh lowest in the IPWRA estimates. This suggests that veterinary sciences takes students with very high earnings potential who subsequently underachieve in terms of their earnings relative to expectation.

As noted, the variation in estimated returns is somewhat smaller than the raw differences in earnings. However, there remain large, statistically significant, differences in the returns to different subjects. These Figures show that medicine and economics degrees have a return around 20% higher than the average degree 5 years after graduation, while creative arts graduates earn around 15% less than the average graduate. Figure 2 in the data descriptives section shows that average graduate earnings 5 years after graduation were around £26,000 for women and £30,000 for men. The 35 percentage point difference in returns between creative arts and medicine graduates could therefore

[31] These are the confidence intervals implied by the standard errors from the weighted estimation of Equation (5). In practice, these weights are estimated from the IPWRA first stage, and the standard errors should be adjusted to reflect this. We therefore expect the confidence intervals given here to be underestimated.

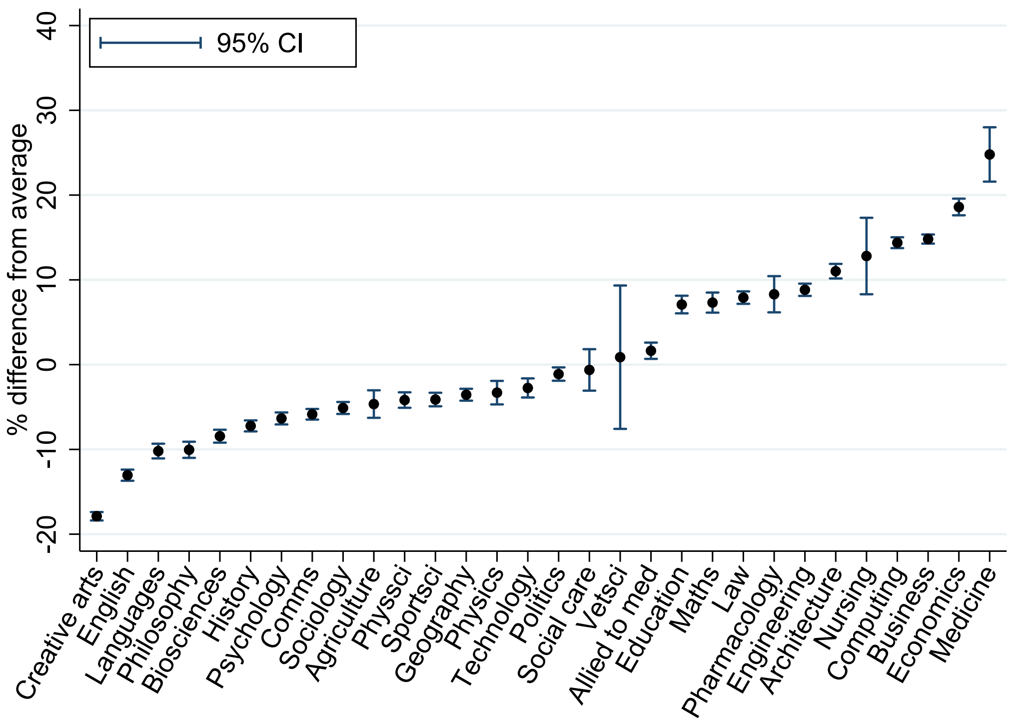
represent an earnings difference of around £10,000 per year. If this difference persists or grows over the lifecycle this will represent a considerable difference in lifetime earnings.

Figure 16: Subject IPWRA coefficients for women




Note: Data behind this figure comes from Table 5.

Figure 17: Subject IPWRA coefficients for men




Note: Data behind this figure comes from Table 5.

### 5.1 Heterogeneity in subject estimates

In this subsection, we explore how subject returns vary across subgroups. We have already seen differences by gender above. We build on this by exploring how returns vary by student socio-economic status (SES) and by level of prior attainment. Our preferred IPWRA estimates for these results are shown in Table 6. High SES is defined as individuals who attend independent school or are in the top quintile of the SES measure defined in the data section. Low SES includes individuals from the bottom two SES quintiles. High (low) prior attainment is defined as individuals with a GCSE point score above (below) the median amongst HE entrants. These estimates include controls for institution attended so these differences are not driven by certain types of individuals attending different institutions.[32]

[32]We also explore heterogeneity between those that enter HE through a traditional A-level versus non-academic route in Appendix Figures B3 and 21. We do not make strong conclusions from these results as they are based on relatively small sample sizes. This is partly because in our sample we condition on being observed in the KS5 NPD record so this will exclude those who do not attend sixth form and enter HE.

Table 6: Returns by subgroup (in %)

| | Women | Men | Women Low SES | Women High SES | Men Low SES | Men High SES | Women Low Ability | Women High Ability | Men Low Ability | Men High Ability |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Agriculture | -7.6 | -4.7 | -4.4 | -8.4 | 13.3 | -7.0 | -6.7 | -8.3 | -7.4 | 1.6 |
| Allied to med | 2.6 | 1.6 | 0.6 | 1.6 | 6.8 | -1.1 | 4.1 | 1.1 | 6.5 | -1.6 |
| Architecture | 10.5 | 11.0 | 12.3 | 13.4 | 4.9 | 10.0 | 13.1 | 8.6 | 12.9 | 6.6 |
| Biosciences | -5.6 | -8.4 | -3.7 | -7.7 | -7.6 | -9.4 | -5.7 | -5.8 | -8.4 | -7.7 |
| Business | 15.2 | 14.8 | 8.2 | 17.6 | 11.6 | 16.4 | 11.2 | 20.3 | 13.1 | 19.3 |
| Comms | -1.7 | -5.9 | -4.1 | -1.2 | -7.8 | -4.4 | -1.7 | -2.6 | -4.9 | -6.4 |
| Computing | 10.7 | 14.4 | 8.6 | 13.8 | 14.9 | 14.2 | 8.1 | 16.5 | 13.9 | 15.3 |
| Creative arts | -13.6 | -17.9 | -12.5 | -14.4 | -15.9 | -20.2 | -11.1 | -16.9 | -14.1 | -24.8 |
| Economics | 19.5 | 18.6 | 12.1 | 22.9 | 12.1 | 21.3 | 5.9 | 25.7 | 14.9 | 22.0 |
| Education | 5.7 | 7.1 | 8.3 | 5.2 | 14.5 | 2.9 | 6.8 | 5.5 | 7.8 | 5.3 |
| Engineering | 9.7 | 8.8 | 9.6 | 6.4 | 7.2 | 8.4 | 9.2 | 10.3 | 7.6 | 11.9 |
| English | -5.2 | -13.0 | -4.3 | -5.6 | -12.4 | -11.9 | -4.4 | -5.8 | -10.9 | -15.9 |
| Geography | -1.9 | -3.5 | -5.3 | -0.2 | -2.7 | -5.5 | -1.5 | -1.4 | -3.6 | -4.1 |
| History | -6.1 | -7.2 | -5.1 | -4.9 | -13.2 | -3.8 | -7.4 | -4.6 | -8.4 | -5.4 |
| Languages | -4.0 | -10.2 | -6.9 | -2.3 | -9.8 | -8.0 | -3.8 | -3.8 | -9.9 | -10.3 |
| Law | 7.4 | 7.9 | 2.9 | 10.4 | 2.1 | 9.2 | 2.1 | 12.1 | 4.4 | 11.3 |
| Maths | 13.4 | 7.3 | 11.3 | 17.2 | 5.2 | 5.4 | 6.4 | 14.9 | 4.3 | 9.1 |
| Medicine | 31.3 | 24.8 | 34.5 | 25.9 | 32.9 | 20.4 | - | 29.5 | - | 21.8 |
| Nursing | 14.1 | 12.8 | 23.2 | 8.6 | - | - | 18.7 | 6.9 | 14.4 | - |
| Pharmacology | 19.4 | 8.3 | 6.8 | 16.0 | 9.7 | 8.4 | 11.1 | 18.8 | 4.8 | 11.3 |
| Philosophy | -8.4 | -10.1 | -9.5 | -7.7 | -5.4 | -11.1 | -5.4 | -10.4 | -9.0 | -12.0 |
| Physics | 2.4 | -3.3 | -1.2 | 1.2 | 0.9 | -6.0 | -7.2 | 1.9 | -5.7 | -3.4 |
| Physsci | -3.3 | -4.2 | 0.6 | -3.8 | -0.9 | -3.6 | -3.0 | -3.2 | -5.2 | -1.9 |
| Politics | 1.8 | -1.1 | 2.2 | 3.5 | 1.0 | 0.4 | 0.3 | 3.3 | -0.8 | -1.0 |
| Psychology | -7.1 | -6.3 | -5.9 | -6.8 | -5.4 | -3.8 | -5.9 | -7.9 | -4.2 | -8.2 |
| Social care | -3.3 | -0.6 | 1.2 | -6.8 | 0.2 | - | -1.6 | -7.3 | 0.8 | - |
| Sociology | -3.9 | -5.1 | -1.9 | -4.5 | -3.6 | -5.0 | -1.6 | -5.7 | -2.1 | -11.1 |
| Sportsci | -3.2 | -4.1 | 0.8 | -3.8 | -0.2 | -4.9 | -0.8 | -5.6 | -2.0 | -9.4 |
| Technology | 0.9 | -2.8 | 1.6 | 4.4 | -2.1 | -2.5 | 2.0 | -0.3 | -5.2 | 1.9 |
| Vetsci | -5.4 | 0.9 | - | -13.5 | - | - | -5.1 | -4.5 | - | 6.2 |
| N individuals | 358,300 | 283,500 | 71,100 | 150,400 | 50,100 | 129,100 | 206,800 | 198,400 | 154,000 | 161,900 |
| N observations | 1,088,300 | 846,700 | 209,900 | 462,000 | 144,400 | 391,800 | 550,000 | 522,700 | 431,800 | 404,200 |

Notes: Coefficients have been converted into percentage points. Heterogeneity in estimates by gender, socio-economic background and ability. High SES is defined as individuals who attend independent school or are in the top quintile of SES. Low SES includes individuals the bottom two SES quintiles. High (low) prior attainment is defined as individuals with GCSE point score above (below) the median amongst HE entrants. All coefficients shown are relative to the average graduate earnings in the subgroup. A dash (-) means the result has been suppressed to prevent disclosure due to small sample sizes.

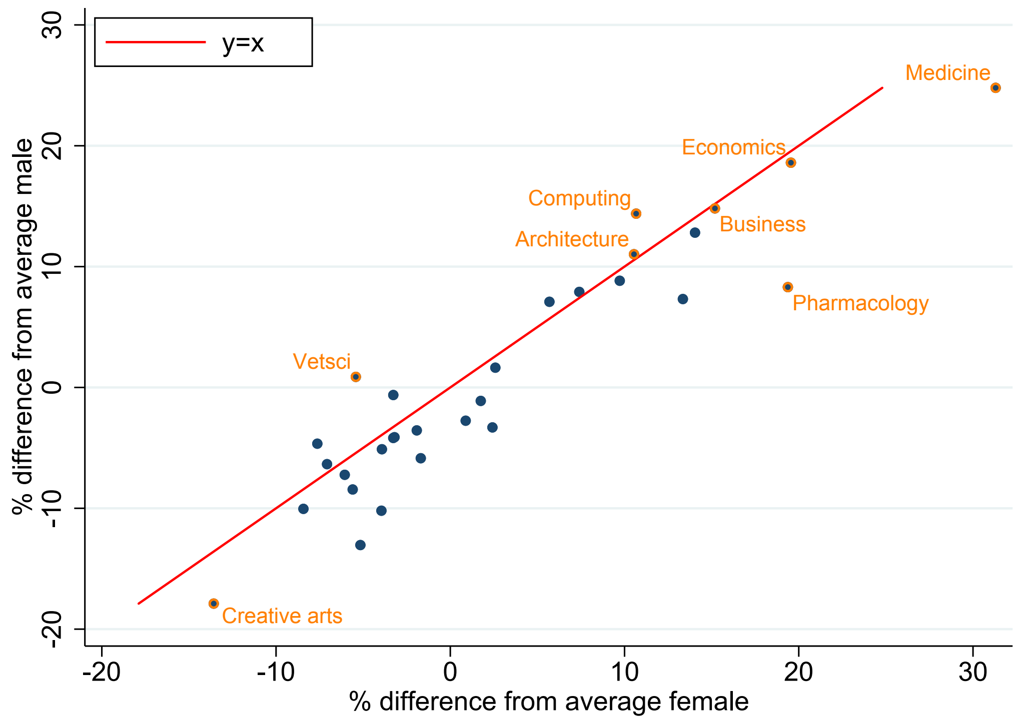
The following figures display these estimates graphically for women vs men, high SES vs low SES (for men) and high vs low prior attainment (for men).[33] All estimates show the return to each subject, compared to the average earnings for each group. This enables us to identify subjects where the return to a particular subject for one group is higher than for the other (in the top left or bottom right corners). Where estimates are on the 45 degree line, it implies that the return to that degree is similar for both groups. Note that this does not imply that individuals in both groups with that degree earn a similar amount, since the return is calculated relative to group-specific average earnings. Instead it implies that the percentage premium earned by one group with a particular subject is similar to the percentage premium earned by the other group with that subject.

Figure 18 shows the relative returns for men and women. This suggests that medicine, phar-

[33] Figures for women are shown in Appendix B.

macology, English and creative arts all have higher relative returns for women than for men. By contrast, computer science, veterinary science and agriculture have higher relative returns for men. Overall, however, there is very high correlation between the relative returns for men and women: medicine has the highest relative returns for both genders and creative arts the lowest.

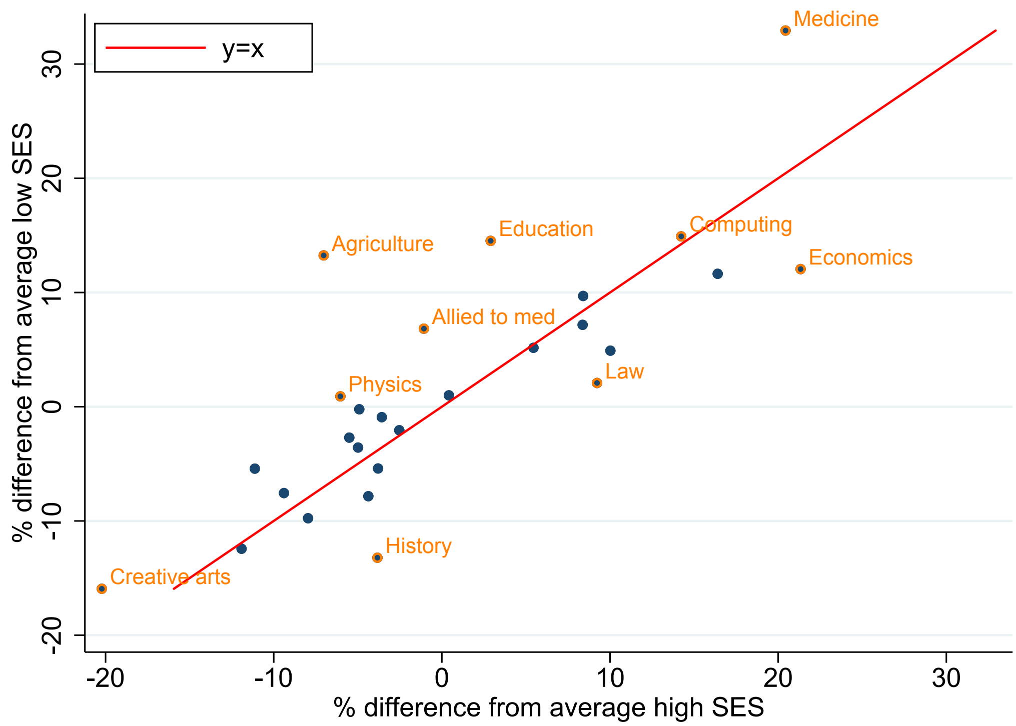
Figure 18: Subject IPWRA coefficients, men vs women




Note: Data behind this figure comes from Table 6.

Figure 19 compares the returns for high- and low-SES men. Medicine, education and agriculture appear to yield a higher return for low-SES students. By contrast, economics and history yield a relatively higher return for high-SES students. These differences in the returns may be driven by different occupations that high- and low-SES students pursue. One explanation may be that low-SES returns are higher in subjects which lead to occupations with controlled wages - such as teaching or medical services - so there is less of an advantage to being from a high-SES background. Again, there is a high degree of correlation between high- and low-SES students, albeit with some exceptions: economics has the highest return for high-SES students compared to medicine for low-SES.

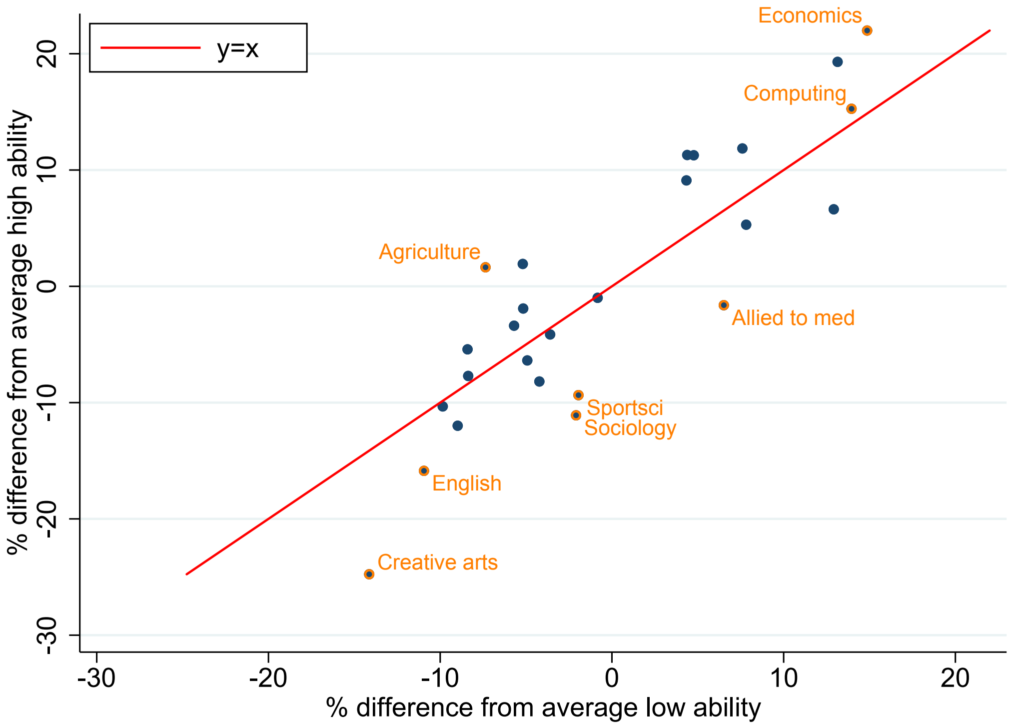
Figure 19: Subject IPWRA coefficients, high SES vs low SES for men




Note: Data behind this figure comes from Table 6.

Figure 20 compares the returns for male students with high and low prior attainment, defined by GCSE performance, which we use as a proxy for ability. Agriculture and economics degrees have higher relative returns for high-ability students, whereas degrees such as creative arts, sports science and subjects allied to medicine have higher returns for low-ability students. It is intuitive that creative arts has a particularly low return for high-ability students as these are individuals with strong academic ability which would yield a higher return in a more academic subject. The binary distinction between high and low ability means that the average ability levels within those groups is likely to differ by subject. For example the maths graduates in the low ability group will on average be at the top of this ability group, while creative arts graduates in the top ability group may be towards the lower end of this category.

Figure 20: Subject IPWRA coefficients, high ability vs low ability for men

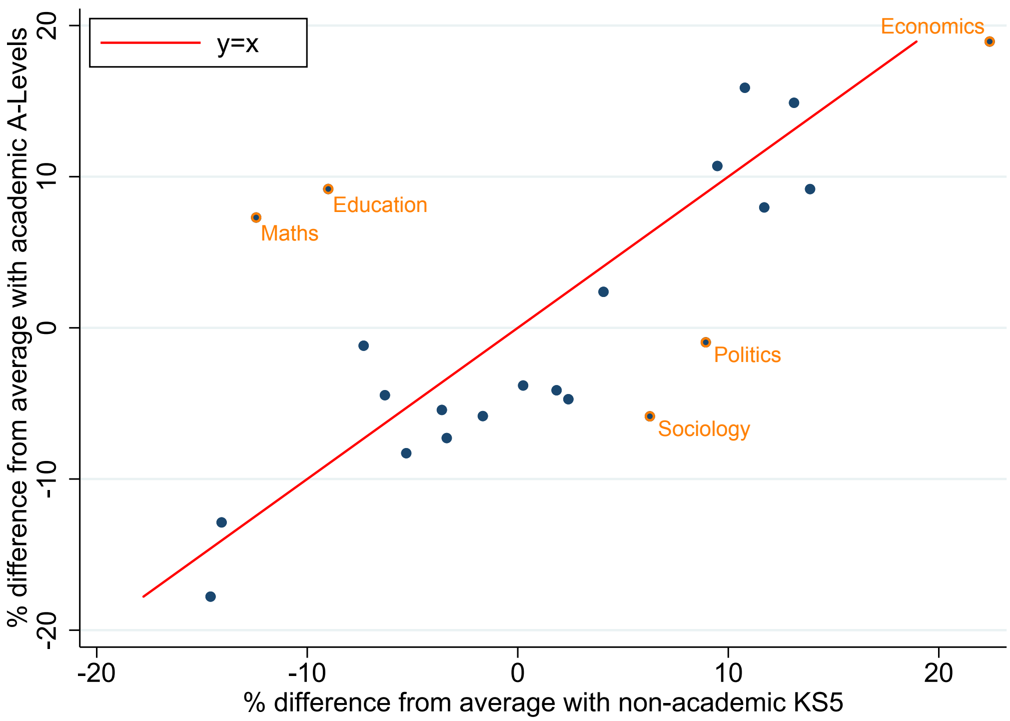



Note: Data behind this figure comes from Table 6.

Finally, Figure 21 shows the returns to studying different degree subjects for those for men who do and do not have any academic A-levels on entry to HE.[34] We define non-academic KS5 as those individuals with only vocational A or AS - levels (e.g. Hospitality, Construction or Retail) or no A or AS- levels recorded in the KS5 NPD. However, note that this analysis still only includes individuals who studied for KS5 in sixth forms and so excludes a number of individuals who attend further education colleges before university, due to data constraints. Again, there is a high correlation between the returns for those with and without academic A-levels with a few notable exceptions. Maths and education provide higher returns for those with academic A-levels while philosophy and sociology have higher returns for those without academic A-levels. However, it is important to bear in mind that the vast majority of individuals who attend sixth form and HE have at least one academic A-level and, as a result, a number of the estimates in this Figure are measured with considerable error (or missing entirely as for medicine).

[34]These estimates are not shown in Table 6 for space reasons but are included in an Online Appendix.

Figure 21: Subject IPWRA coefficients, academic A-level vs non-academic route for men




Note: The sample of graduates with non-academic KS5 qualifications is very small, hence the estimates of returns for this group have very high standard errors and few of the differences with the academic A-level group will be statistically significant. We label the subjects with the largest deviations from the $y = x$ line.

This subsection highlights an important point about the interpretation of our results earlier in this section - namely, that it is not the case that all students, regardless of their prior attainment and A-level subject choices, can expect the same return from doing a given degree.

## 6 Higher education institution estimates

We now turn to estimates of the relative returns to degrees from different higher education institutions (HEIs). The aim of this section is to show how graduates' earnings vary across institutions and to determine how much of that variation is down to the different subject mixes offered at different institutions and of course differences in student intake. Full information is provided in the Online Appendix which shows the complete set of relative return estimates for each institution in our sample.

Graphical representations of the results from these models for women and men respectively are shown in Figures 22 and 23. The coloured dots show the raw earnings differences between any particular institution and average graduate earnings across all institutions. We colour code for ease of exposition, with different colours for institutions belonging to the four mutually exclusive groups defined above.

Figure 22: HEI raw earnings and IPWRA estimates for women

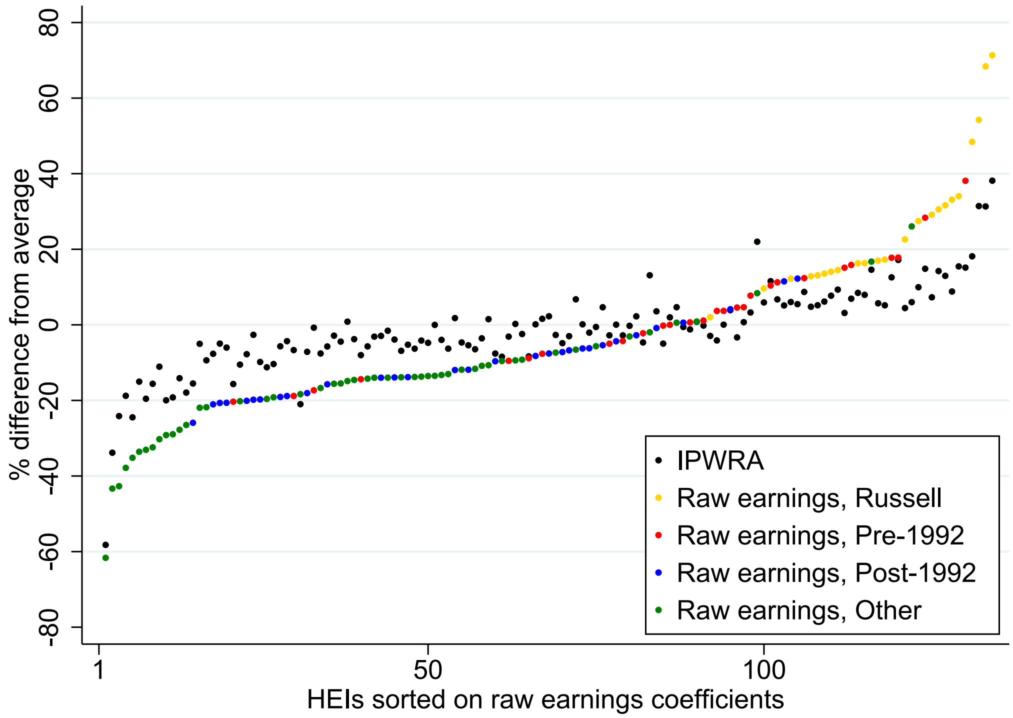
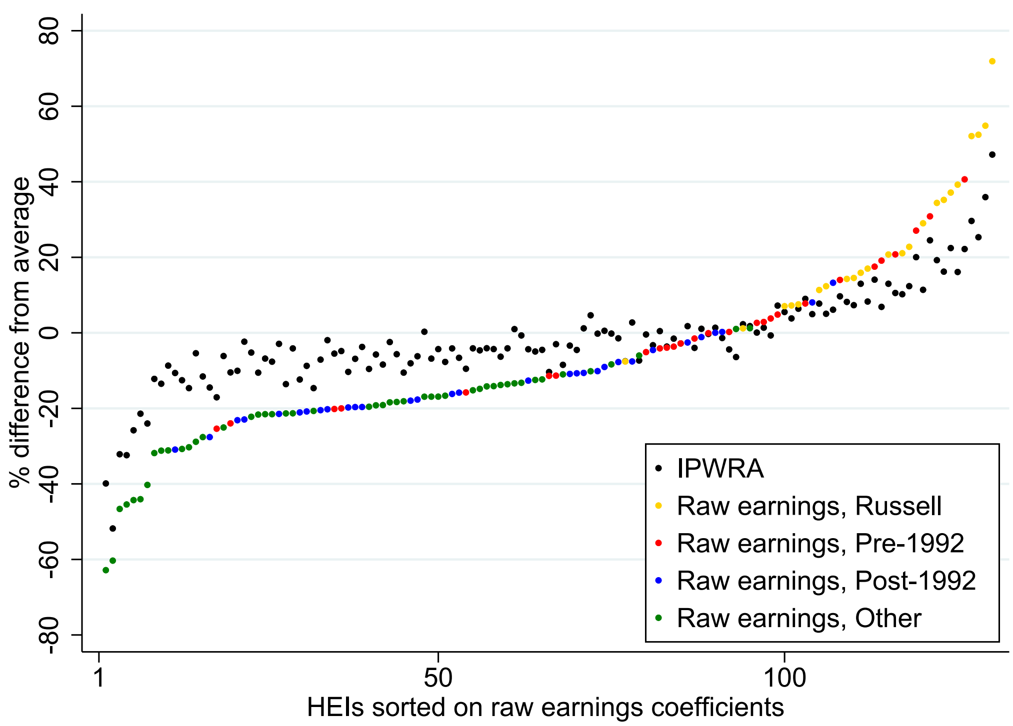



Figure 23: HEI raw earnings and IPWRA estimates for men




Figures 22 and 23 show the significant variation in graduate earnings between universities.

Graduates from LSE earn around 70% more than the average graduate 5 years after graduation while graduates from Guildhall School of Music and Drama earn around 60% less. There is also a clear hierarchy of institutions when one focuses on the raw earnings premia. High-status Russell Group universities dominate the top of the earnings distribution while 'Post-1992' and 'Other' institutions predominantly make up the bottom half of institutions. However, the four institutional groups are not homogeneous. There are a number of 'Pre-1992' universities and indeed some 'Post-1992' universities with earnings premia that are comparable to many Russell Group institutions. There are also some 'Post-1992' Universities and indeed a Russell Group university with below average graduate earnings.

However, controlling for observable differences in the student bodies of these different institutions reduces the large variation in earnings markedly. High-status, high-earnings institutions typically take high-ability individuals who would likely have had high earnings regardless of the institution they attended, whereas low-status universities typically take lower-ability individuals (as we saw in Figure 11). Once we account for these characteristics, the difference in returns to these institutions is considerably smaller. In this estimation, we also account for the subject mix the institution offers so no institution benefits (is penalised) from offering predominantly high- (low-) returns subjects.

Figures 24 and 25 reorder the institutions according to the IPWRA estimates of returns. This shows there are still significant differences in the returns to attending different institutions even once student characteristics and subject studied have been taken into account. The top 10 institutions increase female earnings by more than 14% more than the average institution and the returns to the bottom 20 institutions are more than 10% less than the average. It is also striking that there are still significant differences between different types of universities. The average return amongst Russell Group universities is around 10% more than the average institution while the average return for 'Post-1992' universities is 3% less than the average institution. However, this is not universally true across all institutions in each group: there are many 'Post-1992' universities that have returns similar to or greater than many 'Pre-1992' universities, once we take account of differences in student characteristics on entry.

Figure 24: HEI IPWRA coefficients for women

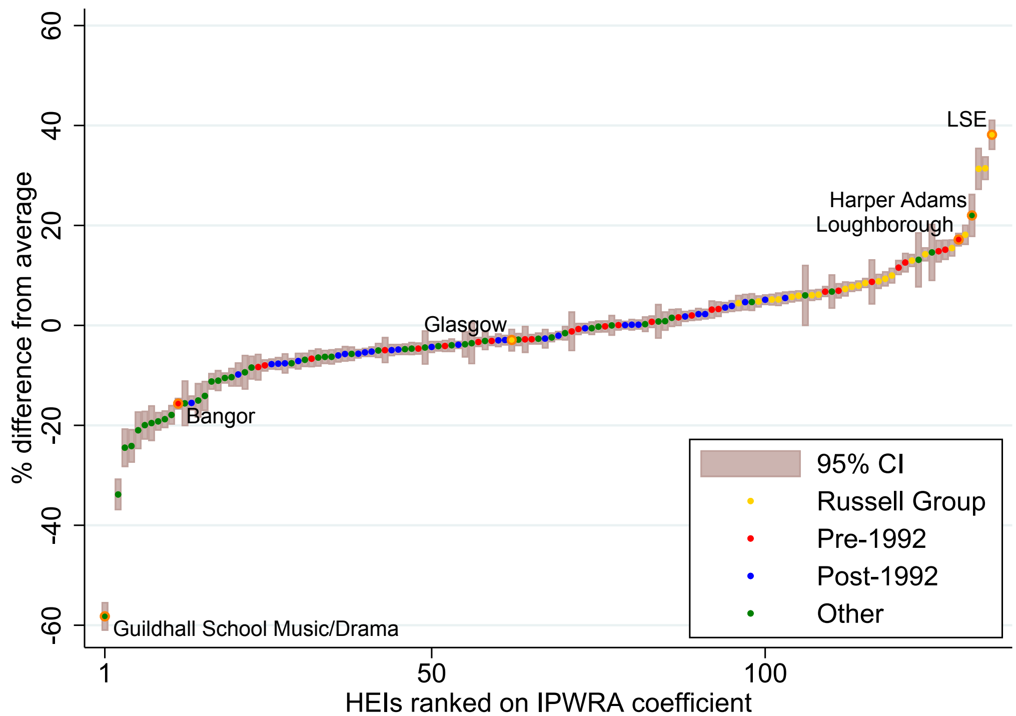
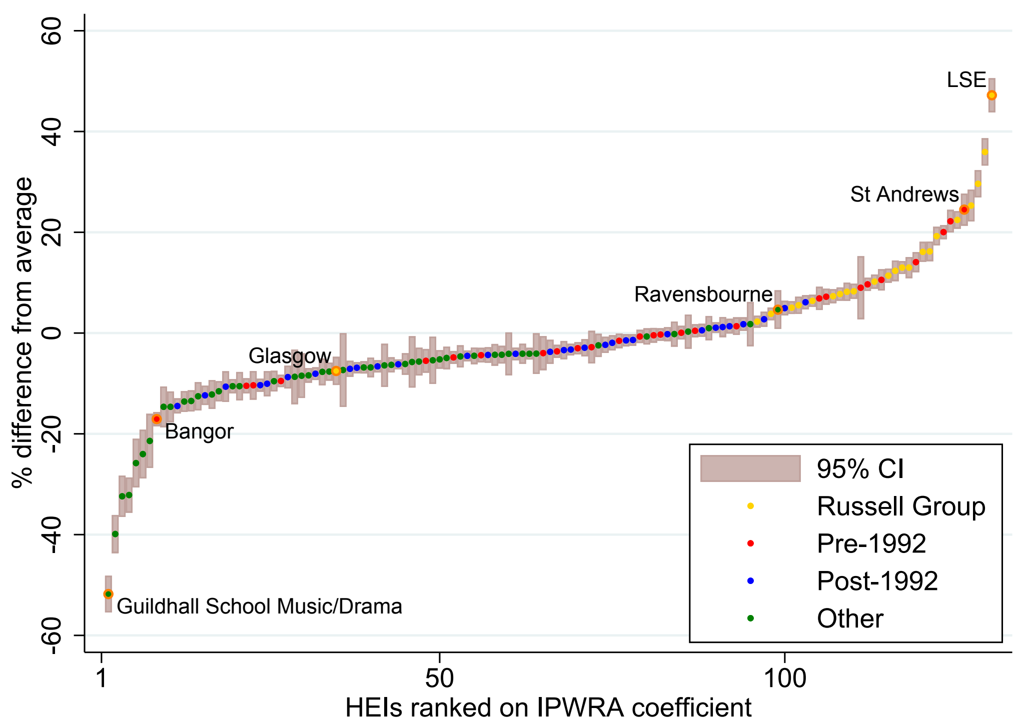



Figure 25: HEI IPWRA coefficients for men




While these institution estimates control for detailed background characteristics of the students, they cannot necessarily be interpreted as the causal impact of the teaching at a given university on the human capital and hence earnings of their graduates. As discussed, there are a number of characteristics which may impact future earnings of graduates which are not observable and these may differ across institutions. If students at a given institution typically have better non-cognitive skills or a greater desire to look for high-pressure high-paid jobs then this would increase the earnings of that university's graduates in a way we cannot control for. This would result in an upward bias in our estimate of that university's return.

Further, if employers are more likely to hire or promote individuals based on the university they attended, then this may lead to a higher perceived return to that institution. This is not pure value or 'human capital' that the university has added to individuals, rather the employer has used attendance at the university as a 'signal' of quality to evaluate prospective employees. If this mechanism is driving some of the differences in the returns between institutions then this has different implications for policymaking. The differences in returns by institution type are striking and whilst the results may reflect genuine average differences in quality across these institutional groupings, we cannot discount the possibility of signalling effects.

Finally, institutions are located in different parts of the country. It is the case that being located in certain parts of the country is beneficial to increasing graduate earnings. For example, it is easier for students in London to have access to the London labour market which has higher salaries. In fact, Figure 6 in the data section showed that there is variation in average graduate earnings between universities in different parts of the country: earnings are around 10% higher on average for graduates who attended universities in London than for those who attended universities in the North West of England. Clearly, we never observe the same institution in multiple locations so we cannot separate this "regional" effect from the institution returns. However, it is worth bearing in mind that some of the differences in returns may result from the different locations of the universities.

# 7 Course (subject-institution) estimates

We now turn attention to the estimated returns to individual courses, that is, the return to studying a specific subject at a specific university. The estimates - controlling for the differences in observable characteristics of the students - are shown in Figures 26 for women and 28 for men. As before, estimates are relative to the average graduate. A full table of results is available in the Online Appendix.

The Figures highlight the wide variation in returns to different courses. The returns to studying maths at Imperial or economics at the LSE are more than 100% greater than the average degree for women, while studying creative arts at the the Liverpool Institute for Performing Arts or English at Middlesex University has returns more than 40% below the average degree. Similarly, for men a degree in economics at Cambridge or maths at the LSE gives returns of around 100% above the average degree, while studying creative arts at Trinity College of Music and Dance or the Guildhall School of Dance and Drama has returns more than 50% below the average. These estimates make an important point: there is wide variation in returns both within universities across subjects and within subjects across universities.

Figures 26 and 28 highlight the returns to degrees from Cambridge, a very high-status university. Clearly, on average the return to a Cambridge degree is high. For both women and men, the Cambridge courses are concentrated towards the top of the distribution of courses in terms of graduate earnings. However, there is variation across subjects, which means that a degree from Cambridge does not guarantee a high return regardless of subject choice. Most starkly, studying English at Cambridge has an average return 4% below the average degree for women and studying creative arts has a return 26% below the average degree for men.

Figures 27 and 29 show that this observation is also true when considering the wider university groups by showing the distribution of course ranks by group for women and men respectively. We showed in Section 6 that Russell Group universities typically have the highest returns, even after accounting for their higher attainment intake. Figures 27 and 29 show that the courses at Russell Group institutions are concentrated amongst the highest-ranked courses, but also that this is not universally the case. There are considerable overlaps between the different university types, with some courses at Russell Group universities amongst the lowest ranked and some 'Other' university courses amongst the highest ranked.

Figure 26: Course IPWRA estimates for women relative to average course, highlighting Cambridge

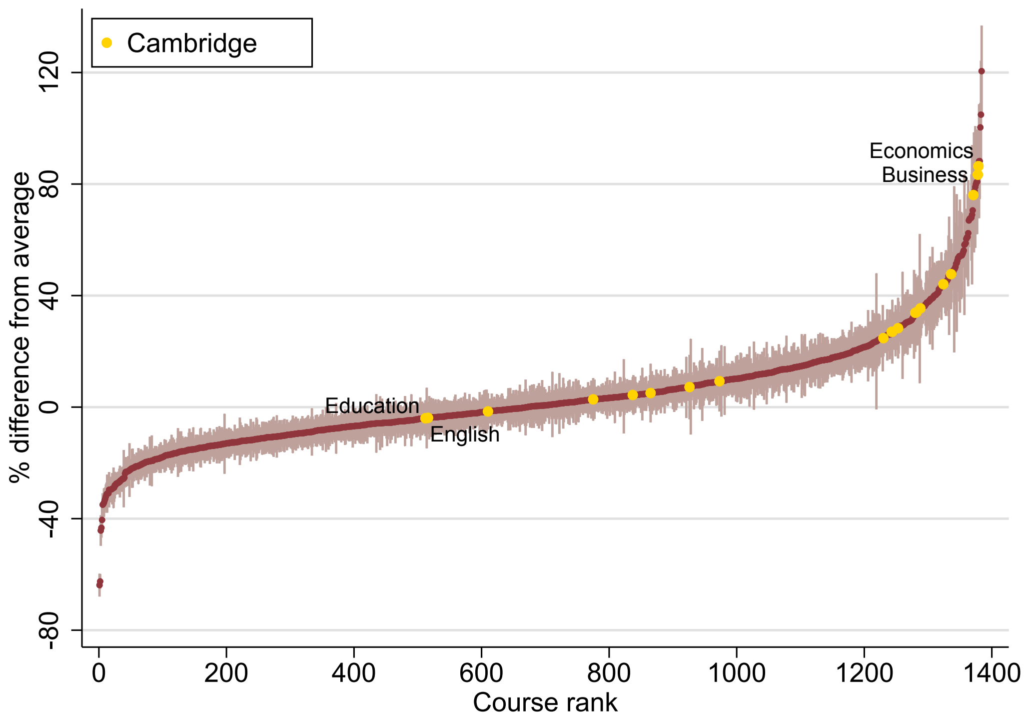
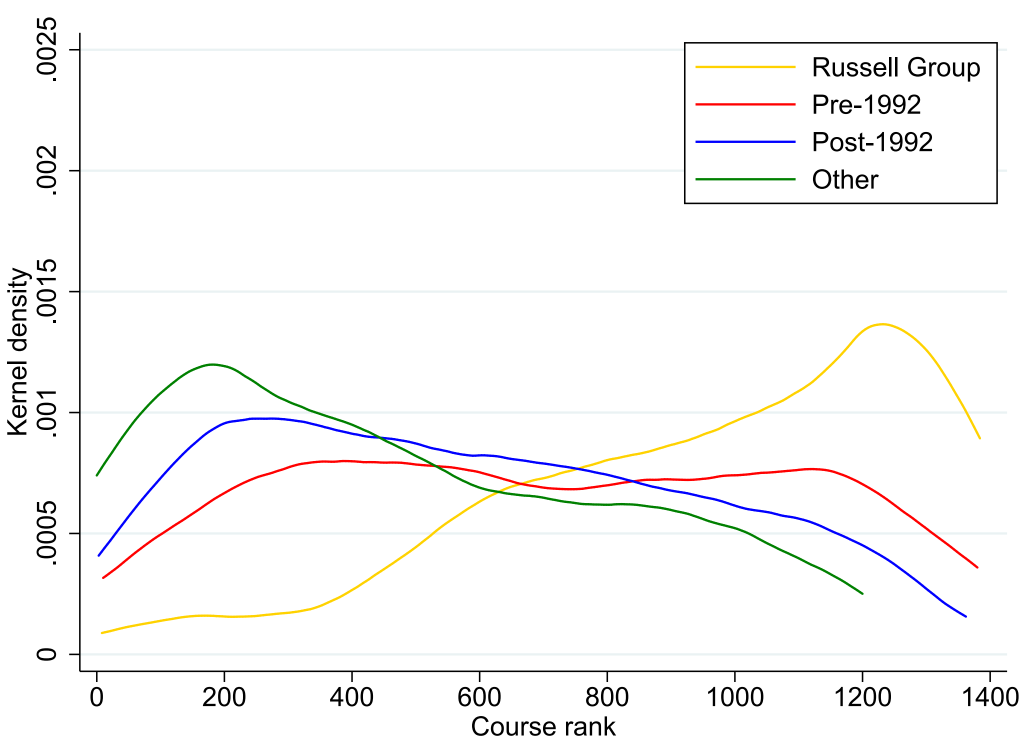



Figure 27: Distribution of course rank by university group for women




Notes: The kernel density shows the distribution of course rank by university grouping. This means that the higher density for the Russell Group for high course ranks than for low course ranks implies that more Russell Group courses have very high returns than have very low returns.

Figure 28: Course IPWRA estimates for men relative to average course, highlighting Cambridge

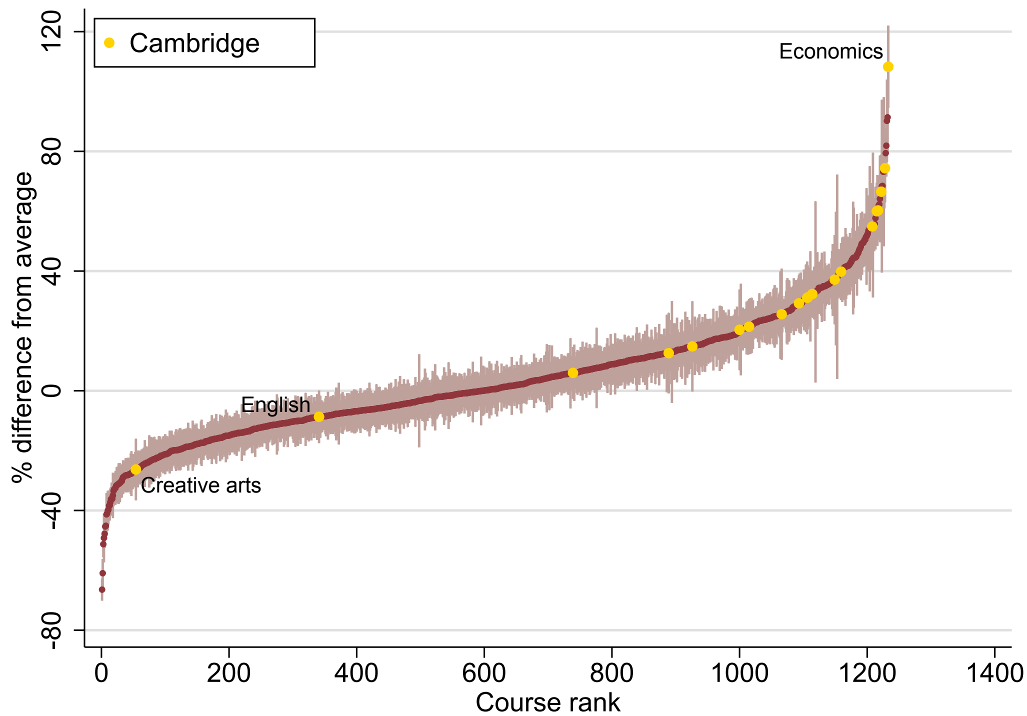
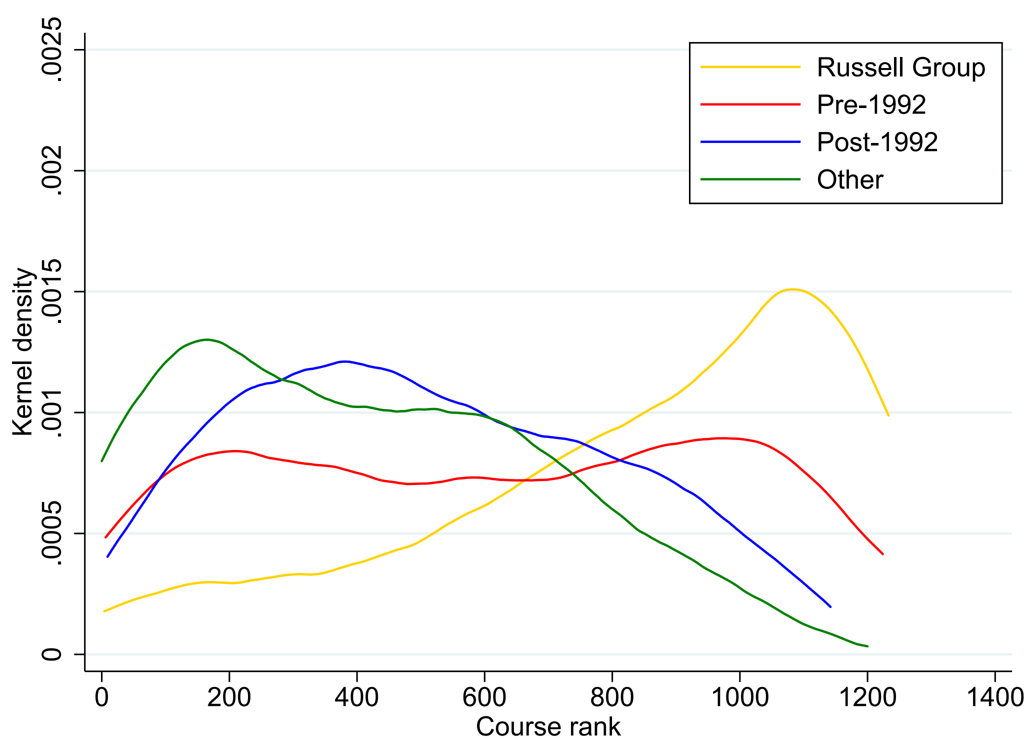



Figure 29: Distribution of course rank by university group for men




Notes: The kernel density shows the distribution of course rank by university grouping. This means that the higher density for the Russell Group for high course ranks than for low course ranks implies that more Russell Group courses have very high returns than have very low returns.

Figures 30 and 31 repeat the course estimate Figures from above but instead highlight the spread of business degrees. As we saw in Section 5, business degrees have a higher return overall, with a return 15% higher than the average subject. This is reflected in these Figures, with many business courses lying to the right, showing higher-than-average returns. But not all business degrees have high returns. The lowest business degree has a return 18% below the average degree for women and 14% below the average degree for men (as we noted in Section 6, geographical location of the university is a potential driver of some of these differences).

Figure 30: Course IPWRA coefficients for women relative to average course, highlighting business

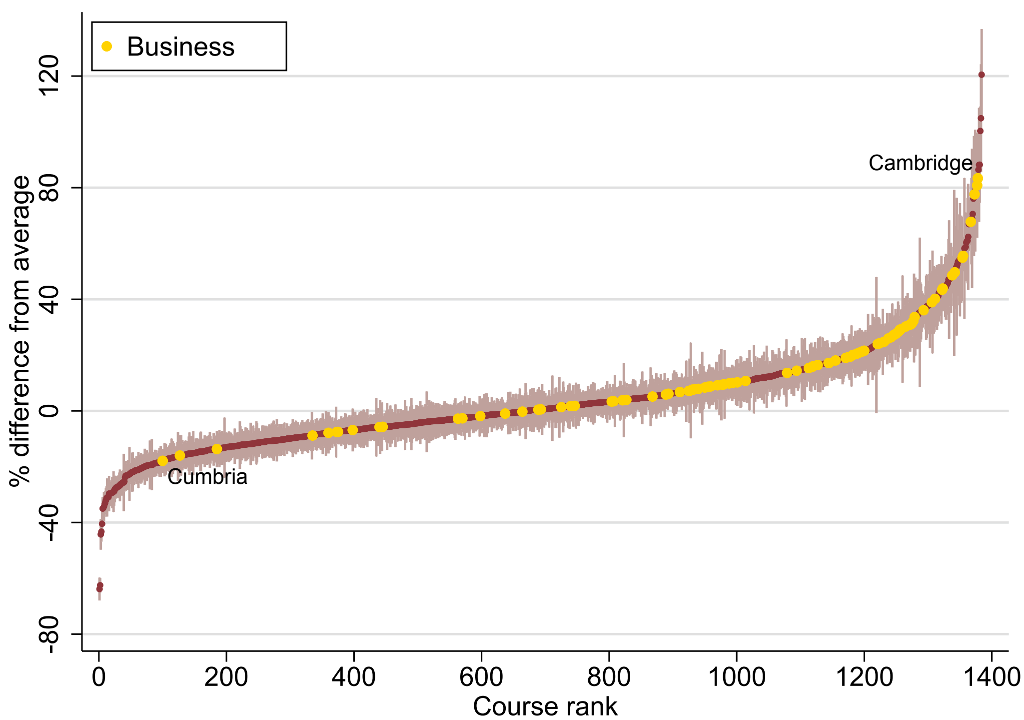
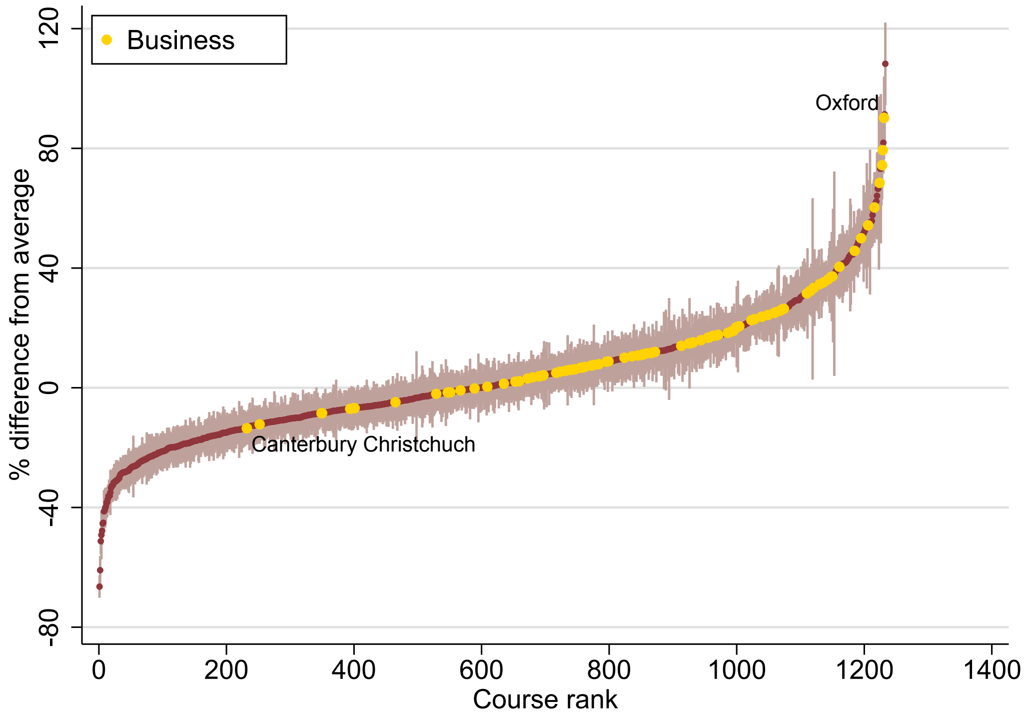


Figure 31: Course IPWRA coefficients for men relative to average course, highlighting business




Figures 32 and 33 show this variation for all subjects, displaying the minimum, maximum and interquartile range of returns by subject. The variation in returns is not unique to business. Nearly every subject has some courses which have high average returns and some courses with below-average returns. This highlights the importance of institution choice even conditional on degree subject. The Figures show that there is a lot of variation in the 'best' institutions for different courses. For example, for women studying creative arts, Bournemouth has the highest return, while Durham is best for English and Warwick is best for philosophy.

The highest-ranked courses for women are economics at LSE and maths at Imperial and law at Oxford (see the Online Appendix for a full list). For men, the highest-ranked courses are economics at Cambridge, maths at the LSE and business at Oxford. At the other end of the scale, 17 of the lowest 30 courses for women and 20 of the lowest 30 for men are creative arts courses.

Figure 32: Boxplot of IPWRA course returns by subject for women

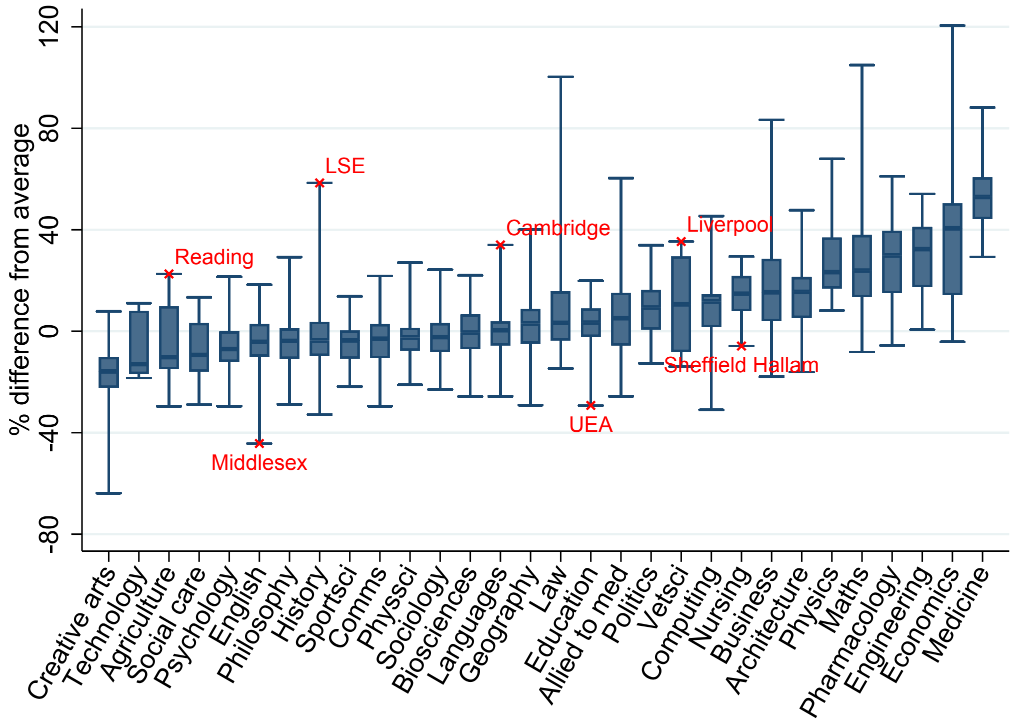
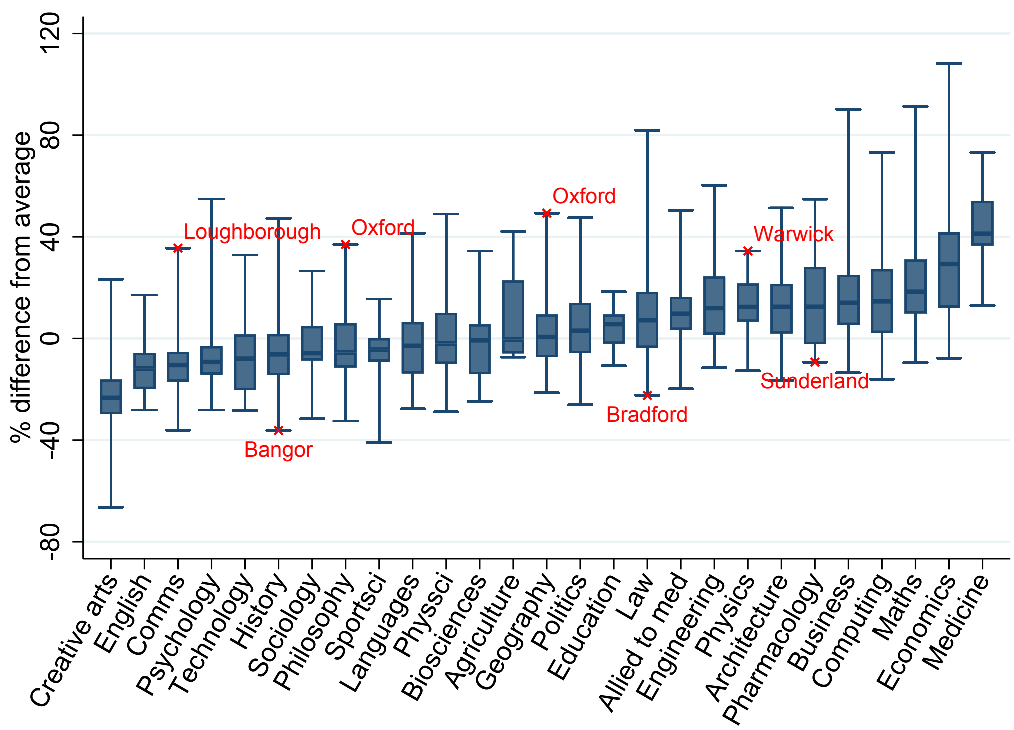



Figure 33: Boxplot of IPWRA course returns by subject for men



# 8 Earnings returns and A-level subject mix

We have shown that there is significant variation in the returns to different degrees even after accounting for differences in the characteristics of the students, and we have shown that this variation persists even within institutions and within subjects. Here we briefly describe how these returns differ by other observable characteristics of the courses - namely, the proportion of the student body which had a maths or science A- or AS-level[35] before attending the course. This is not showing the causal earnings returns to specific A-levels as A-level subject choices are controlled for in the estimation of these returns (as set out in Section 4). Instead, we are merely showing how the returns differ by an indicative characteristic of the course. Degrees with a higher proportion of students with a maths or science A-level might be thought of as more STEM-like courses.

Figures 34 and 35 show scatter plots of the male subject returns from Section 5 against the proportion of students in the subject with a maths and science A- or AS-level, respectively (equivalent figures for women are shown in Appendix Figures B6 and B7). There is a pattern that the higher the proportion of students with a maths A- or AS-level, the higher the subject returns. This may be because subjects which require or desire a maths A- or AS-level teach skills that are better rewarded in the labour market, or because student populations who have better maths ability are on average easier to teach. There is also wide variation around this trend. Computer science, for example, has high returns but only around 30% of students have a maths A- or AS-level. For physics, nearly every student has a maths A- or AS-level but the returns are close to average. There is a similar pattern for science A- or AS-levels but the relationship is less strong.

[35] A science A- or AS-level is defined as an A- or AS level in biology, human biology, chemistry, physics, science, electronics, geology or computer studies.

Figure 34: Subject returns by proportion of intake with a maths A- or AS-level, men

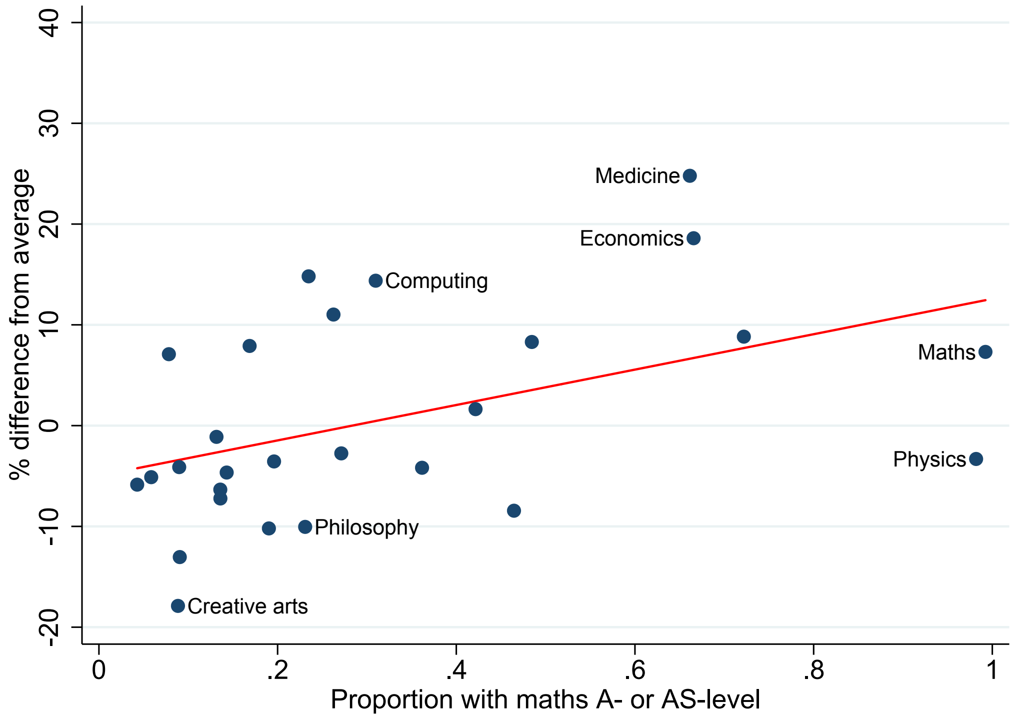
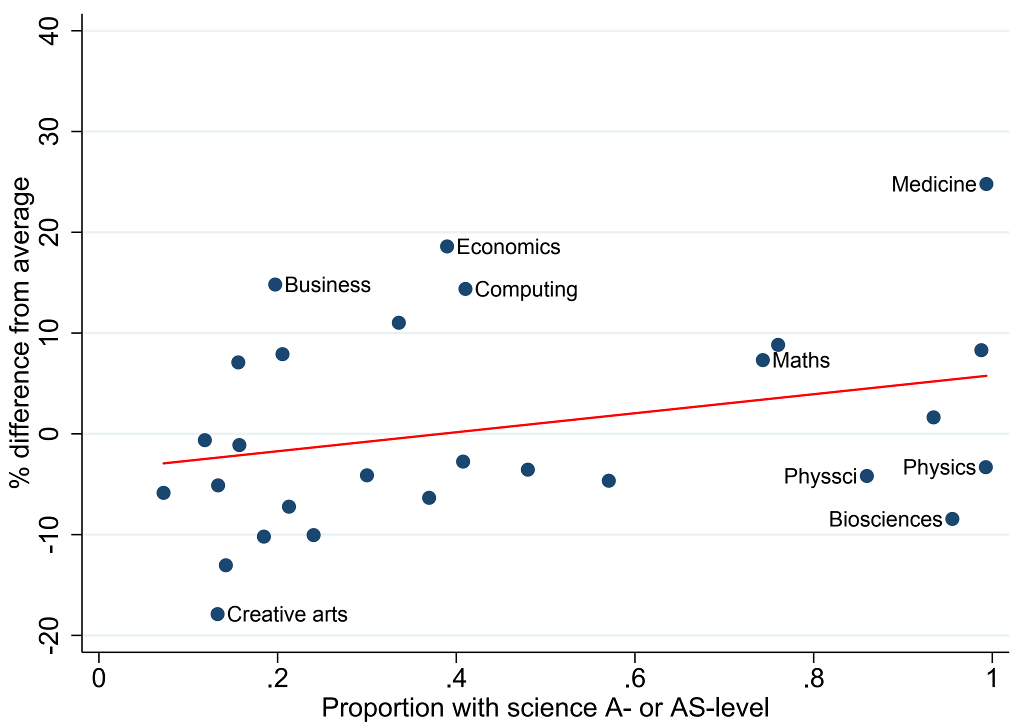



Figure 35: Subject returns by proportion of intake with a science A- or AS-level, men




We can delve into this issue in greater detail, looking at the relationship between the proportion of students with maths A- or AS-level and the returns to specific institutions' courses within a given subject. Figures 36 and 37 show these relationships for economics and creative arts respectively. These two figures tell very different stories. In economics, there is a clear relationship: the more students with a maths A- or AS-level, the higher the estimated returns. However, perhaps unsurprisingly, there is no such relationship in creative arts.

Figure 36: Economics course returns by proportion of intake with a maths A- or AS-level, men

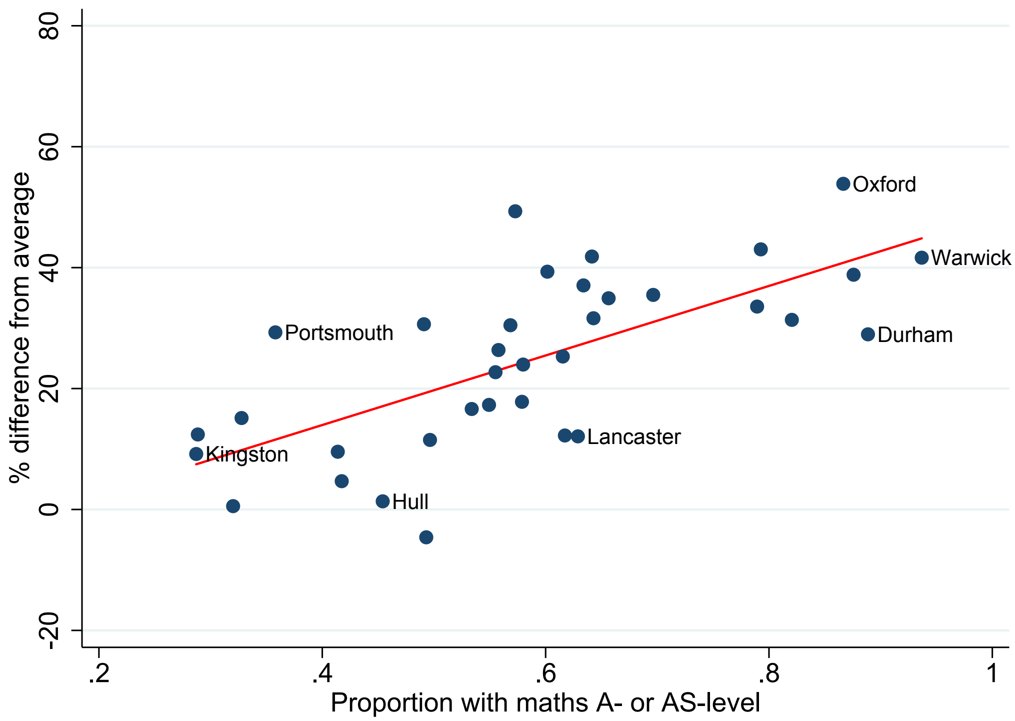
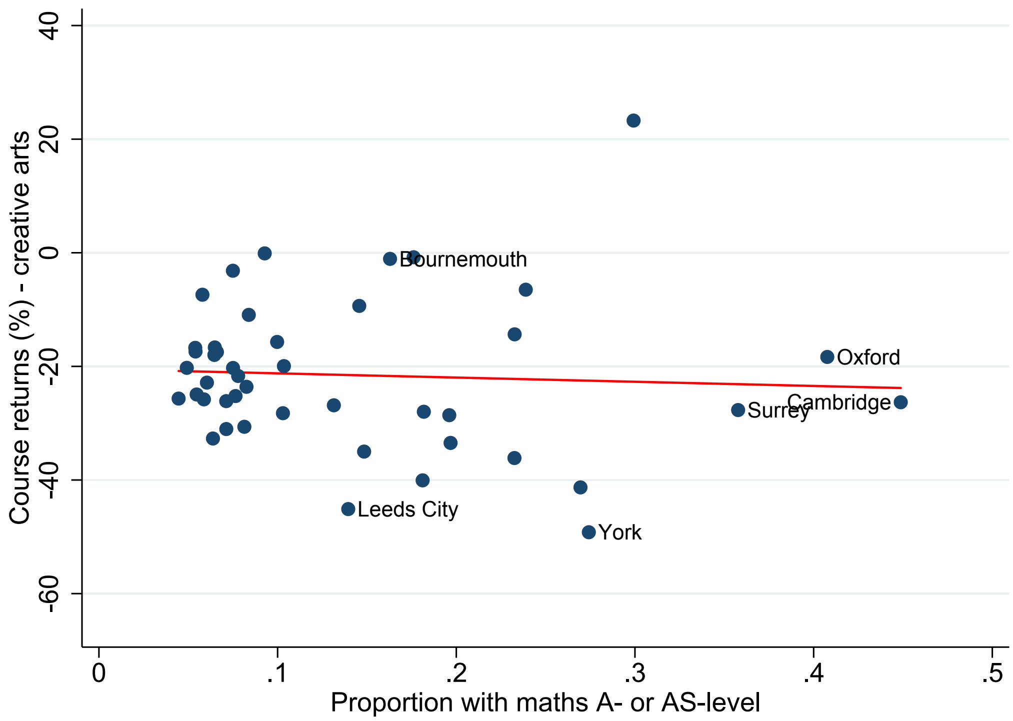


Figure 37: Creative arts course returns by proportion of intake with a maths A- or AS-level, men




# 9 Employment

Thus far we have focused on the impact of degrees on the earnings of graduates who are in work. However, HE qualifications can clearly also affect the likelihood of gaining employment. In this section we estimate these employment returns for different subjects and institutions. As discussed in Section 4 we use a slightly different method to model employment outcomes. The model is estimated on data for 2013-14 to 2015-16, and only includes outcomes 5 years after graduation. This is because Self Assessment tax records are only available for these years, and it is crucial to incorporate these when investigating employment prospects. We model the impact of different subjects and institutions on the probability students are in employment, self-employment or further study 5 years after graduation. Hence, a positive coefficient of say, 5% for a particular subject would imply that graduates who took that subject have a 5 percentage point greater probability of being in employment relative to the average graduate.

Figures 38 and 39 show the employment coefficients by subject for women and men respectively. There is clear variation in the probability of being in employment by subject. For women, pharmacology, medicine and maths degrees lead to the biggest positive impact on employment, increasing the probability women are in employment by around 3-5 percentage points relative to the average. For men, studying social care and medicine increases the probability of being employed by up to 6-7 percentage points compared to the average degree. These are relatively large effects given an average employment rate of 89% for women and 86% for men across the sample as a whole.

Figure 38: Subject employment returns 5 years after graduation for women .

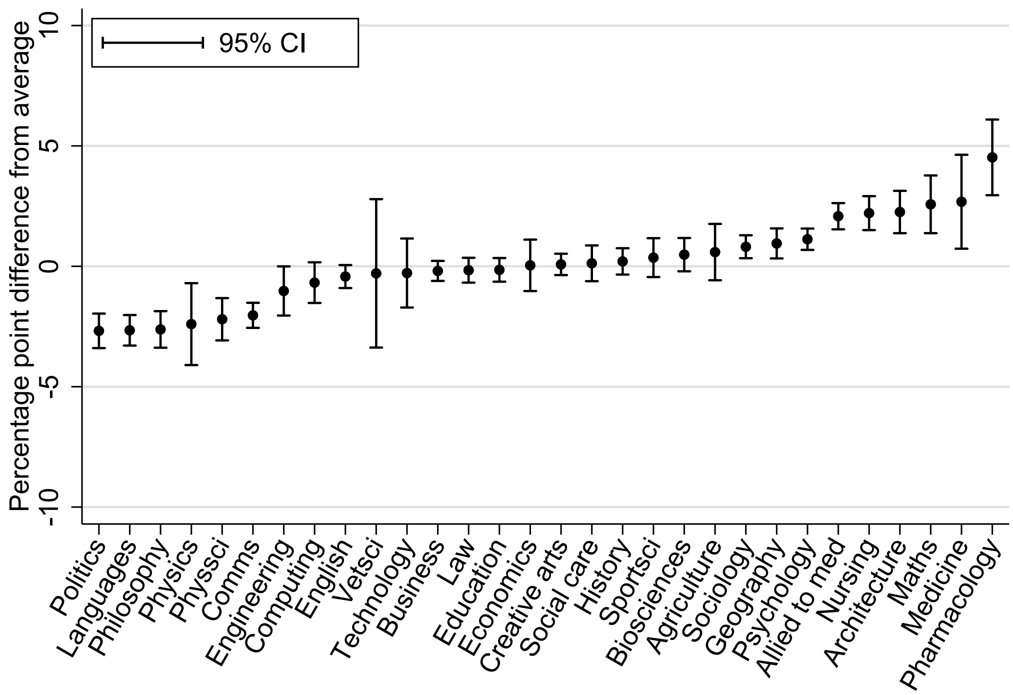
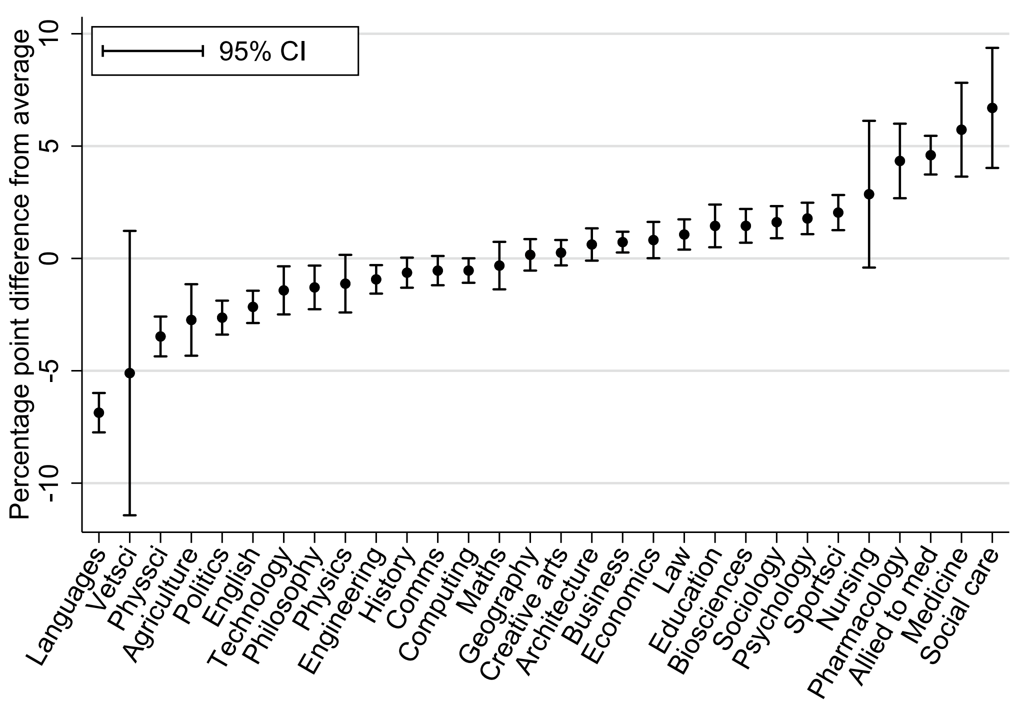



Figure 39: Subject employment returns 5 years after graduation for men




Figures 40 and 41 show the variation in relative employment probabilities by institution for women and men respectively. The results are striking. The graph clearly shows that 'Other' institutions have a greater impact on employment prospects than Russell Group institutions for both women and men. This could be the result of 'Other' universities offering more vocational courses which have better job prospects. However, whilst the magnitude of some of the differences is relatively large, these estimates are less precisely estimated and the vast majority are not statistically significantly different from the average. Also, the unexpected ordering of the results may be affected by the fact that we do not have employment information on graduates who move abroad, who would therefore count as not being in employment. This might be more common amongst graduates from Russell Group institutions.

Figure 40: Institution employment returns 5 years after graduation for women

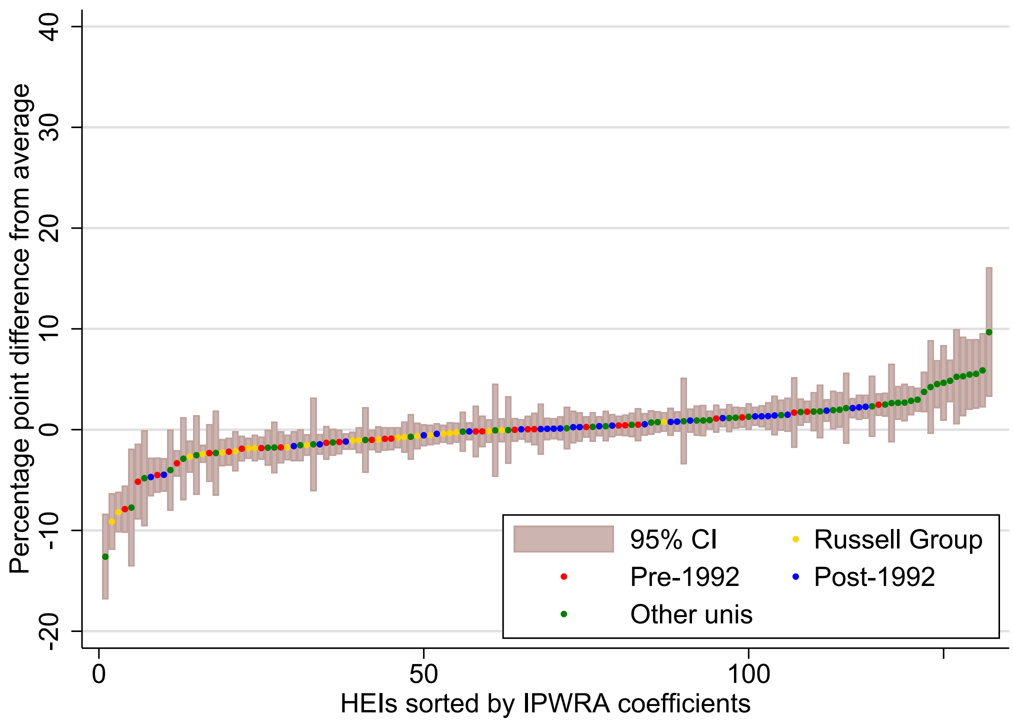
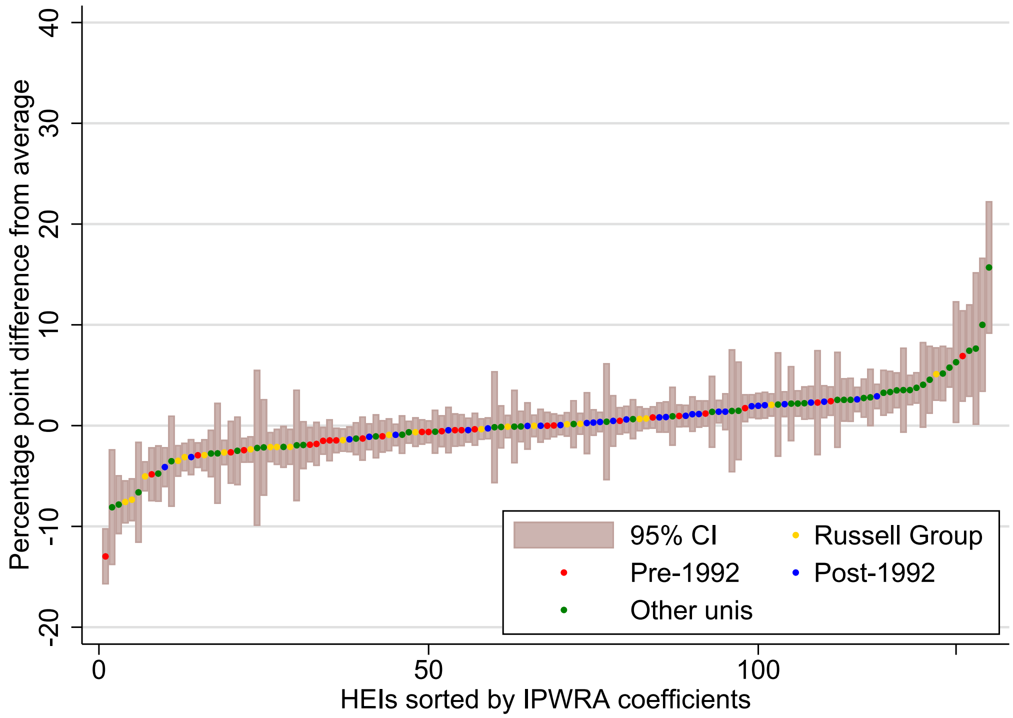


Figure 41: Institution employment returns 5 years after graduation for men




## 10 Discussion and conclusions

The large differences in the outcomes of graduates who study different degrees in the UK have been well documented (Britton et al., 2016). In this paper we investigate the returns between different university course choices, which means our estimates are all relative to the average graduate and are not compared to the outside option of not attending university. We will investigate the latter in a future paper. We show that a large proportion of the raw earnings differences can be explained by differences in the characteristics of students taking different degrees. High-earnings subjects and institutions typically take students with higher prior attainment and from higher socio-economic backgrounds who would have gone on to have higher earnings anyway.

However, even after accounting for these differences there remains significant variation in the impact of different degrees on graduates' earnings and employment prospects. Some of these differences are considerable. Economics and medicine degrees increase earnings by around 20% more than the average degree 5 years after graduation while creative arts increases earnings by around 15% less. Average graduate earnings are around £26,000 to £30,000 5 years after graduation and so these differences could amount to earnings differentials of more than £10,000 a year. If these persist over the lifecycle this could represent a significant difference in lifetime income.

The variation in returns to different institutions, conditional on student composition, is greater. The institutions with the highest returns increase earnings by at least 30% more than the average and the lowest-return institutions increase earnings by around 40% less than average. In line with Britton et al. (2016), we find that the LSE is amongst the top-performing universities, and this holds even conditional on intake. Oxford, Cambridge and Imperial College are amongst the other highest-performing institutions conditional on intake. In general we show that it is typically the high-status Russell Group universities which have the highest returns on average, after allowing for the fact that these universities typically admit students with higher earnings potential.

We have also shown there is considerable variation in the returns to attending different institutions within the same subject, meaning institution choice is very important even conditional on subject choice. For example, the best business studies degrees have returns in excess of 70% more than the average degree while the worst business degrees have returns below average.

These figures represent the average returns based on the students who take these subjects. However, different types of students experience different returns. For example, we show that studying medicine, education and agriculture has a higher relative return for men from lower socio-economic backgrounds, while economics and history attract a higher return for men from higher socio-economic backgrounds.

These results highlight that students' decisions about which institution to attend and what subject to study are likely to be important in determining later-life labour market outcomes. The evidence on returns provided in this report provides new information for students to consider when making this decision. However, these returns cannot be interpreted as causal. They may reflect differences in unobservable characteristics between different student bodies if, for example, some courses are more likely to take students with better socio-emotional skills or greater preferences for work. These estimates also provide the *average* returns based on the sample of students who study these courses; this is not necessarily the return that every student who could take the course will get. The estimates are solely based on English students and hence may not be representative of the return for the average student at institutions with a large proportion of non-English students. These returns are likely to change over time as the content of courses is altered and the labour market reward for different skills changes. Since our estimates are based on degrees taken 5-10 years ago they may not reflect the returns individuals are likely to face in the future.

Our results show that there are significant differences in returns between institutions. This contributes to the body of evidence on differential returns, and potentially improves the information available for students making choices of where to study, and for policymakers evaluating quality of provision at different institutions. Indeed, if these differences are the result of different teaching practices which improve labour market outcomes then these could be applied in other universities to the benefit of graduates. However, some of the differences may result from employers using a institution attended as a signal of quality, rather than rewarding actual skills, which means that the success of practices may not be easy to replicate elsewhere. We also note that these results focus entirely on labour market returns in terms of earnings, but there are numerous other benefits to degrees both to the individual and society as whole, which should be kept in mind when evaluating the performance of universities.

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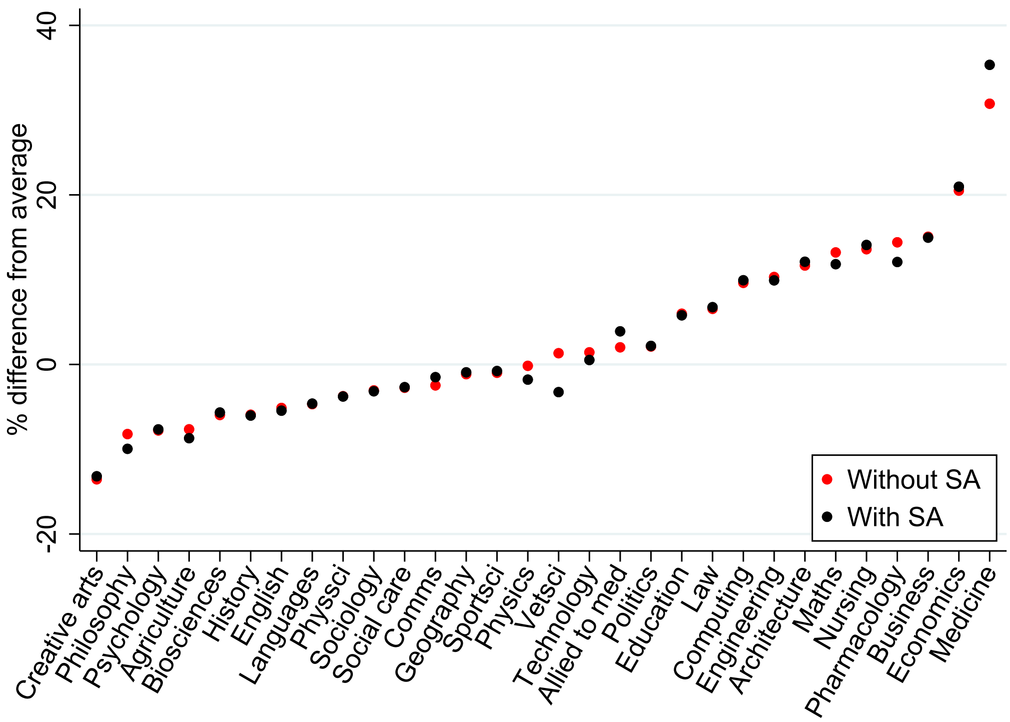
# Appendix

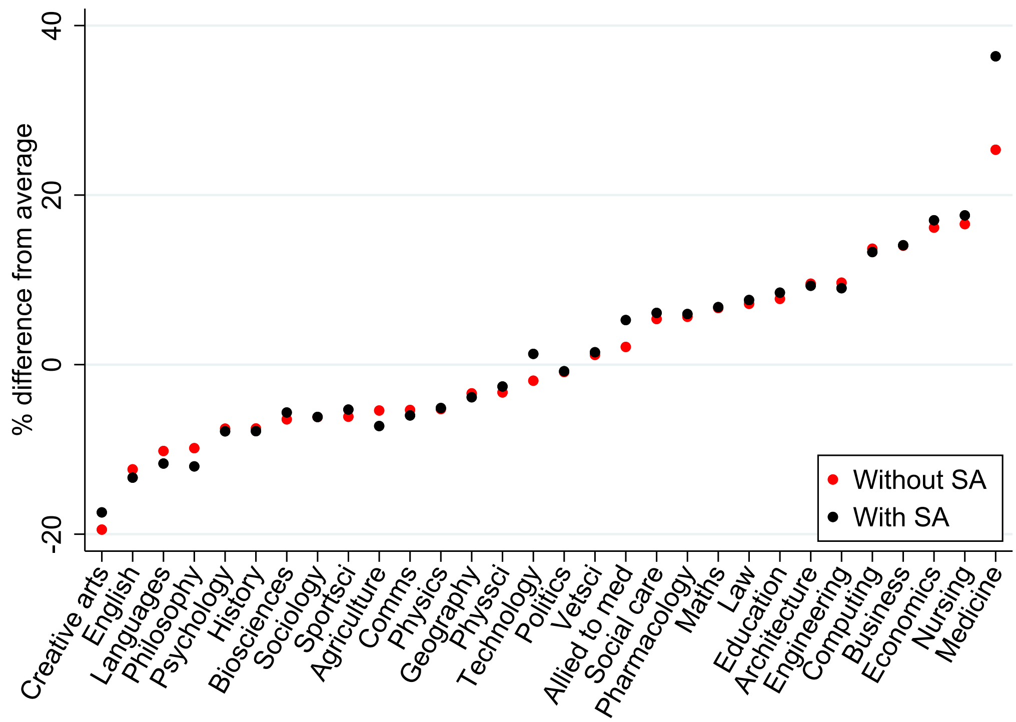
## A Sensitivity checks

Figure A1: Subject IPWRA coefficients for women with and without SA data



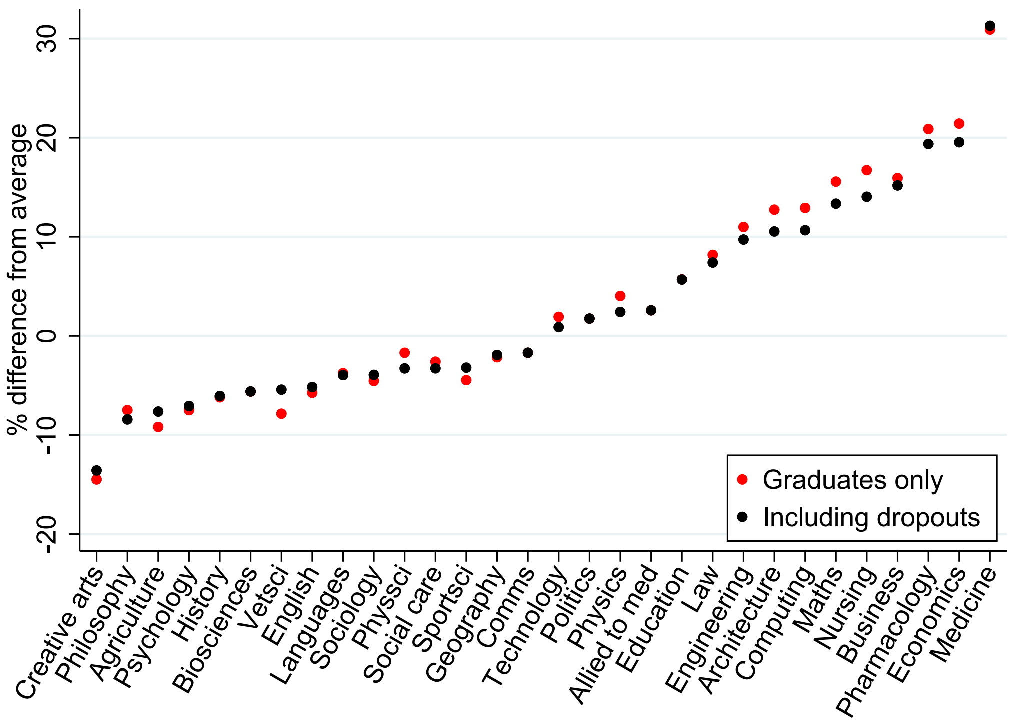

Notes: SA data is only available for three tax years, from 2012/13-2014/15. The 'without SA' estimates here are estimated on the same subset of years for comparison, and therefore differ slightly from the main estimates. The 'without SA' estimates are conditioned on being in sustained employment, while we do not observe this in the SA data. The 'with SA' estimates therefore includes everyone with positive SA earnings in a given tax year.

Figure A2: Subject IPWRA coefficients for men with and without SA data



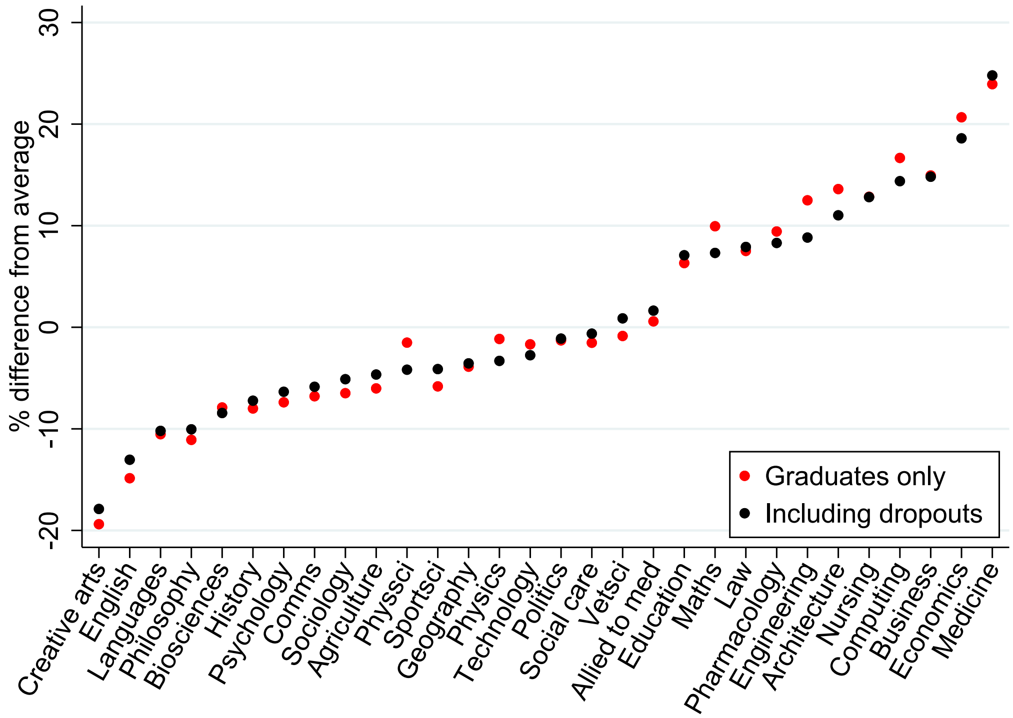

Notes: SA data is only available for three tax years, from 2012/13-2014/15. The 'without SA' estimates here are estimated on the same subset of years for comparison, and therefore differ slightly from the main estimates. The 'without SA estimates' are conditioned on being in sustained employment, while we do not observe this in the SA data. The 'with SA' estimates therefore includes everyone with positive SA earnings in a given tax year.

Figure A3: Subject IPWRA coefficients for women with and with dropouts




Notes: 'Including dropouts' indicates we are looking at all entrants, including graduates and dropouts. Dropouts are individuals who leave a course before completing and do not start another course in the sample period. Individuals who start another course are then classified as a graduate or dropout for that course. Estimation includes those in sustained employment only. Estimates are relative to the average for population. I.e. entrant returns are relative to average entrant and graduate returns relative to average graduate.

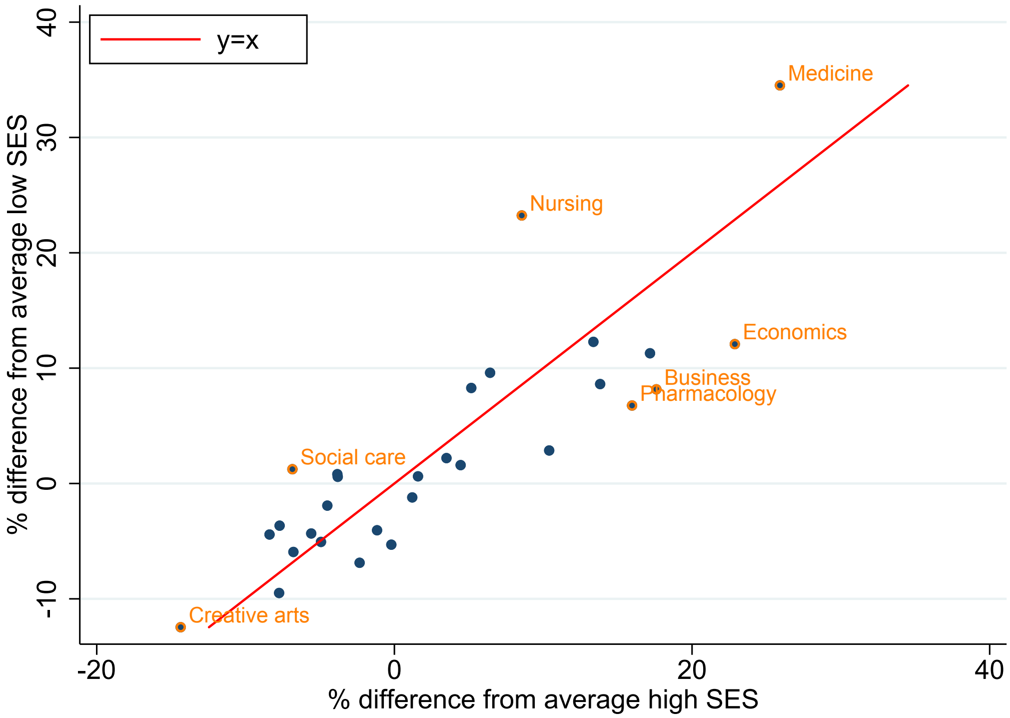
Figure A4: Subject IPWRA coefficients for men with and without dropouts




Notes: 'Including dropouts' indicates we are looking at all entrants, including graduates and dropouts. Dropouts are individuals who leave a course before completing and do not start another course in the sample period. Individuals who start another course are then classified as a graduate or dropout for that course. Estimation includes those in sustained employment only. Estimates are relative to the average for population. I.e. entrant returns are relative to average entrant and graduate returns relative to average graduate.

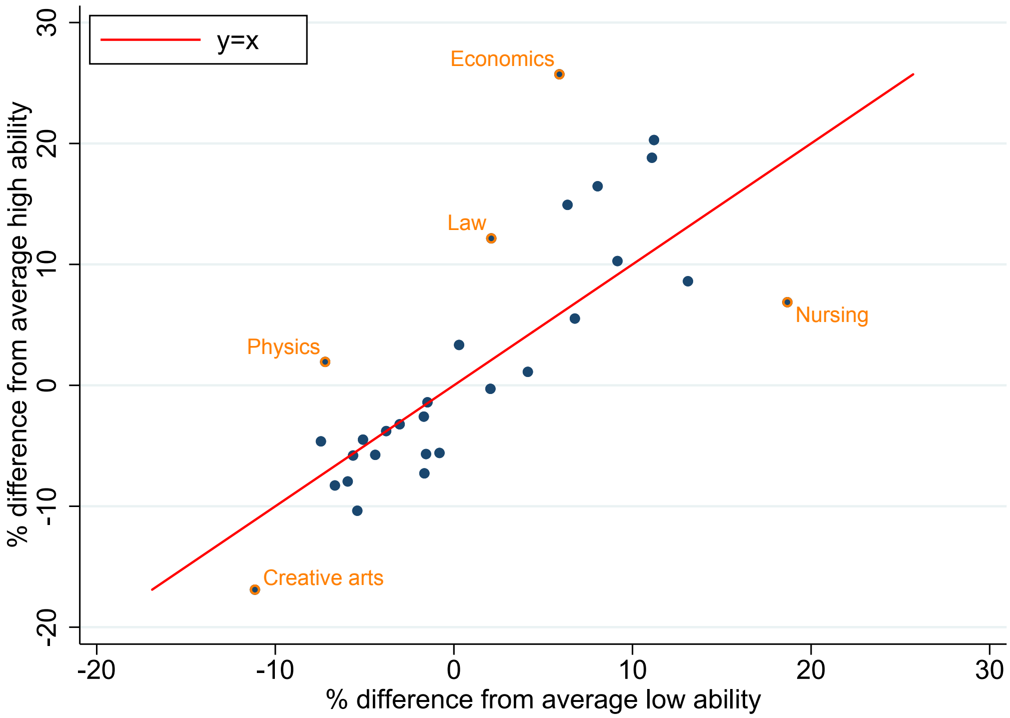
# B Results for women

Figure B1: Subject IPWRA coefficients, high SES vs low SES for women.



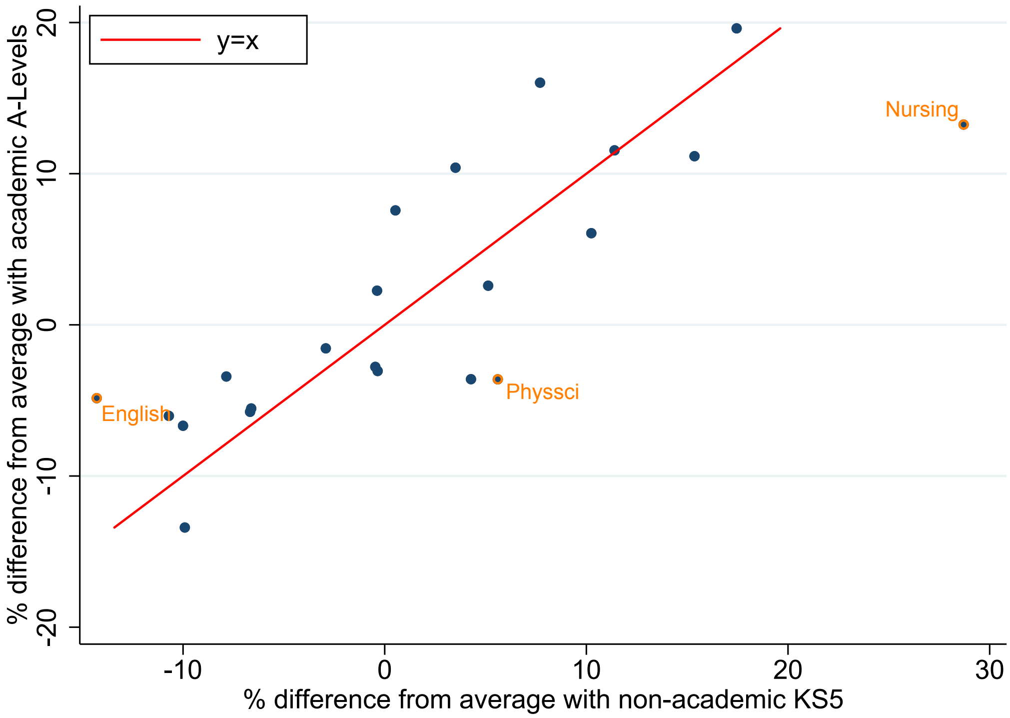

Note: Data behind this figure comes from Table 6.

Figure B2: Subject IPWRA coefficients, high ability vs low ability for women.




Note: Data behind this figure comes from Table 6.

Figure B3: Subject IPWRA coefficients, academic A-level vs non-academic route for women




Note: The sample of graduates with non-academic KS5 qualifications is very small, hence the estimates of returns for this group have very high standard errors and few of the differences with the academic A-level group will be statistically significant. We label the subjects with the largest deviations from the $y = x$ line.

Figure B4: Share of students studying each subject with a maths A- or AS-level for women

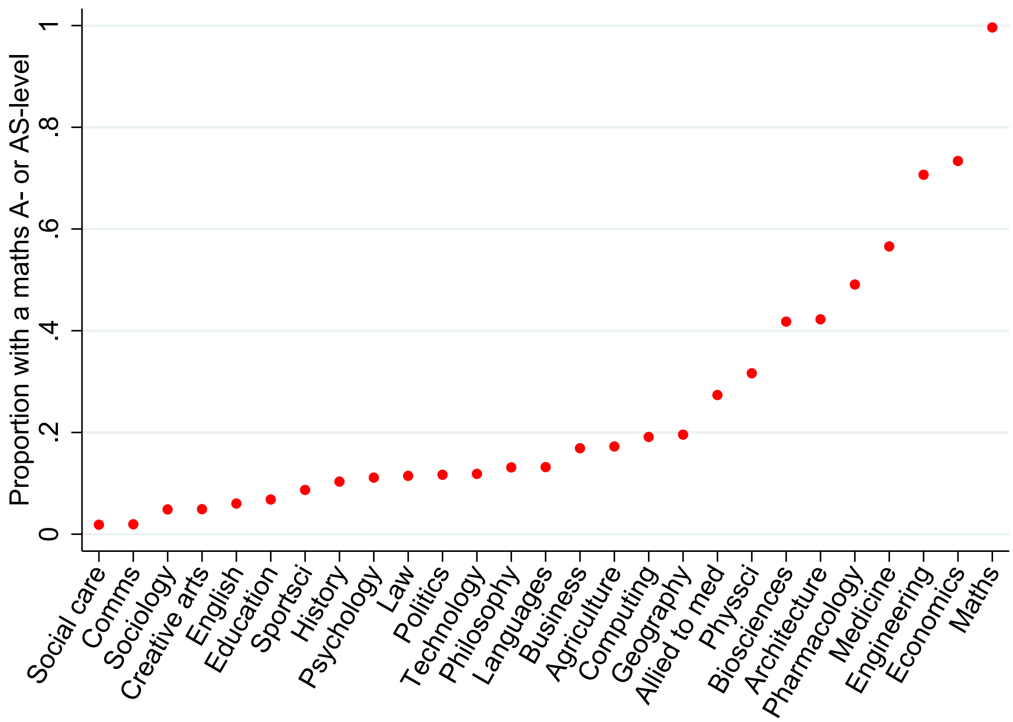



Figure B5: Share of students studying each subject with a science A- or AS-level for women

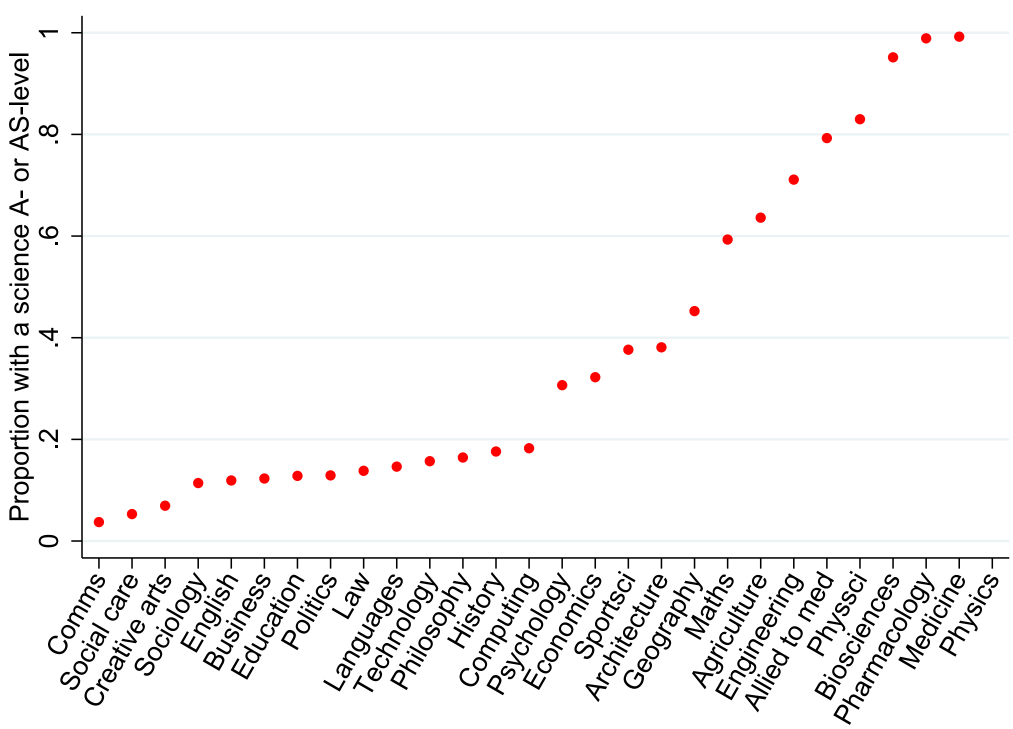


Figure B6: Subject returns by proportion of intake with a maths A- or AS-level for women

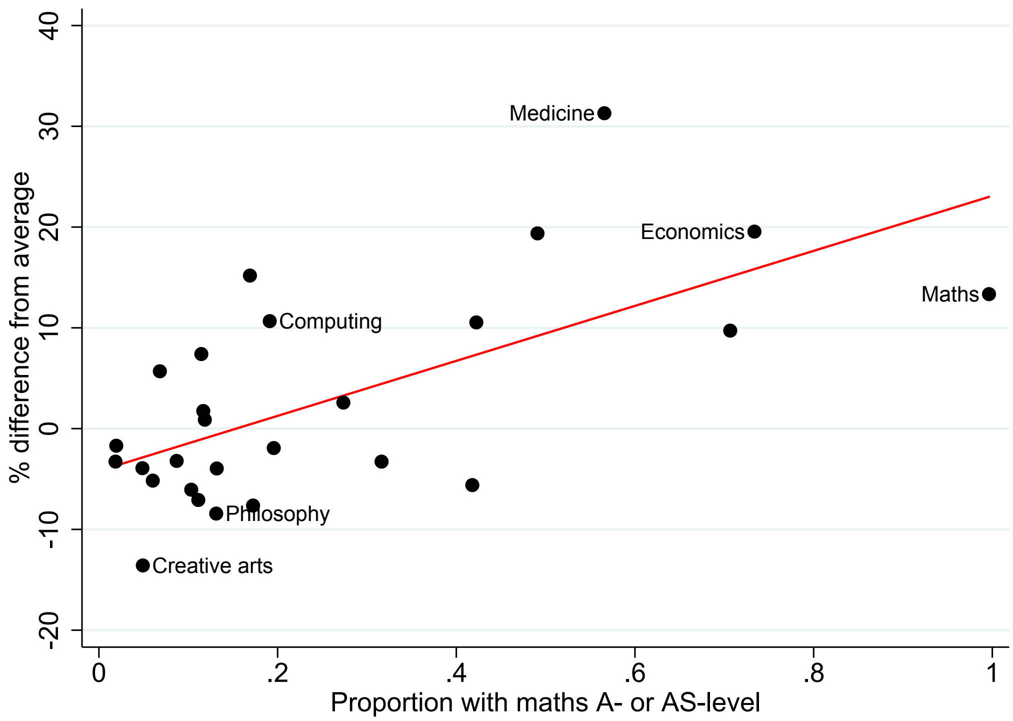



Figure B7: Subject returns by proportion of intake with a science A- or AS-level for women

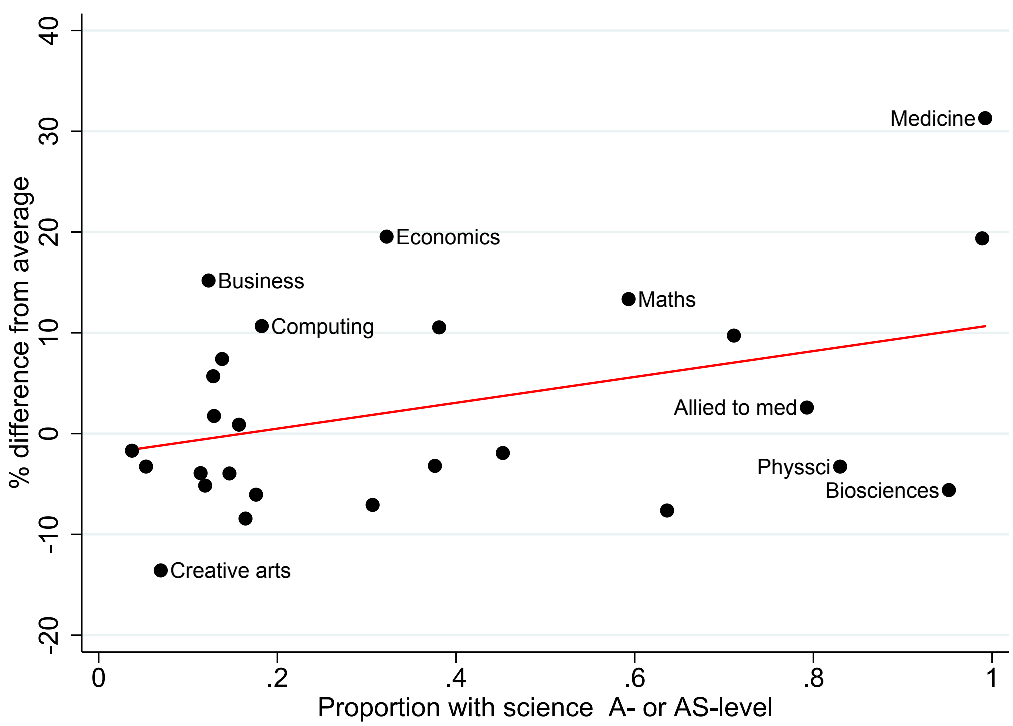


Figure B8: Economics course returns by proportion of intake with a maths A- or AS-level for women

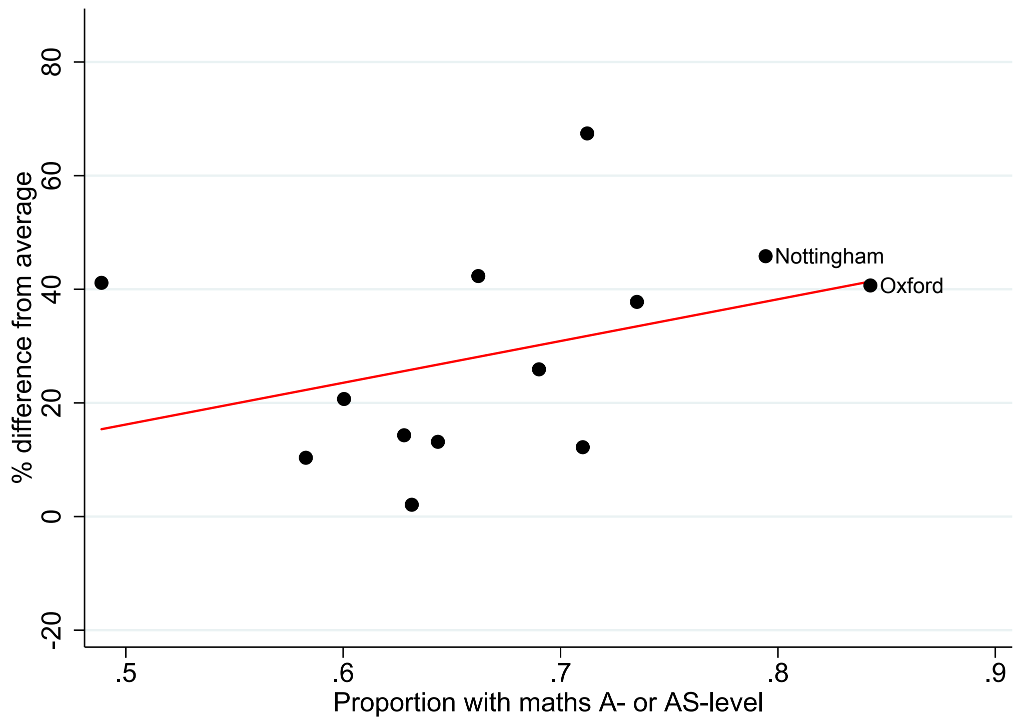
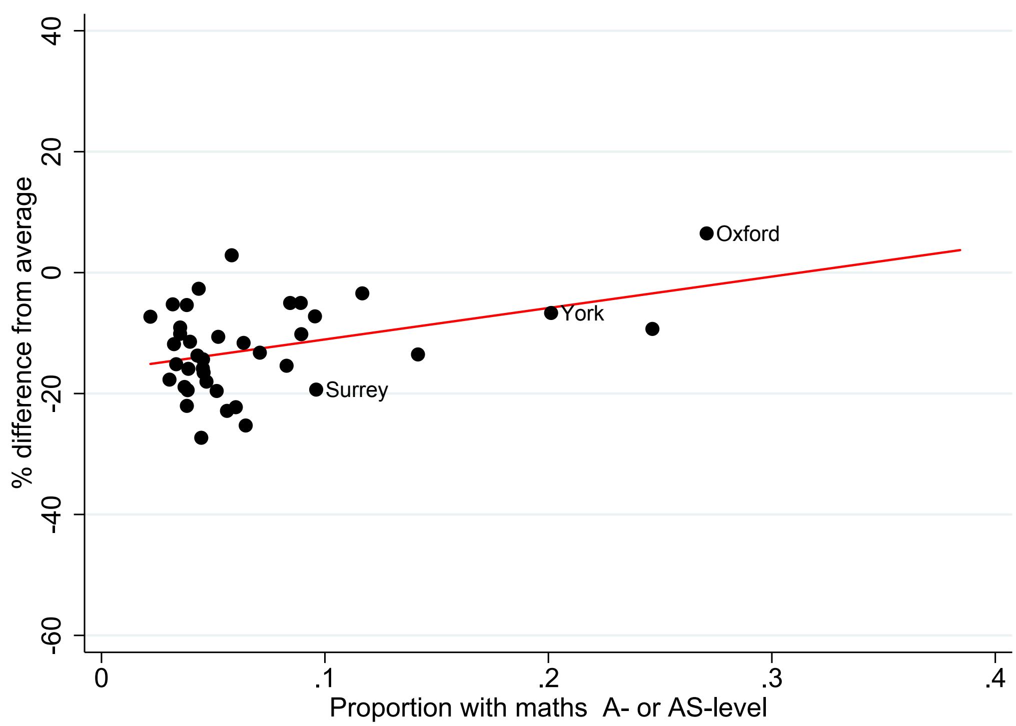



Figure B9: Creative arts course returns by proportion of intake with a maths A- or AS-level for women



# C Coefficients on control variables

Table C1: Coefficients on parameters in subject-level IPWRA estimation

| | Male | Female |
|---|---|---|
| EAL | -0.023*** | -0.038*** |
| | (0.004) | (0.003) |
| FSM | -0.011*** | -0.03*** |
| | (0.004) | (0.003) |
| SEN | -0.068*** | -0.072*** |
| | (0.004) | (0.004) |
| KS2 eng point score | -0.005*** | -0.009*** |
| | (0.002) | (0.001) |
| KS2 mat point score | 0.022*** | 0.034*** |
| | (0.002) | (0.001) |
| KS2 sci point score | -0.02*** | -0.028*** |
| | (0.002) | (0.002) |
| KS4 pts raw | 0.001*** | 0.001*** |
| | (0.000) | (0.000) |
| KS5 UCAS points score (/100) | 0.026*** | 0.028*** |
| | (0.000) | (0.000) |
| SES q2 | -0.026*** | -0.023*** |
| | (0.002) | (0.002) |
| SES q3 | -0.044*** | -0.044*** |
| | (0.002) | (0.002) |
| SES q4 | -0.069*** | -0.06*** |
| | (0.002) | (0.002) |
| SES q5 | -0.08*** | -0.09*** |
| | (0.003) | (0.003) |
| Independent school | -0.014*** | -0.007*** |
| | (0.003) | (0.002) |
| Humanities A level | -0.015*** | 0.009*** |
| | (0.002) | (0.001) |
| Languages A level | 0.02*** | 0.014*** |
| | (0.002) | (0.002) |
| Maths A level | 0.025*** | 0.043*** |
| | (0.002) | (0.002) |
| Other A level | 0.006*** | 0.007*** |
| | (0.001) | (0.001) |
| Science A level | 0.002 | 0.003** |
| | (0.002) | (0.002) |
| Social science A level | 0.032*** | 0.033*** |
| | (0.001) | (0.001) |
| Move region for uni | 0.02*** | 0.041*** |
| | (0.002) | (0.001) |

Coefficients on parameters in subject-level IPWRA estimation (cont)

| | Male | Female |
|---|---|---|
| Home region - North East | -0.066*** | 0.002 |
| | (0.014) | (0.012) |
| Home region - North West | -0.044*** | 0.016 |
| | (0.014) | (0.012) |
| Home region - Yorkshire | -0.046*** | 0.013 |
| | (0.014) | (0.012) |
| Home region - East Mids | -0.003 | 0.041*** |
| | (0.014) | (0.012) |
| Home region - West Mids | -0.014 | 0.043*** |
| | (0.014) | (0.012) |
| Home region - EoE | 0.086*** | 0.118*** |
| | (0.014) | (0.012) |
| Home region - London | 0.069*** | 0.157*** |
| | (0.014) | (0.012) |
| Home region - South East | 0.076*** | 0.114*** |
| | (0.014) | (0.012) |
| Home region - South West | 0.004 | 0.045*** |
| | (0.014) | (0.012) |
| Asian - Bangladesh | -0.091*** | -0.078*** |
| | (0.009) | (0.007) |
| Asian - Chinese | -0.099*** | -0.025*** |
| | (0.009) | (0.008) |
| Asian - Indian | 0.001 | 0.033*** |
| | (0.005) | (0.004) |
| Asian - Pakistan | -0.058*** | -0.138*** |
| | (0.006) | (0.005) |
| Black - Africa | -0.116*** | -0.094*** |
| | (0.007) | (0.005) |
| Black - Other | -0.121*** | -0.052*** |
| | (0.013) | (0.01) |
| Other Ethnicity | -0.027*** | -0.023*** |
| | (0.003) | (0.002) |

Notes: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Coefficients are in log points. These are the control variables from the final specification of the subject IPWRA estimation as shown in Table 5, columns (5) and (10). 20 UCAS points is roughly equivalent to one A-level grade. For further interpretation, see Table 2 for summary statistics of these variables. Additional coefficients (including ethnicity, home region, cohort, age start degree) are provided in an Online Appendix. SES quintile and independent school estimates are relative to the top SES quintile. SEN is a binary variable for non-statemented special educational needs; pupils with statemented SEN are excluded.

# D Other graphs and tables

Table D1: Course aims in sample 2011-12

| | Proportion of sample in 2011/12 |
|---|---|
| First degree with honours | 87.1% |
| First degree leading to QTS | 3.1% |
| First degree leading to health/social care qual | 4.2% |
| First degree leading to registered architecture board | 0.3% |
| First degree with honours (enhanced pattern) | 0.7% |
| First degree with honours and diploma | 0.2% |
| Other | 0.9% |
| Integrated masters | 3.4% |

Notes: Proportion of final sample who graduate in each year that have various course aims, as defined in HESA student record.