The impact of undergraduate degrees on lifetime earnings

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Executive Summary

This report provides estimates of the returns to undergraduate degrees for English domiciled students over the course of their working lives. We account for individuals' background characteristics and prior attainment to estimate the net private returns to undergraduate degrees, as well as the returns to the taxpayer. This is the third in a series of reports by researchers at the Institute for Fiscal Studies, commissioned by the Department for Education (DfE), that make use of the Longitudinal Education Outcomes (LEO) data set to improve information on the value of higher education (HE) degrees. The data set, developed in collaboration with DfE, tracks students through school, university and into the labour market. The previous report in the series, Belfield et al. (2018*b*), estimated the earnings premium *at age 29* of attending HE and found a large average premium of around 26% for women, while the equivalent for men was just 6%. This report extends that work by estimating how these returns are likely to evolve over the life cycle.

Our estimates are based on the earnings of individuals who were born in the mid-1980s and went to university in the mid-2000s. These are the oldest individuals for whom we have detailed education records. As we observe the earnings of these individuals only up to age 30, we have to simulate earnings profiles for the remainder of their working lives. This is a difficult and somewhat imprecise exercise, made even more challenging by a lack of data on cohorts that are currently in the middle or near the end of their careers. Once we have simulated the earnings and employment trajectories of each individual in this cohort up until retirement age, we adjust their earnings to reflect today's earnings levels and apply the current tax and student loan system to calculate lifetime returns net of the tax and student loan system, as well as returns per student for the exchequer.

All lifetime figures are given in discounted present value terms; they can be interpreted as equivalent to cash at the point of entering university. We use a real discount rate of 3.5% for the first 30 years and 3.0% after that as recommended by the Treasury's Green Book. As there is no universal consensus on the appropriate discount rate, we show results using alternative discount rates whenever practicable – and we see that it matters *a lot*.

The resulting estimates are subject to several sources of uncertainty. It is not knowable today what retirement patterns are going to look like in 50 years' time, whether the earnings trajectories of future graduates will be similar to those of past graduates, and what is likely to happen to real earnings growth. The uncertainty is particularly acute for women, who have experienced much more significant changes to their education choices and their earnings patterns in recent years. Given this level of uncertainty, we have not disaggregated our estimated returns to the same extent as in Belfield et al. (2018*b*), where we reported returns at the subject–institution level. In this report, we only break our estimates down by subject and by institution groups.

Furthermore, the general limitations of non-experimental studies apply to our work: while the LEO data set provides very rich background information on students, and therefore allows us to control for the influence of a large array of confounding factors, it is possible that there are remaining unobservable factors that influence both degree choice and earnings. This would skew our estimates to some extent. Lastly, it should be kept in mind that these results purely show the *earnings* benefit of HE for individuals and the tax benefits for government. Wider benefits such as increased health, happiness or job satisfaction, which may constitute an important part of the overall return to HE, are not included in our estimation.

Keeping these caveats in mind, the results provided in this report give our best estimates of the likely lifetime returns to HE overall, and by subject and university-type, given the best data currently available. Our main findings are as follows:

- **Median earnings of male graduates grow strongly throughout their 30s, and this earnings growth far outstrips that of non-graduates.** For male graduates who were 30 in 2016, we predict earnings to rise by £15k from age 30 to age 40, compared with a rise of just £5k in the median earnings of non-graduate men. The gap in median earnings between graduate and non-graduate men continues to grow strongly until individuals' mid-40s.

- **Median earnings growth for female graduates in their 30s is moderate, but still higher than that of non-graduates.** We predict median real earnings of female graduates who were 30 in 2016 to rise by around £5k from age 30 to age 40, compared with no growth for non-graduate women. Among degree subjects, law and medicine stand out in that their female graduates do see large growth in median earnings between ages 35 and 40.

- **Accordingly, the causal effect of undergraduate degrees on earnings grows after age 30 for both men and women, but much more strongly for men.** Average pre-tax returns for men at a given age increase from around 5% on average at age 30 to more than 30% on average at age 40, after which they increase more slowly to reach around 35% from age 50. For women, average pre-tax returns increase from around 25% at age 30 to more than 40% at age 40, but then fall again to between 30% and 35% at ages 50 and 60.

- **These average returns hide substantial heterogeneity by subject and university group.** Returns for creative arts or social care are lower (and negative for men), while returns to economics and medicine are much higher. For men, we see higher returns at more selective universities.

- **The average lifetime earnings gain from undergraduate degrees is substantial for both men and women, but much smaller than the difference between the gross earnings of graduates and non-graduates.** The discounted difference in lifetime earnings between graduates and non-graduates is £430k for men and £260k for women. Once we account for differences in characteristics between those who do and do not attend HE, we obtain a discounted lifetime increase in gross earnings of £240k for men and £140k for women as a result of attending HE.

- **The average gain in *net* lifetime earnings is even smaller due to the progressivity of the tax system.** Once taxes and student loans have been taken into account, the earnings premium declines to around £130k for men and £100k for women (£350k and £230k with no discounting). In percentage terms, this represents a gain in average net lifetime earnings of around 20% for both men and women.

- **There is substantial variation in net lifetime returns across subjects, though the differences are reduced by the progressivity of the student loan repayment system and the tax system.** Net discounted lifetime returns for women are close to zero on average for creative arts and languages graduates, but more than £250k for law, economics or medicine. We see a similar pattern among men, but an even larger spread of returns, with negative average returns for men studying creative arts and social care, and average returns of around £500k for men studying medicine or economics.

- **Within each subject, there is substantial variation in returns across individuals.** This variation is particularly large among men studying subjects with high average returns. In contrast, some of the lower-returning subjects see very small variation in returns. This is particularly true for women studying education and nursing, who do not achieve particularly high average returns but almost universally achieve positive returns, as the variation in returns is small.

- **We see little variation in average lifetime returns across university groups for women, but substantial differences for men.** More selective universities offer much higher returns on average for men but not for women. For both men and women, Russell Group universities offer higher returns for those at the top of the returns distribution, but similar returns compared with other universities for those at the bottom. These results mirror similar patterns in the distribution of lifetime earnings.

- **Overall, we expect 85% of women and around three-quarters of men to achieve positive net lifetime returns.** This means that around one in five undergraduates would have been better off financially had they not gone to university. On the other end of the spectrum, the 10% of graduates with the highest returns will on average gain more than half a million pounds in discounted present value terms.

- **Financing undergraduate degrees is expensive for the taxpayer, but on average this expense is more than counterbalanced by increased tax revenues.** Overall, we estimate that the expected gain to the exchequer of individuals attending HE is around £110k per student for men and £30k per student for women (£400k and £170k with no discounting).

- **However, these gains are driven mainly by the highest-earning graduates.** We expect the exchequer to gain more than half a million pounds on average from the 10% of graduates with the highest returns, but to make a loss on the degrees of around 40% of men and half of women. This means that nearly half of all students receive a net government subsidy for their degrees, even after tax and National Insurance payments have been taken into account.

- **As for private returns, there is considerable variation in exchequer returns by subject.** Once losses on student loans are taken into account, for women the taxpayer loses out on a third of all subjects. On the other hand, the exchequer gains around £260k per student from women studying medicine and £220k per student from women studying economics. For men, the taxpayer returns for some subjects are even higher, with returns above £500k per economics or medical student; at the other end of the spectrum, a quarter of subjects have negative average taxpayer returns.

- **On average, exchequer returns are zero or positive for all university groups for both genders.** There is again significant variation *within* university groups: we estimate that around half of all women in each university group have negative exchequer returns, but large contributions from the highest-earning graduates push up the average, especially at Russell Group universities. For male graduates, there is also large variation in taxpayer returns *across* university types, with average exchequer gains from men going to the least academically selective universities being close to zero and those for men from Russell Group universities being around £240k per student on average.

- **Adding together net private and exchequer returns yields the total return to HE, which is large and positive for both men and women.** Total returns can be thought of as the overall earnings impact of undergraduate degrees, irrespective of to whom these earnings accrue. We estimate a total lifetime gain from HE per individual of £240k for men and £130k for women (£750k and £390k with no discounting). However, around 30% of both men and women have negative total returns.

1 Introduction

Understanding the private and social returns to undergraduate degrees is very important both for policy and for prospective students. The government spends around £8 billion per year on undergraduate degrees, while students take on very large debts of up to £60k for a three-year degree. Despite the importance of the decision about whether to go to university, the evidence base on the value of these degrees is still rather limited, primarily due to data limitations. This report makes use of new and extremely rich data to provide a substantially more robust estimate of the overall return to undergraduate degrees than has previously been possible. The richness of the data also enables us to investigate returns by subject studied and the type of university attended.

We use the Longitudinal Educational Outcomes (LEO) data set also used in our previous work on this topic (Belfield et al., 2018*a*,*b*). This data set links school, university and tax records for the population of individuals who attended secondary school in England. We observe tax records in every year from 2005/06 to 2016/17 inclusive,[1] and have complete linked data on all birth cohorts from 1985/86 onwards. Our earliest fully linked cohort is therefore observed up to age 30 in the tax data.

We also have a significant additional tranche of LEO data that links the university and tax records for roughly ten more birth cohorts, taking us back to people who were born in the mid 1970s. The years of earnings data that we have are fixed (2005/06 to 2016/17), so for the oldest cohort we observe earnings data between ages 29 and 40. These data are not linked to school records, so we do not have the rich background characteristics on these individuals' prior attainment and family background. However, these data provide us with valuable information about what happens to the earnings of graduates in their 30s.

Drawing on the additional LEO data as well as subject-level earnings data from the Labour Force Survey (LFS), we simulate the remainder of the (working-age) lifetime earnings profile – including spells of inactivity or unemployment – for every individual in the 2002 GCSE cohort, the vast majority of whom were born in the 1985/86 academic year. For this cohort, we observe their actual earnings up to age 30, and we simulate their earnings thereafter up to age 67 and assume they retire at 68. This enables us to estimate the returns to undergraduate degrees at each age, by gender, subject and university type, and to construct a counterfactual earnings profile for each graduate capturing what they would have earned had they not attended university. From these simulated and counterfactual earnings profiles we calculate the discounted present value of pursuing an undergraduate degree, as well as the benefits to the taxpayer.

Our work complements existing international evidence on the lifetime returns to higher education in the US (Hoxby, 2018) and in Norway (Bhuller, Mogstad and Salvanes, 2017). The closest precedent to this work in the UK is Walker and Zhu (2013), who used LFS data from 1993 to 2010 to estimate average net lifetime returns of £170k for men and £250k for women, and average ex-

[1] Note that this is one additional year of tax data compared with our previous work.

chequer returns of £260k for men and £320k for women. In a recent cross-country comparison, the OECD (2019) found average net lifetime returns for the UK of $250k for men and $200k for women, and lifetime exchequer returns of $110k for men and $80k for women. In earlier work, Conlon and Patrignani (2011) found net average lifetime returns of £120k for men and £80k for women, and average exchequer returns of £100k for men and £60k for women, based on LFS data between 1996 and 2009.[2] Compared with Walker and Zhu (2013), our estimates are somewhat smaller for men and significantly smaller for women. Our findings are very similar to those of Conlon and Patrignani (2011), although we estimate a slightly larger gap between men and women in exchequer returns; they are also broadly in line with OECD (2019).

However, it should be noted that these previous estimates are not directly comparable to ours. Most importantly, our results are in 2018 prices, are based on the 2019 tax and student loans system, and rely on the most recent macroeconomic forecasts. Furthermore, we use Green Book discounting, which is similar to but not the same as the 3.5% real discount rate used by Conlon and Patrignani (2011) and Walker and Zhu (2013), and a lot higher than the 2% discount rate used in OECD (2019). Unlike earlier work, in this report we are able to make use of earnings data from tax records, rather than self-reported earnings, and are able to follow individuals for longer periods. The richness of our data also means we are able to break the estimates down to show significant variation in returns by subject and institution type.

The remainder of the report is set out as follows. We describe the data in Section 2 and we discuss our methodology in Section 3. We then show the simulated lifetime earnings profiles in Section 4, before presenting our main estimates of the returns by age in Section 5 and over the whole lifetime in Section 6. We show returns for the taxpayer in Section 7 and combined private and taxpayer returns in Section 8. Section 9 concludes.

2 Data

We first give more detail on the data we use in this report. We start by summarising the data linkage we use, which is crucial for understanding our methodology, as we make use of a variety of sources. We then give a sense of student numbers from our data set, before showing some simple earnings descriptives and overall sample sizes.

2.1 Data linkage

Table 1 gives an overview of the data available for each birth cohort. We make use of the Longitudinal Educational Outcomes (LEO) data set, which links National Pupil Database (NPD) school records and Higher Education Statistics Agency (HESA) university records to HM Revenue &

[2] In other related work, Blundell, Dearden and Sianesi (2005) estimate earnings returns to higher education (HE) for men born in 1958 in their 30s and find an average return to HE of 22% compared with having just A levels and 29% compared with having just O levels.

Customs (HMRC) earnings and employment data and Work and Pensions Longitudinal Study (WPLS) benefits data. More information on these data is provided in Belfield et al. (2018*a*).

Table 1: LEO data summary

Birth cohort	GCSE year	NPD	HESA	Usable HMRC	HMRC age range
1975/76	1992	x	✓	✓*	29 – 40
1976/77	1993	x	✓	✓*	28 – 39
1977/78	1994	x	✓	✓*	27 – 38
1978/79	1995	x	✓	✓*	26 – 37
1979/80	1996	x	✓	✓*	25 – 36
1980/81	1997	x	✓	✓*	24 – 35
1981/82	1998	x	✓	✓*	23 – 34
1982/83	1999	x	✓	✓*	22 – 33
1983/84	2000	x	✓	✓*	21 – 32
1984/85	2001	x	✓	✓*	20 – 31
1985/86	2002	✓	✓	✓	19 – 30
1986/87	2003	✓	✓	✓	18 – 29
1987/88	2004	✓	✓	✓	17 – 28
1988/89	2005	✓	✓	✓	16 – 27
1989/90	2006	✓	✓	✓	16 – 26
1990/91	2007	✓	✓	✓	16 – 25

Note: We only observe a HESA record for those who attended an HE provider in the UK. Those who did not are still included in the data set, so long as they have an NPD record. Age in 2016/17 is based on the most common age halfway through the tax year. * indicates that the tax records are only usable for individuals who attended HE.

The NPD records provide us with the rich background characteristics and prior attainment data needed in order to calculate returns to higher education. It contains information on a student's educational career such as subject choices and GCSE results, as well as background information such as ethnicity and home region. These data are available starting with the 2002 GCSE cohort. A HESA record contains information about the individual's higher education course, as well as their performance in the course. It also has some limited background information on the student. HESA records are available for all university students between the 1995/96 and 2015/16 academic years.

The HMRC record contains information about earnings from employment from the 2005/06 tax year until the 2016/17 tax year. From the 2013/14 tax year onwards, we also have self-employment earnings from self-assessment records. All earnings are adjusted to the 2018 prices level using the Consumer Prices Index (CPI). As the HMRC records do not contain information about hours worked, all earnings data presented in this report refer to annual earnings. The earnings impact of undergraduate degrees that we report here represents the impact of undergraduate degrees on both hourly wages and hours worked.[3] In contrast to Belfield et al. (2018*a*,*b*), we do not take into account whether individuals are in *sustained employment*, mainly because no equivalent

[3] As discussed in Belfield et al. (2018*b*), the effect on hours worked is likely to be especially important for women.

measure is available from the Labour Force Survey.

The focus of our previous work (Belfield et al., 2018*b*) was on the cohorts for which we have full linked NPD–HESA–HMRC data – namely, the 1985/86 to 1990/91 cohorts.[4] A key innovation in this report is that we also use data from the ten additional cohorts born between September 1975 and August 1985, for which we have linked HESA–HMRC data if they attended university, but no NPD records. For people who did not attend university, we do not have additional administrative tax records that we can use, because our HMRC data have no record of age and sex.

2.2 Student numbers in the HESA data

In order to estimate returns to higher education (HE) after age 30, this report makes use of the earnings information of students from the 1975/76 to 1984/85 birth cohorts – individuals aged 31 to 40 in the latest year of the linked HESA–HMRC data – to learn about the likely future earnings patterns of students from the 2002 GCSE cohort, which is the earliest cohort for which we have an NPD record. In this section, we show some descriptives for these earlier cohorts and compare them with more recent cohorts of students. We show that these older cohorts look broadly similar to our younger cohorts, which gives us confidence that, assuming no large and unforeseen changes to the labour market, future earnings patterns of more recent cohorts will be similar to those of earlier cohorts.

We include in our sample all individuals who entered HE full time for an undergraduate degree between the ages of 17 and 21.[5] For those who study for multiple degrees, we count the first one that was successfully completed. If none is successfully completed, we use the first degree started. In defining an 'undergraduate degree', we largely follow the HESA definition of a 'first degree', except where this leads to significant changes in definitions over time.[6]

Table 2 shows the proportion of first-degree students studying each subject in different cohorts of our linked HESA–HMRC sample, as well as the total number of students. The large rise in the total number of students over the period in our sample is driven largely by the expansion of the HE sector in the UK, but also partly by improvements in data availability and match quality over time.[7]

[4]Individuals born after 1990/91 will have only very recently entered the labour market in the last year of our data, and hence their outcomes will not yet be representative of their later outcomes.

[5]Although we sometimes use the term 'graduates', we generally include dropouts. The exception to this rule is that we do not include dropouts who started their courses before 1996. The reason is that we cannot reliably infer the age of these students from the data we have.

[6]This differs from our earlier work, which took a more expansive view of what constitutes an undergraduate degree, and included all courses classified by HESA as being level H or I.

[7]More details on sample selection and data quality are given in the online appendix.

Table 2: HESA data by subject

Subject	**1975/76**	**1980/81**	**1985/86**	**1990/91**
Agriculture	1.0%	0.8%	0.7%	0.7%
Allied to med	3.0%	3.5%	3.4%	3.2%
Architecture	2.1%	1.9%	2.3%	2.1%
Biosciences	5.5%	4.9%	3.6%	3.7%
Business	12.2%	13.4%	12.7%	12.6%
Celtic	0.1%	0.1%	0.1%	0.1%
Chemistry	1.7%	1.2%	1.1%	1.2%
Combined	3.3%	1.4%	0.6%	0.4%
Comms	1.8%	2.9%	3.6%	3.6%
Computing	4.4%	7.0%	5.0%	4.5%
Creative arts	10.0%	10.7%	11.8%	12.1%
Economics	2.4%	2.1%	1.9%	2.0%
Education	3.4%	3.0%	3.9%	4.1%
Engineering	6.4%	5.8%	4.9%	4.9%
English	3.8%	4.0%	4.1%	4.2%
Geography	3.1%	3.0%	2.5%	2.4%
History	4.3%	3.6%	4.1%	3.7%
Humanities n.s.	0.1%	0.1%	0.1%	.
Languages	5.0%	3.8%	3.2%	2.9%
Law	4.0%	4.1%	5.1%	4.4%
Maths	2.4%	2.2%	1.9%	2.3%
Medicine	1.9%	2.0%	2.3%	1.9%
Nursing	0.6%	1.0%	2.0%	2.7%
Pharmacology	0.9%	0.9%	1.0%	1.0%
Philosophy	1.4%	1.3%	1.3%	1.3%
Physics	1.3%	1.1%	1.0%	1.0%
Physsci	2.2%	1.3%	1.3%	1.3%
Politics	2.1%	1.7%	2.0%	1.9%
Psychology	2.9%	3.5%	4.2%	4.3%
Social care	0.3%	0.6%	1.0%	1.1%
Sociology	3.9%	3.5%	3.5%	3.6%
Sportsci	.	1.1%	2.9%	3.8%
Technology	0.9%	0.7%	0.8%	0.6%
Vetsci	0.2%	0.2%	0.3%	0.3%
Unknown	1.3%	1.7%	.	.
Total	153,043	228,225	255,251	301,471

Note: Percentage of students studying each subject in the HESA data sample. Students studying multiple subjects are counted according to the proportion of their degree in each subject. A dot indicates where sample sizes are too small to be shown for statistical disclosure purposes.

The decline in 'combined studies' coincides with improvements in the way HESA collects data on degrees with multiple subjects, so we disregard this subject entirely in the rest of the analysis to ensure comparability across years.[8] Similarly, we drop from the sample all students whose subject is unknown. Student numbers in Celtic and veterinary science are too small to draw reliable conclusions about lifetime earnings from the data, so they are also dropped from the analysis. Lastly, we do not include sports science in our analysis, as very few people studied this in the earliest cohorts for which we have data. The large overall increase in student numbers has been spread fairly evenly across subjects and hence the proportions studying each subject have stayed relatively constant. Some exceptions are nursing and social care, which have expanded quite dramatically in recent years, and languages, which has seen a decline.

Table 3 shows how the proportion of students at different universities has changed over time. In line with the overall expansion in HE, the number of students at all types of institution has risen for most of the period shown. The expansion has been most pronounced among the more selective newer universities, and least pronounced at Russell Group universities. As a result, a somewhat higher proportion of students now attend universities in the 'other (more selective)' group,[9] and Russell Group students make up a slightly smaller proportion of the total, even though the actual numbers of students have gone up significantly. The proportion of students in pre-1992 universities and the least selective 'other' universities has stayed remarkably constant over time.[10] Overall, student numbers have stabilised in the more recent cohorts across institutions.

Table 3: HESA data by institution type

Subject	**1975/76**	**1980/81**	**1985/86**	**1990/91**
Russell Group	46,256	65,626	71,639	76,641
Pre-1992 universities	29,965	45,094	52,751	61,009
Other (more selective)	46,231	73,240	86,167	108,027
Other (least selective)	30,591	44,265	44,694	55,794
Total	153,043	228,225	255,251	301,471

Note: 'Other (least selective)' contains the 40 least selective universities by total GCSE score of students from the 2004 to 2007 GCSE cohorts.

A final relevant factor for our analysis is the split by both subject and institution type. While most subjects are taught in significant numbers at all institution types, some are too small or too concentrated to allow us in general to split by both subject and institution. For this reason, we pool across institution types for agriculture, architecture, chemistry, medicine, nursing, pharmacology, philosophy, physics, social care and technology for parts of the analysis.[11]

Overall, the relatively stable split across subjects and institution types suggests that earnings patterns by subjects and institution types may not change dramatically across cohorts.[12] While

[8] The same applies to the much smaller 'humanities not further specified'.

[9] See the online appendix for a list of the universities included in each group.

[10] It should be noted that 'least selective' here only refers to academic selectivity. Some of the universities we call 'least selective' will be selective according to other criteria such as artistic ability.

[11] Proportions of students by institution type and subject for the earliest cohort of the HESA data are shown in Appendix A.

[12] The estimated returns for the subjects and institution groups that have seen very large changes, such as languages,

one might be concerned about the overall rise in student numbers, there is a rich body of academic evidence that university expansion in the UK and in other developed countries has not decreased the overall return to education for different cohorts (see, for example, Blundell, Green and Jin (2016) for evidence from the UK). However, this does not preclude the possibility that university expansion might have led to lower earnings specifically for graduates of the least selective universities, while the graduate premium may have risen at the most selective institutions.[13] To the extent that this is the case, our projections are likely to overestimate returns for students at the least selective institutions and underestimate them for students at the most selective universities.

2.3 Mid-career earnings

In order to show how the evolution of earnings over the life cycle differs across gender and subject, this section presents mid-career earnings at different ages based on the linked HMRC–HESA data for the 2016/17 tax year.[14] Figure 1 shows the median pre-tax earnings of women at ages 30, 35 and 40 by university subject (excluding women with zero earnings). The ordering of university subjects by median earnings is roughly the same at age 40 as it is at age 30: the highest-earning subjects at both ages are medicine and economics, and the lowest-earning subjects are social care and creative arts. Across the board, earnings for women are very similar at ages 30 and 40, except for those who studied law or medicine, who see much higher earnings at age 40.

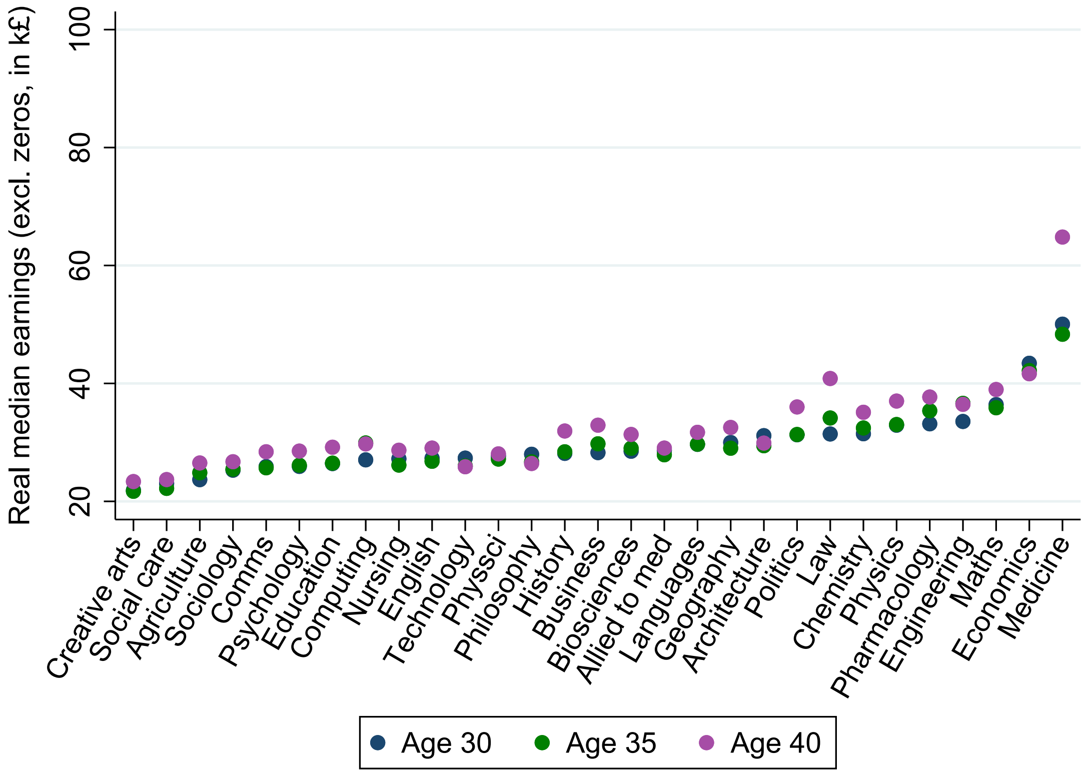
Figure 2 shows a rather different picture for men. Median earnings are much higher for men at age 40 than at age 30 for graduates of all subjects. While we see the same subjects at the top (medicine and economics) and the bottom (creative arts and social care), earnings differences are far from even across subjects. Notably, there are large differences between age 30 and age 40 earnings for graduates of technology, law, economics and medicine, but relatively small differences in creative arts, social care and nursing.

nursing and social care, should be treated with a higher level of caution than those for other subjects. People studying these subjects in later cohorts might have different backgrounds and prior attainment compared with those from earlier cohorts, and hence different earnings and employment profiles.

[13]Limited evidence for this is presented in Hussain, McNally and Telhaj (2009).

[14]While our analysis uses all tax years from 2013/14 to 2016/17, 2016/17 data are presented here because only in that year do we have tax data up to age 40. Additional descriptive statistics of the HMRC–HESA data are presented in Appendix A.

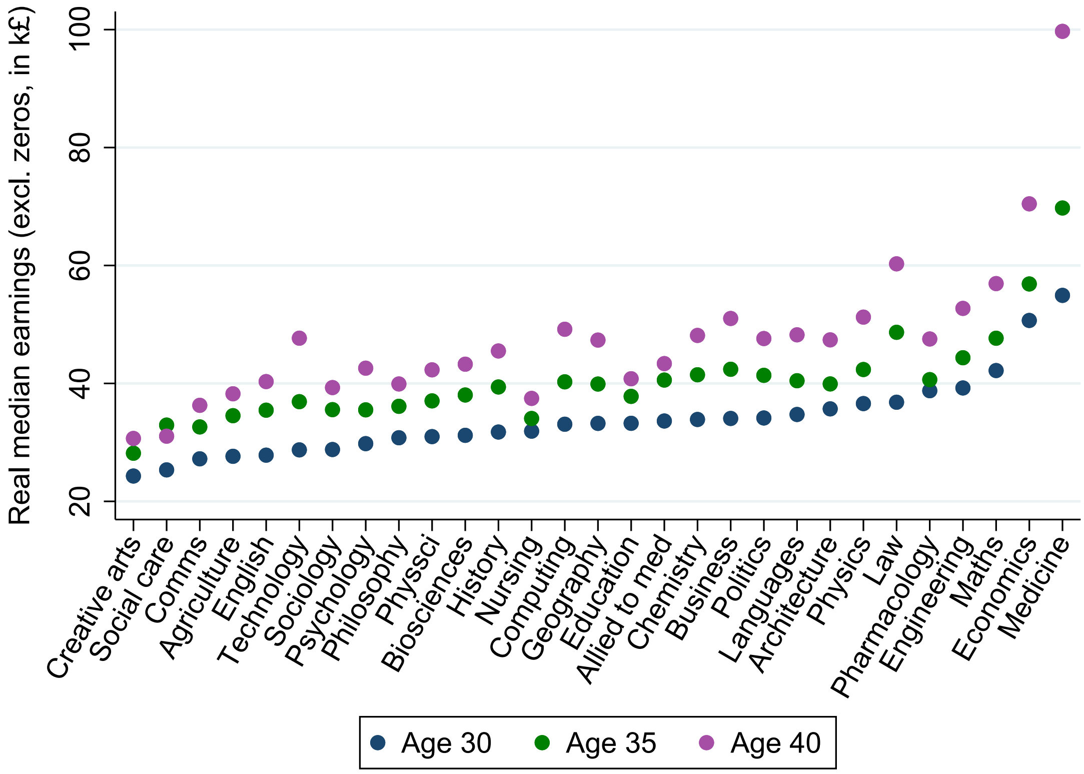
Figure 1: Women's median pre-tax earnings by subject in 2016



Note: Median pre-tax earnings by subject for individuals at different ages, in the 2016/17 tax year in 2018 prices, conditional on positive earnings. Earnings are Winsorised by subject and weighted by subject shares. Includes earnings of graduates only; earnings were imputed in cases of missing earnings data.

Comparing men and women, we see that while median earnings of women with HE are only slightly lower than those of men with HE at age 30, they are much lower at age 40. The relative magnitudes of earnings across subjects are similar for both genders: those who studied medicine earned about twice as much at age 30 as people of the same age who studied creative arts, and about three times as much at age 40.

Figure 2: Men's median pre-tax earnings by subject in 2016



Note: Median pre-tax earnings by subject for individuals at different ages, in the 2016/17 tax year in 2018 prices, conditional on positive earnings. Earnings are Winsorised by subject and weighted by subject shares. Includes earnings of graduates only; earnings were imputed in cases of missing earnings data.

2.4 Labour Force Survey

Our aim is to simulate earnings for the entire working life, up to age 67. For graduates, we can make use of administrative data up to age 40, while for non-graduates we can use it up to age 30. After age 40 for graduates, and age 30 for non-graduates, we then use earnings information from the Labour Force Survey (LFS) for the remainder of working life.

The LFS is a quarterly survey of approximately 40,000 UK households. Individuals from each household are surveyed for five consecutive quarters. The survey includes questions on education, including subject studied at university,[15] employment and earnings, with the last asked in waves one and five only. Britton, Shephard and Vignoles (2019) give more information on the LFS data and show how they compare with earnings data from HMRC tax records.

[15]Since 2012, it has also included information on university attended. We do not make use of these data, because the resulting sample sizes are too small to draw reliable conclusions.

Figure 3: Median earnings at different ages

Note: Median women's and men's earnings from the Labour Force Survey in 2018 prices, conditional on positive earnings. Non-HE includes all individuals whose highest qualification is NVQ level 2 or above (equivalent to at least five A*–C grades at GCSE), but no HE qualification. HE includes individuals with a qualification at first-degree level. Individuals with a university qualification below degree level are not included in either group.

Figure 3 shows median earnings from the LFS data that we use. We extract information from the LFS to estimate earnings dynamics, worklessness rates and the evolution of the cross-sectional distribution of earnings at each age for which we do not have tax records. However, we only use measures of *changes* in our variables of interest from the LFS rather than their levels. The reasons are: first, that the definitions of key variables differ between the LFS and our administrative data; second, that the LFS does not include earnings for the self-employed; and third, that its smaller sample size makes it necessary to pool across decades of data including the Great Recession, which may not be representative of the workings of the labour market in normal times.

2.5 Fully-linked LEO analysis sample

All analysis of returns in this report will be done on actual (up to age 30) and predicted (ages 31 to 67) earnings of students in the 2002 GCSE cohort, nearly all of whom were born in the 1985/86 academic year. The reason we have chosen to focus on this cohort is that it is the earliest cohort for which we have an NPD record. This means that, among the cohorts for which we have rich information on background characteristics that we can use to convincingly estimate returns, it is the cohort for which we can observe earnings at the oldest age.[16]

Table 4: Analysis sample: 2002 GCSE cohort

Institution Type	**Women**	**Men**	**Total**
Non-HE	19,043	18,877	37,920
Russell Group	24,519	22,576	47,095
Pre-1992 universities	14,115	13,426	27,541
Other (more selective)	23,923	18,579	42,502
Other (least selective)	16,602	11,588	28,190
Total	98,202	85,046	183,248

Note: Number of individuals in each institution type used in our analysis, as well as those not attending HE, from the 2002 GCSE analysis sample. Total number of individuals given at the bottom of the table. Non-HE conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Table 4 presents the number of students in this cohort used in our analysis by university type, with those not entering HE included as another category. The non-HE category is limited to people who could have chosen to enter university at age 18, which for the purposes of this report we define as those with at least five A*–C GCSEs and a Key Stage 5 record.[17] Individuals are only included in the HE sample if they attended university for a degree that is classified as a 'first degree' according to the HESA definition. Those who have only attended university for an 'other undergraduate degree' such as a foundation degree are included neither in the HE nor in the non-HE group. The result of these sample selection rules is that the non-HE group is relatively small; it is roughly comparable in size to the university type categories.[18] There are more women than men in all categories, reflecting the higher educational attainment and rate of university entry of women.

3 Methodology

The main methodological challenge in estimating returns to HE beyond age 30 is that no data of the same quality and comprehensiveness as were used in Belfield et al. (2018*b*) are available for earlier cohorts. The rich background data from the NPD, which are crucial for estimating returns, are only available starting from the 2002 GCSE cohort, for which we only observe earnings up to

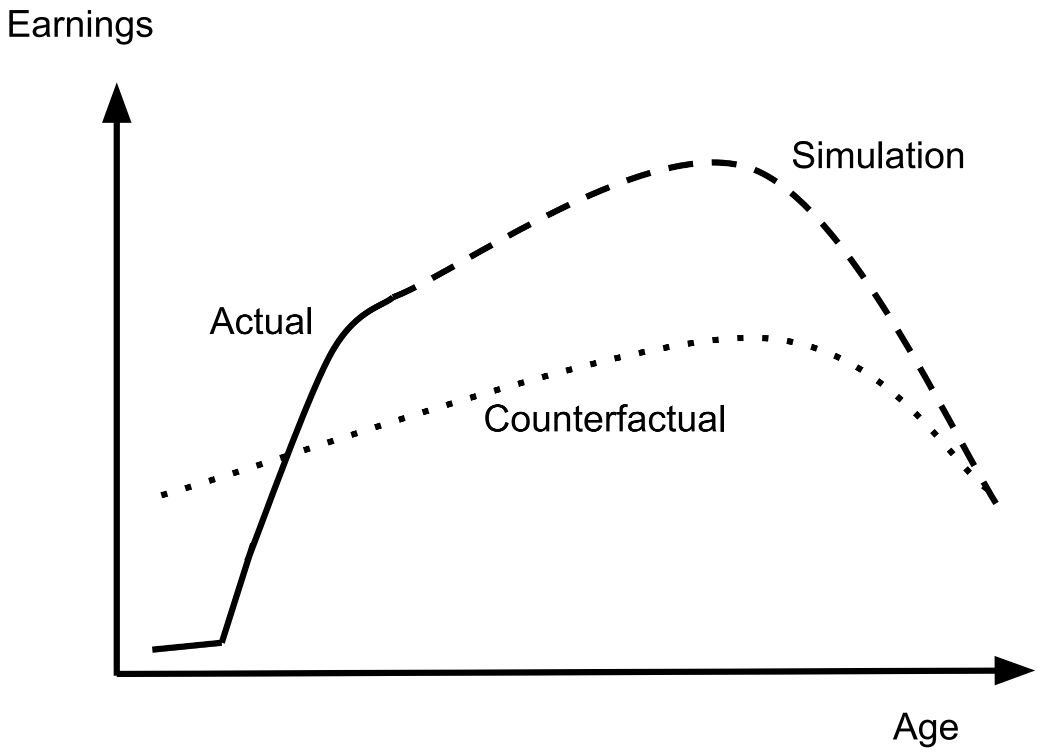
[16]One might be concerned that this cohort is not well suited for our analysis, because the Great Recession hit just as this cohort finished university, which might have led to 'scarring' effects. This does not appear to be the case. As Figure 35 in Appendix A shows, although the members of the 2002 GCSE cohort had lower earnings than previous cohorts in their 20s, these earnings are in line with all later cohorts for which we have data. Furthermore, they are on track to catch up with or even overtake earlier cohorts in their 30s.

[17]Note that this definition is narrower than that used in Belfield et al. (2018*b*), where we did not require any Key Stage 5 participation. Our requirement is more plausible for the 2002 cohort than for the later cohorts included in Belfield et al. (2018*b*), as university entry with vocational qualifications was less common among earlier cohorts.

[18]Details on sample selection are presented in the online appendix.

age 30. We address this lack of data by simulating lifetime earnings paths for all individuals from the 2002 GCSE cohort – the oldest cohort for which we have all the required data – who achieved at least five A*–C grades in their GCSE exams and who have a Key Stage 5 record. The core idea is that we can use information on previous cohorts to learn about the likely patterns in the mid- and late-career earnings of this cohort. Then we can fit similar models to Belfield et al. (2018*b*) to estimate the returns to attending HE at each age, and use these estimated returns to generate counterfactual earnings profiles for those who did attend university. A schematic representation of this method is given in Figure 4.

Figure 4: Schematic representation of our methodology



Note: The figure provides a schematic representation of the actual, simulated and estimated counterfactual earnings for a graduate from the 2002 GCSE cohort.

As we have access to linked HESA–HMRC data for university graduates back to anyone attending a higher education institution (HEI) in the 1995/96 academic year, we can differentiate in our earnings projections for graduates up to age 40 by gender, subject and type of institution attended. This wealth of data is crucial for our earnings predictions; capturing the earnings dynamics of graduates in their 30s is of particular importance, as for many but by no means all university graduates, earnings rise considerably over this period. The HESA data also offer limited information about the background characteristics of students, which we use to capture differences in earnings trajectories by socio-economic status.

For non-graduates beyond age 30 and graduates beyond age 40, our earnings projections are based on the Labour Force Survey. Given that only a small subset of the population are interviewed in the LFS every year, this means that we need to work with much smaller sample sizes than for earlier ages. As detailed below, this requires some adjustments to our approach; most importantly, we cannot take institution type or socio-economic status into account in our projections of changes in the earnings of graduates beyond age 40. However, this limitation is unlikely to materially affect our main estimates. First, most differences between graduates of different types of institutions and from different socio-economic backgrounds are likely to manifest by age 40. Second, with Green Book discounting, any inaccuracies in earnings projections beyond age 40 will only have a minor impact on lifetime values.

Given an actual/simulated and a counterfactual earnings series for each individual, we can calculate the net lifetime returns, exchequer returns and total lifetime returns to undergraduate degrees. *Net lifetime returns* (Section 6) are the lifetime gain or loss in earnings as a result of attending HE for the individual, after taking into account the effect of the tax and student loans system. *Exchequer returns* (Section 7) are the lifetime gain or loss per student for the taxpayer, counting all outlays for tuition and maintenance loans and teaching grants, as well as receipts from taxes, National Insurance payments and student loan repayments. *Total lifetime returns* (Section 8) combine net individual returns and exchequer returns into a measure of total lifetime returns.

The remainder of this section presents methodological details of our earnings simulations and our estimation strategy. Subsection 3.1 describes our earnings simulation for graduates aged 31–40 based on linked HMRC–HESA data. Subsection 3.2 presents our simulation methods for non-graduates from age 31 and graduates from age 41 based on LFS survey data. Details of our technique for estimating returns are given in Subsection 3.3. The language of these subsections is more technical than that in the rest of this report; readers who do not wish to delve into the details of our methodology can skip them without loss of continuity.

3.1 Modelling earnings: graduates aged 31–40

The most difficult aspect of modelling earnings is to obtain a simulated later-life earnings distribution that captures not only the observed cross-sectional distribution of earnings, but also the dependence of earnings on an individual's university course, background characteristics and earnings history. We address this challenge in two ways.

First, we divide the data into groups by gender and – for those who go to university – subject studied, university type[19] and an indicator of local area participation in higher education (POLAR).[20] This means that, for example, the earnings prediction for a woman from an affluent

[19] We categorise universities into Russell Group universities, pre-1992 universities and two different groups of other universities depending on their selectivity. See the online appendix for a list of the universities included in each group.

[20] We split graduates by POLAR because it is a good proxy for socio-economic background, which is known to have an independent effect on later-life earnings (Britton et al., 2019). The division by institution type and POLAR is only done to the extent that it is possible while preserving a reasonable sample size, which we take to be at least 200 earnings

local area who has studied business at a Russell Group university will be based on the earnings of women from earlier cohorts matching the same description.

Second, in order to capture persistence in earnings, we use a *copula method*. Copulas are common in insurance mathematics and are used in the education economics literature as a flexible, data-driven way of modelling graduate earnings (Dearden et al., 2008; Dearden, 2019; Armstrong et al., 2019).[21] Copulas are a flexible way of describing the statistical links between different variables. We use the copula method to model the joint distribution of earnings over an individual's lifetime. Intuitively, the copula function *joins up* the marginal distributions; it captures the dependence of percentile ranks of earnings over time. We separately estimate copulas for each gender, subject and insitution type in order to capture differences between the groups defined by these categories.[22]

At the core of the copula approach to modelling earnings dynamics is a fundamental result known as Sklar's Theorem. A direct implication of Sklar's Theorem is that if y_t is an individual's income in the tth year of their working life, the joint distribution of an individual's lifetime earnings $F(y_1, y_2, ..., y_T)$ can be written as

$$F(y_1, y_2, ..., y_T) = C\left[F_1(y_1), F_2(y_2), ..., F_T(y_T)\right]$$

where $C : [0,1]^T \to [0,1]$ is the so-called copula function and F_t is the marginal, or cross-sectional, distribution of y_t. In words, the joint distribution of lifetime earnings can be decomposed into the marginal distributions at each age and a copula function C that captures intertemporal dependence.

The copula approach enables us to separate the modelling of each marginal distribution F_t from the copula C summarising rank dependence. In practice, this means that we do not have to make restrictive assumptions about the distribution of earnings, as we can take fully non-parametric marginal earnings distributions from the data. We only need to parameterise the copula function, which links up these marginal distributions. This allows us to take full advantage of the detailed information on earnings distributions from the linked HESA–HMRC data.

In order to maximise sample size, we pool across the cohorts of linked HESA–HMRC data that cover all students who enter university between ages 17 and 21 in the data, and which contain earnings observations in students' 30s.[23] This means that we use one cohort at age 40, two cohorts at age 39, three cohorts at age 38 and so on down to ten cohorts at age 31. To control for earnings growth and macroeconomic disturbances, we de-mean (log) earnings for all cohort/age pairs within each gender/subject/institution-type group g. Mathematically, adjusted income $y^*_{i,a}$ for an

observations at each age.

[21]This contrasts with traditional approaches that impose a more explicit theoretical structure on the model. The copula approach allows us to avoid committing to any particular theoretical framework.

[22]For agriculture, architecture, chemistry, medicine, nursing, pharmacology, philosophy, physics, social care and technology, we model employment and rank dependence jointly for all institution types, as there are very few students of these subjects attending some types of institutions. As we model 29 subjects overall, this yields 19 subjects $\times$ 4 institution types $\times$ 2 genders $+$ 10 subjects $\times$ 2 genders $=$ 172 gender/subject/institution-type groups.

[23]This is true for all cohorts from the 1975/76 to the 1985/86 cohorts.

individual in cohort c and group g is given by

$$y^*_{i,a} = \exp\left[\log y_{i,a} - \frac{1}{N}\sum_{i=1}^{N}\log y_{i,a}\right]$$

where $i = 1, \ldots, N$ denotes an individual in cohort c and group g.[24]

These de-meaned log earnings by group are the fundamental building block of our model. First, we estimate a model for employment/worklessness with separate parameters by group and age using these data. Second, we do the same for the rank dependence of earnings using copulas. Third, we add the group (log) means of age 30 earnings for the 2002 GCSE cohort and within-group earnings growth projections to these de-meaned earnings in order to obtain appropriate marginal earnings distributions for the 2002 GCSE cohort in their 30s.

3.1.1 Modelling employment/worklessness

The probability of employment at age a is allowed to vary by gender/subject/institution-type group g, employment in the past two periods and, if observed, an individual's within-group earnings rank in the previous two periods. We choose to include data from the past two periods because the second-to-last period appears to add information over and above the last period, but including data from three periods would be infeasible as too many parameters would need to be estimated. Other background characteristics available in the HESA data such as POLAR quintiles are not included in the model, in order to guard against overfitting.[25]

In paricticular, we estimate three probit models at each age and for each group g depending on employment in the previous two periods:

- For individuals who were **employed in both of the past two periods**, we model the probability of being in employment in the current period as a function of the individual's earnings ranks in the previous two periods. We estimate this probability using a probit model of the form

  $$P(E_{i,a} = 1 | E_{i,a-1} = 1, E_{i,a-2} = 1; r_{i,a-1}, r_{i,a-2}) = \Phi\left(\alpha^{EE}_{0,a} + \alpha^{EE}_{1,a} r_{i,a-1} + \alpha^{EE}_{2,a} r_{i,a-2}\right)$$

  where i indexes individuals, a is age, the αs are the estimated probit coefficients and $r_{i,a}$ is an individual's rank in the earnings distribution within a gender/subject/institution-type group conditional on employment.[26]

[24] g and c superscripts have been dropped for readability.

[25] An alternative approach here would be to treat worklessness simply as the lowest earnings rank and impose average rates of worklessness from the data. This route has usually been taken in previous work using copulas to model earnings dynamics. While this approach is simpler and greatly reduces the number of parameters that need to be estimated, it can lead to substantial bias, mainly because those out of work tend to have very different income dynamics from those on a very low income.

[26] As above, g superscripts have been dropped to avoid notational clutter.

- For individuals who were **employed in the previous period but inactive in the period before**, we model the probability of being in employment in the current period as a function of the individual's earnings rank in the previous period. We estimate this probability using a probit model of the form

$$P(E_{i,a} = 1 | E_{i,a-1} = 1, E_{i,a-2} = 0; r_{i,a-1}) = \Phi \left(\alpha^{IE}_{0,a} + \alpha^{IE}_{1,a} r_{i,a-1} \right)$$

  with variables and indices defined as above.

- For individuals who were **inactive in the previous period but employed in the period before**, we model the probability of being in employment in the current period as a function of the individual's earnings rank two periods before. We estimate this probability using a probit model of the form

$$P(E_{i,a} = 1 | E_{i,a-1} = 0, E_{i,a-2} = 1; r_{i,a-2}) = \Phi \left(\alpha^{EI}_{0,a} + \alpha^{EI}_{1,a} r_{i,a-2} \right)$$

  with variables and indices defined as above.

For individuals who were **inactive in both of the previous two periods**, we save the sample mean employment rate of such individuals in the data, which is given by

$$\hat{P}(E_{i,a} = 1 | E_{i,a-1} = 0, E_{i,a-2} = 0) = \frac{1}{N^{II}} \sum_{i=1}^{N^{II}} E_{i,a} 1(E_{i,a-1} = 0) 1(E_{i,a-2} = 0)$$

where N^{II} is the number of individuals in gender/subject/institution-type group g that were inactive in both of the past two periods, i ranges over individuals within g, and $1(.)$ is the indicator function, which is equal to 1 if the condition in brackets is fulfilled and 0 otherwise. All models are estimated on PAYE earnings data from 2010 until 2016 in order to achieve the necessary sample size. To guard against outliers, sparse data and convergence problems, we then smooth all parameters over age using Nadaraya–Watson kernel regression. Finally, the parameters are adjusted to match the overall difference in parameters between estimation on PAYE earnings since 2010 and total earnings (including self-employment earnings) since 2013.[27]

3.1.2 Modelling rank dependence conditional on employment

Analogous to the employment model, we also model earnings rank within each group g separately depending on past employment and earnings rank using copula functions. As in the employment models, we allow for dependence on earnings rank in the past two periods, so the copula functions

[27] In particular, we estimate the parameters on a sample where we are pooling across subjects and institutions, but still separating by gender and age, once on 2010–16 PAYE data and once on 2013–16 PAYE and self-assessment data. We then adjust all parameters from the disaggregated estimates in proportion to the ratio of the two sets of parameters from the pooled sample. In the case of the re-entry rates of those unemployed for two periods, we adjust by the ratio of differences from 1, as these parameters are bounded above at 1.

we estimate are at most bivariate.[28]

At each age a, we estimate three different copulas:

- For individuals who were **employed in both of the past two periods**, we model earnings rank at a given age a as a function of earnings rank in the previous two years. Hence we estimate the three-dimensional copula $C^{EE}(r_{i,a}, r_{i,a-1}, r_{i,a-2})$ for those with an earnings observation in all three periods, where $r_{i,a}$ is the within-group rank at age a as above.

- For individuals who were **employed in the previous period but inactive in the period before**, we model earnings rank at a given age a as a function of earnings rank in the previous period. Hence we estimate the two-dimensional copula $C^{IE}(r_{i,a}, r_{i,a-1})$.

- For individuals who were **inactive in the previous period but employed in the period before**, we model earnings rank at a given age a as a function of earnings rank two years before. Hence we estimate the two-dimensional copula $C^{EI}(r_{i,a}, r_{i,a-2})$.

Using the estimated copulas, we can simulate conditional earnings ranks for earnings at age a conditional on the within-group earnings rank at $a-1$ and/or $a-2$. While the copulas are estimated at the gender/subject/institution-type level, with institution types pooled for selected subjects as described above, in simulation we also constrain earnings ranks within institution-type/POLAR groups, as far as this is possible while preserving sufficient sample size. For individuals who were **inactive in both of the past periods**, we assume no intertemporal dependence. In simulation, we draw their earnings ranks from the distribution in the data conditional on two periods of zero earnings.

All copulas are parameterised as two-dimensional t-copulas, which extensive experimentation has shown to be the best fit for summarising rank dependence in the data. We separate the three-dimensional t-copula $C^{EE}(r_{i,a}, r_{i,a-1}, r_{i,a-2})$ characterising rank dependence for individuals who are employed in three consecutive years into three two-dimensional copulas using the D-vine decomposition described in Aas et al. (2009). Each bivariate t-copula is characterised by two parameters: a degrees of freedom parameter, ν, and a persistence parameter, r.

We estimate these two parameters at each age a and for each group g from PAYE earnings data since 2010 using the BFGS algorithm for numerical maximisation of the (pseudo-)likelihood. Like the employment parameters, the copula parameters are smoothed with age using Nadaraya–Watson kernel regression and then adjusted to match the overall difference between PAYE earnings since 2010 and total earnings (including self-employment earnings) since 2013.[29]

[28] As in modelling employment, we choose to include data from the past two periods because the second-to-last period appears to add information over and above the last period, but including data from three periods would be infeasible as too many parameters would need to be estimated.

[29] This is done in the same way as the adjustment of the employment parameters. Like the re-entry rates of those unemployed for two periods, the persistence parameters of the copulas are adjusted by the ratio of differences from 1, as these parameters are also bounded above at 1.

3.1.3 Assigning earnings to ranks

In order to assign earnings to ranks, it is necessary to adjust both the level and the growth rate of y^*_{ia}, the de-meaned earnings of the older cohorts described earlier. As we are interested in simulating the earnings of the 2002 GCSE cohort, we adjust the level of earnings to match the earnings of that cohort at age 30. For the growth rate, we add the average percentage earnings difference between people of adjacent ages from the last four years in the data, for which we observe both PAYE and self-employment earnings, and a prediction for earnings growth in the overall economy. In particular, for each gender/subject/institution-type/POLAR group g, we calculate

$$y^{**}_{i,a} = \exp\left\{\log y^*_{i,a} + \frac{1}{N}\sum_{j=1}^{N}\log y^{1985}_{j,30} + \sum_{b=31}^{a}\Delta_b\right\}$$

where j ranges over individuals with positive earnings at age 30 in the 2002 GCSE cohort who are members of a given group g, and N is the number of such individuals. Δ_b is the predicted growth rate at age b for group g, which is calculated as the average percentage earnings difference between people of adjacent ages from the last four years in the data. Mathematically,

$$\Delta_b = \frac{1}{T_b}\sum_{t=2017-T_b}^{2016}\left(\frac{1}{N^{bt}}\sum_{i=1}^{N^{bt}}\log y_{i,b} - \frac{1}{N^{b-1,t}}\sum_{j=1}^{N^{b-1,t}}\log y_{j,b-1}\right) + \Delta_b^{OBR}.$$

T_b is the number of relevant tax years at age b: $T_b = 4$ except for age 38 onwards, when data are only available from the most recent year(s). i and j range over the members of group g at time t with positive earnings at ages b and $b-1$, respectively. Δ_b^{OBR} is whole-economy predicted earnings growth as forecast by the Office for Budget Responsibility (OBR).[30] The group-specific age–earnings profiles $\{y^{**}_{i,a}\}_{a=31}^{40}$ are then smoothed like the probit and copula parameters in order to guard against outliers and lessen the impact of data quality issues for the earliest cohorts.

For each simulated age a, we use *systematic sampling* to assign each employed individual from the 2002 GCSE cohort a simulated income $y^{**}_{i,a}$ from the respective group g according to the individual's predicted rank in the within-group distribution. Systematic sampling is a technique for sampling from a distribution in such a way that the empirical distribution of the sample matches the distribution being sampled from as precisely as possible. This technique helps us to minimise random noise in our earnings simulations.

It should be noted that the method described above is only one possible way of extracting measures of earnings growth with age from the data on previous cohorts. One alternative is to look at the growth in earnings of a particular cohort over time, rather than at earnings differences across cohorts within a given year as we do here. Other methods from the literature include those of Deaton and Paxson (1994) and of Chamon and Prasad (2010). All of these methods rely on different assumptions, none of which is likely to hold precisely in reality. The general difficulty

[30] We use the March 2019 average earnings forecast, which is given in table 1.6 of the supplementary economy tables of the Economic and Fiscal Outlook. The data can be downloaded at `https://obr.uk/efo/economic-fiscal-outlook-march-2019/`.

here is known as the age–period–cohort problem in the economics literature.

There are a number of reasons why we have chosen the method described above. First, it is the simplest and thus most transparent method available, making our results easier to check and replicate for other researchers. Second, it is the most common method in the literature on the returns to higher education, making our results more comparable to those of other studies, including our own previous work. Third, it is less sensitive to macroeconomic conditions compared with other methods, which is especially important in our context given the potential long-term effects of the Great Recession on earnings growth. Fourth, for men in particular, extrapolating from trends for recent cohorts seems to align with the age profiles obtained by our method (see Figures 35 and 36 in the appendix). Fifth, for women, alternative methods give implausible results that are not in line with the previous literature. The robustness of our results to alternative methods is discussed in detail in the online appendix.

3.2 Modelling earnings using LFS survey data

For those without HE aged 31 and above, and with HE aged 41 and above, no suitable administrative data are available, so we need to use data from the Labour Force Survey. As these data are much sparser and of lower quality than the HESA–HMRC data, we employ a simplified version of the procedure outlined above for the prediction of earnings. The most significant changes are: first, that rather than relying on two periods of past earnings, we only use information about the previous period, as no information about the second-to-last period is available;[31] second, while we can still split the sample by gender and subject studied for graduates, we do not have information about institution type or POLAR category; and third, due to sample size limitations, copulas and employment parameters are estimated at the level of subject groups rather than individual subjects, where, following Walker and Zhu (2013), we categorise subjects into STEM (science, technology, engineering and maths), LEM (business, economics and law) and 'other' subjects.

3.2.1 Modelling employment

For those **employed in the previous period**, we now model employment as a function of employment in the last period only rather than in the last two periods as before. The reason is that the Labour Force Survey only has a panel dimension of one year, and in any case the sample size is too small to reliably estimate more parameters. Hence we estimate the probit model

$$P(E_{i,a} = 1 | E_{i,a-1} = 1; r_{i,a-1}) = \Phi\left(\alpha^E_{0,a} + \alpha^E_{1,a} r_{i,a-1}\right).$$

[31] The reason is that individuals only participate in the labour force survey for at most five quarters.

For individuals who were **inactive in the previous period**, we save the sample mean employment rate of such individuals in the data, which is given by

$$\hat{P}(E_{i,a} = 1 | E_{i,a-1} = 0) = \frac{1}{N^I} \sum_{i=1}^{N^I} E_{i,a} 1(E_{i,a-1} = 0)$$

where N^I is the number of individuals in gender/subject group g that were inactive in the past period, i ranges over individuals within g, and $1(.)$ is the indicator function. To guard against outliers, sparse data and convergence problems, as before we smooth all parameters with age using Nadaraya–Watson kernel regression. As the Labour Force Survey uses a different definition of employment, and the estimation sample we use covers a different time period, we adjust the estimated employment parameters so that they are consistent with the parameters estimated from administrative data at age 30. This is done by fitting an identical model to the administrative data at age 30, saving the ratio of the parameters and adjusting the parameters for later ages accordingly.[32]

3.2.2 Modelling rank dependence conditional on employment

For individuals who were **employed in the previous period**, we similarly and for the same reasons model earnings rank as only dependent on rank in the past year. Hence we estimate the two-dimensional copula $C^E(r_{i,a}, r_{i,a-1})$. As with the employment parameters, we adjust the estimated copula parameters so that they are consistent with the parameters estimated from administrative data at age 30.[33] For individuals who were **unemployed in the previous period**, we assume no intertemporal dependence on rank. In simulation, we draw their earnings ranks from the distribution in the data conditional on unemployment in the previous period.

3.2.3 Assigning earnings to ranks

We construct adjusted earnings $y_{i,a}^{**}$ as above, adjusting the level to the simulated within-group level at age 40 for those with HE and the actually observed level at age 30 for those without. However, instead of the actual distribution from the LFS data, we keep the age 40 empirical distribution from the HMRC–HESA data and adjust it to match the change in mean and standard deviation (in logs) of the LFS data. For those without HE, we determine average (log) earnings growth at each percentile and age for both genders, using the same method as for the HESA data. Then we smooth these growth rates across percentiles at each age and assign earnings growth by percentile.

[32]For women, we only adjust the parameters halfway as a compromise between internal consistency and over-extrapolation from recent trends towards higher labour force participation of young women. As for the adjustment of the parameters estimated from HESA data, we adjust the re-entry rate of those unemployed using the ratio of differences from 1, as it is bounded above at 1.

[33]Our main reason for this is that survey earnings data usually have a higher measurement error than administrative data, which biases the copula parameters. As before, the persistence parameter of the copula is adjusted by the ratio of differences from 1.

3.2.4 Modelling retirement

In order to model the rise in the retirement age that is expected to accompany rising life expectancy, we follow Britton, van der Erve and Shephard (2019) and hold all model parameters fixed for a number of years at the peak of the life-cycle earnings profile. This has the methodological advantage that life-cycle earnings growth is zero at that point, so no further assumptions about life-cycle earnings growth must be made; it is also consonant with the notion of retirement being pushed back. In particular, we fix model parameters for eight years at age 51, with parameters from ages 60 to 67 corresponding to ages 52 to 59 in the data.

3.3 Estimation

3.3.1 Returns at each age

We estimate the returns to undergraduate degrees at each age using multiple ordinary least squares (OLS) regressions on the simulated data. The advantages of this relatively simple method are its transparency and direct comparability with our earlier work in Belfield et al. (2018*b*).[34] At each age between 19 and 30, we estimate a regression model of the form

$$\log y_{ia} = \delta_a + Treatment_i'\beta_a + x_i'\gamma_a + \epsilon_{ia}.$$

Here y_{ia} is individual i's (simulated) income at age a, $Treatment_i$ is a vector of treatment variables of interest, such as subject or institution type, and x_i is a vector of observable characteristics whose effect is allowed to vary by age. Our main estimates consider university attendance, institution type and subject studied as treatments. As in Belfield et al. (2018*b*), x_i includes a dummy variable for over-18 entry, so all of our results should be interpreted as returns for those who entered university at age 18 or below.

For ages above 30, we estimate the same model holding γ_a, the parameter vector summarising the effect on earnings of the observable characteristics, fixed at its age 30 value, so that the regression model becomes

$$\log \dot{y}_{ia} = \delta_a + Treatment_i'\beta_a + \epsilon_{ia}$$

where $\log \dot{y}_{ia} = \log y_{ia} - x_i'\hat{\gamma}_{30}$. The assumption here is that in relative (log) terms, the effect of background conditions will be roughly constant across the life cycle from age 30. This assumption is necessary as from age 30 onwards, we are relying on simulated earnings that are unlikely to completely capture dependence on background conditions. For example, this allows us to incorporate that among individuals with identical earnings at ages 29 and 30 who studied the same subject at the same university, those who went to private school may still have higher future earn-

[34]In contrast to Belfield et al. (2018*b*), we do not report estimates with inverse probability weighting (IPWRA). The main reason is that our sample sizes are smaller to begin with, as we focus on the 2002 GCSE cohort. Weighting would reduce the effective sample size further, leading to less precise estimates. We also note that the differences between the IPWRA and OLS estimates reported in Belfield et al. (2018*b*) are minimal.

ings expectations than those who did not.[35]

3.3.2 Lifetime returns

Following Blundell, Dearden and Sianesi (2005) and Walker and Zhu (2013), we estimate lifetime returns using a richer specification of our regression model that allows for differential effects of background conditions for those who do and do not attend university. We also allow for differential effects of all possible combinations of subject studied and institution type. This granularity allows us to generate a different returns estimate for each individual at each age. While these individualised estimates are subject to a relatively high margin of error, granularity in returns estimates is crucial for the estimation of net lifetime returns given the high degree of non-linearity in the tax and student loans system.

In particular, for all ages between 19 and 30, we estimate the regression model

$$\log y_{ia} = \delta_a + (Subject_i * HEItype_i)'\beta_a + x_i'\gamma_{1a} + anyHE_i x_i'\gamma_{2a} + e_{ia}$$

where $Subject_i * HEItype_i$ denotes the full set of interactions between subject and institution type and $anyHE_i$ is an indicator variable for whether an individual has attended university. For ages above 30, we estimate

$$\log \ddot{y}_{ia} = \delta_a + (Subject_i * HEItype_i)'\beta_a + e_{ia}$$

where

$$\log \ddot{y}_{ia} = \log y_{ia} - x_i'\gamma_{1,30} - anyHE_i x_i'\gamma_{2,30}.$$

On the basis of the estimated coefficients from these regressions, we simulate counterfactual earnings paths for all university attendees in the 2002 GCSE cohort. We proceed as follows:

1. Generate the panel of predicted log earnings $\widehat{\log y_{ia}}$ based on the estimated coefficients of the regression model.

2. Generate the *counterfactual* panel of predicted log earnings $\widehat{\log y_{ia}}^*$ for everyone who has attended university by setting $anyHE_i$, $Subject_i$ and $HEItype_i$ to zero.

3. Calculate the predicted return for each individual as $\widehat{r}_{ia} = \widehat{\log y_{ia}} - \widehat{\log y_{ia}}^*$.

4. Generate counterfactual earnings as $y_{ia}^* = \exp(\log y_{ia} - \widehat{r}_{ia})$.[36]

[35] An alternative assumption would be that all dependence on background conditions from age 30 onwards is indeed captured in the earnings and employment history of the previous two periods as summarised by the copula model. While neither assumption is directly testable with the data available, we have rejected this alternative strategy because it implies implausibly low dependence of late-career earnings on background characteristics. More details are given in the online appendix.

[36] We use y_{ia}^* as our measure of counterfactual earnings instead of $\exp(\widehat{\log y_{ia}}^*)$ in order to preserve the variation of earnings across individuals. Due to the non-linearity of the tax and student loans system, not having any unexplained variation across individuals would bias our results: we would overestimate the average counterfactual net earnings and underestimate the average counterfactual exchequer receipts. Preserving variation is consistent with an interpretation of the unexplained variation across individuals from the regression model as representing unobserved factors such as ambition: those with high ambition could be expected to earn more than others, whether or not they went to university.

While this procedure yields a counterfactual earnings panel containing everyone with positive actual earnings, whether someone attends university will also have an effect on the probability of having positive earnings in any given year. (Most obviously, attending university lowers the probability of positive earnings at the time of attendance.) In order to take this into account, we first calculate a counterfactual worklessness probability for all individuals as a function of background characteristics x_i using the parameters γ_a^E of the probit model

$$P(E_{i,a} = 0|x_i) = \Phi(x_i' \gamma_a^E)$$

which we estimate using data only on individuals who did not attend university. We then add or remove counterfactual earnings for some individuals in order to match the mean counterfactual employment rates for each subject. If the counterfactual employment rate for a subject at a given age is above the actual employment rate, we add counterfactual earnings for an appropriate number of individuals; these earnings are set to $\exp(\widehat{\log y_{ia}}^*)$. If the counterfactual employment rate for a subject at a given age is below the actual employment rate, we remove counterfactual earnings for an appropriate number of individuals. In each case, we randomly select which individuals will be affected by a change in counterfactual employment status in a given year, with the probability weights given by their predicted employment probability according to the probit model.[37]

While our example cohort is the 2002 GCSE cohort, we apply the tax and student loans system applicable to students entering university in 2019 so as to make the calculation more relevant to current policy. All features of the tax and student loans system are assumed to remain fixed in real terms except for the student loans repayment thresholds, which, following government policy, we assume will rise in line with average earnings growth. In order to capture real earnings growth between the two cohorts, we adjust the earnings of the 2002 GCSE cohort in line with earnings growth for the whole economy in the period between 2005 and 2019, when the respective cohorts would be at or entering university.[38]

We convert income streams into 'lifetime' values using the net present value method. The formula for converting an individual's earnings stream $\{y_{ia}\}_{a=19}^{67}$ into a lifetime earnings figure Y_i counting from age 19 is

$$Y_i = \sum_{a=19}^{67} \frac{y_{ia}}{(1+d)^{a-19}}$$

where d is the discount rate. The discount rate governs the value of future income relative to current income. While a discount rate of 0% would indicate that future income and current income are always equally valuable, a discount rate of 50% would imply that a given income today would only be two-thirds as valuable in a year and less than half as valuable in two years' time. This

[37] Mathematical details are presented in the online appendix.

[38] We also adjust the predicted future earnings growth in the overall economy that enters the earnings simulation to the appropriate years. As there was little earnings growth over the 2005–19 period, and earnings growth in the next few years is predicted to be roughly in line with its long-run value, both adjustments are small.

adjustment is made to take account of the fact that for the government (and many individuals), money now is perceived to be worth slightly more than money in the future.

High discount rates can have a large effect on the expected lifetime returns to higher education, as attending HE usually requires people to give up some earnings in their early 20s for higher earnings later in life. In what follows, we mostly use the Green Book's recommended discount rate of 3.5% for the first 30 years of earnings beyond age 19 and a real discount rate of 3.0% thereafter.[39] However, in many cases, we also show alternative results with no discounting or with discounting at a lower rate of 0.7%, which the Treasury uses to value the student loan book.

4 Simulated earnings over the life cycle

In order to contextualise our results, this section presents the simulated lifetime earnings profiles of our HE and our non-HE groups, separately by gender. We start by looking at simple plots of median earnings and worklessness by age, before moving on to net lifetime earnings in present value terms.[40] It is important to keep in mind that while the data presented in this section represent a forecast for people with and without HE, none of it reflects the *returns* to higher education. The earnings shown are raw earnings, i.e. there is no attempt to adjust for differences in the background characteristics between those who do and do not go to higher education – we do that in the next section.

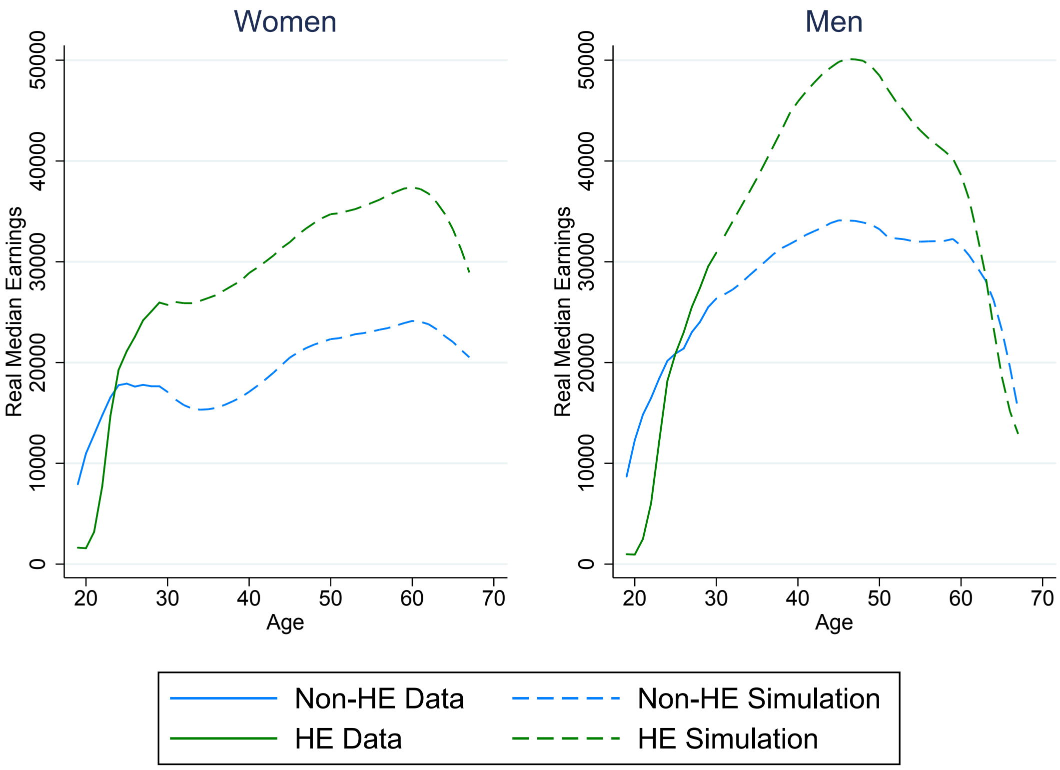
4.1 Earnings and worklessness by age

Figure 5 shows median pre-tax earnings for graduates and non-graduates, separately by gender. Up to age 30, the earnings are the actual observed earnings for the 2002 GCSE cohort. Beyond age 30, we use the simulated earnings profiles for this cohort, drawing on the methodology described in the previous section.

[39]This differs from the 3.5% discount rate for all earnings that is used in Conlon and Patrignani (2011) and Walker and Zhu (2013). As a result, our returns estimates are not precisely comparable to theirs; had we used a discount rate of 3.5% at all ages, our returns estimates would be slightly smaller.

[40]Simulations of lifetime exchequer receipts are presented in Appendix B.

Figure 5: Median life-cycle earnings (2002 GCSE cohort)



Note: Median earnings in 2018 prices. Includes zero earnings. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

For both men and women, the earnings of those with HE start below the earnings of those without HE, likely due to the three years' additional work experience of the non-HE group. The earnings of HE graduates see much stronger growth than those of their non-HE counterparts and, in the mid 20s, median earnings of HE graduates overtake those of the non-HE group. For women who did not attend HE, the mid 20s also mark the point where earnings start to flatline, while earnings for female graduates continue to grow. In the 30s, median earnings of female non-graduates even drop, before recovering again in the mid 40s. Beyond this point, the HE/non-HE earnings gap grows only very modestly for women.

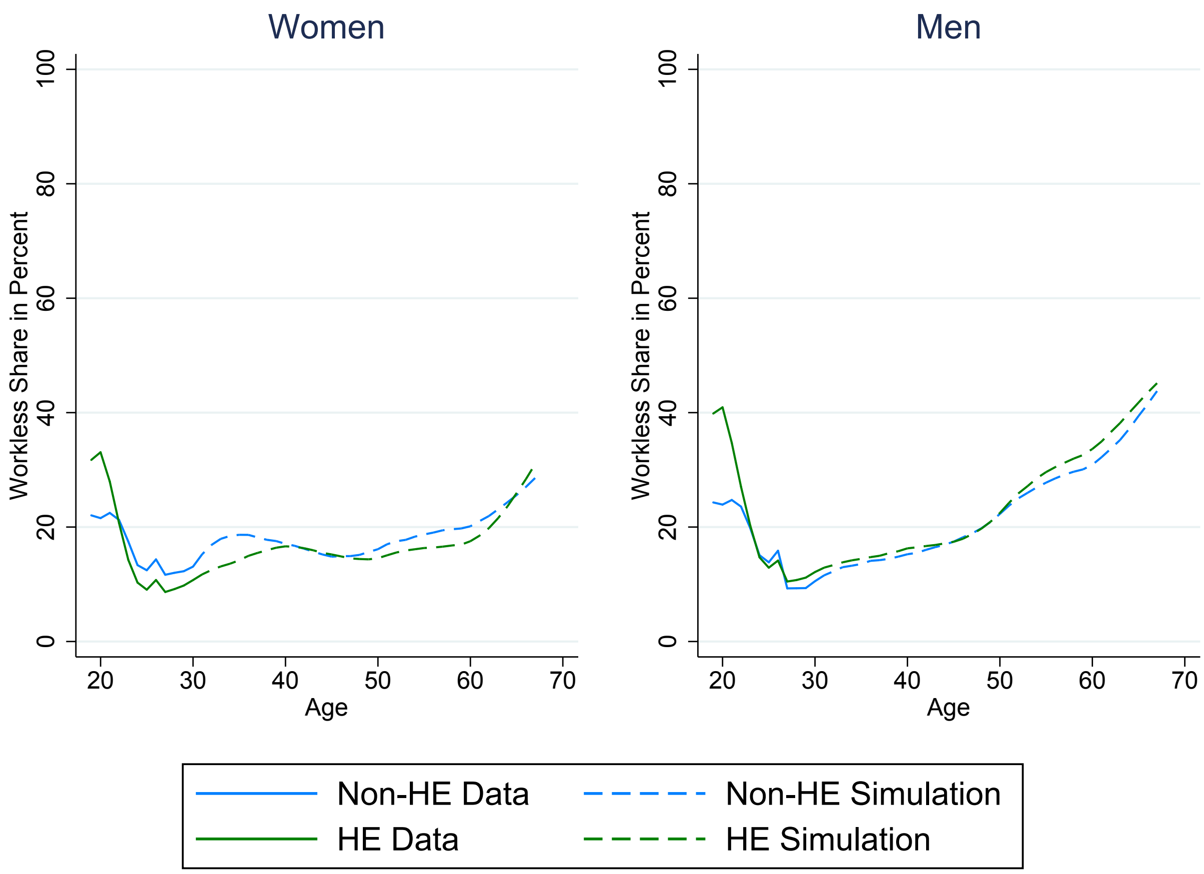
Unlike non-HE-educated women, non-HE-educated men see significant earnings growth during their 30s, and accordingly the gap between graduate and non-graduate earnings is smaller for men at those ages. This gap does continue to increase up to the mid 40s, as graduate earnings growth keeps ahead of non-graduate earnings growth. Towards the end of working life, median earnings decline for all groups as people start to reduce their working hours, and more individuals drop out of the labour market altogether as they approach retirement.[41]

Figure 6 highlights the 'workless' share, which we use as a catch-all term for those with zero

[41] We assume in these projections that the retirement age will rise by eight years between the 2000s and the year 2050.

earnings as we are unable to distinguish between the unemployed and those not looking for work (we also treat those in self-employment with zero or negative profits as workless). Even for the HE groups at around age 20, when most of them will still be in university, the workless share is only around 30–40%, highlighting the large share of graduates having (part-time) jobs alongside studying (possibly for a short period of the year only, such as during the summer).

Figure 6: Life-cycle worklessness rates (2002 GCSE cohort)



Note: Worklessness refers to zero earnings in the relevant tax year. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

A notable feature is that beyond around age 25, the worklessness rates of the HE and non-HE groups are remarkably similar, with the only obvious exception being women during their 30s, when many are taking time out to care for children. (However, it is important to remember that the non-HE group excludes those without five A*–C GCSEs, for whom worklessness rates are much higher.) Another surprising feature is the lack of large gender differences; the gender gap in Figure 5 is driven to a large extent by women working fewer hours or earning lower wages rather than by them dropping out of the labour force entirely.[42]

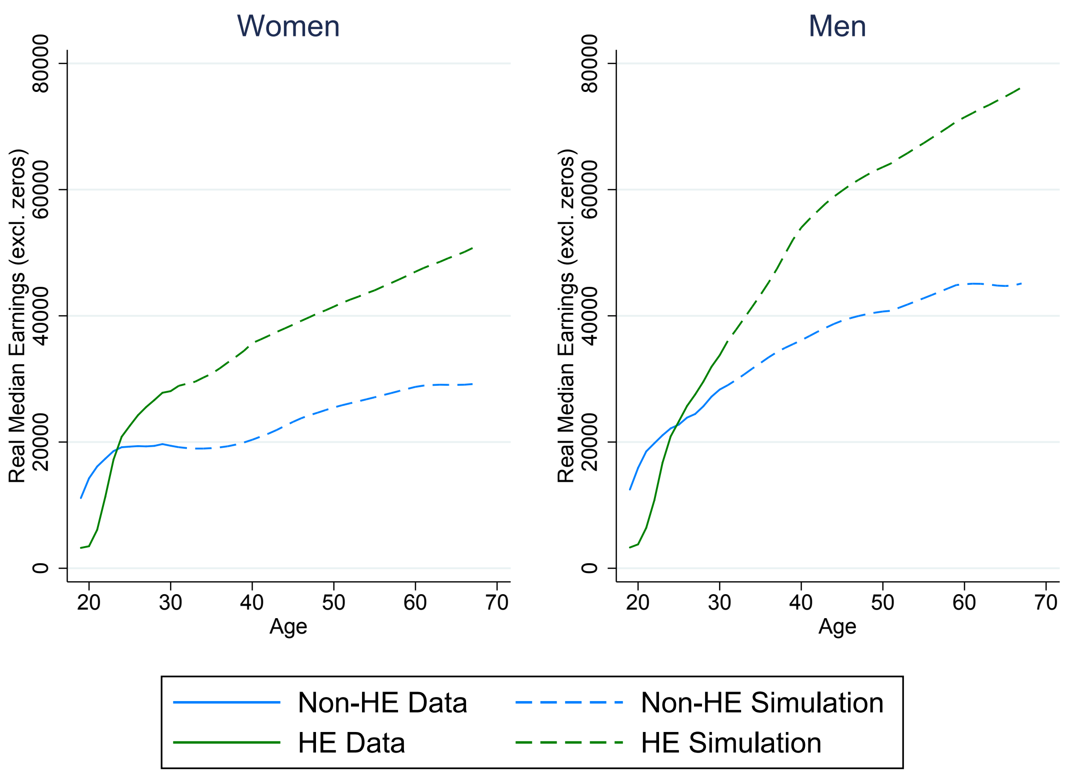
The high worklessness rate of men relative to women beyond age 50 is also quite stark. It is important to note that while this is based on the underlying data, it is our forecast for what is going to happen for the 2002 GCSE cohort. One of many challenges here is the changing of the retirement age. In the data, we see lots of men dropping into worklessness from around age 50. The retirement age will be higher for our 2002 GCSE cohort than it is for those who are already in their 50s in the most recent LFS data; hence we expect this pattern of men moving into worklessness to continue into their 60s. We are also forecasting that the higher labour market attachment we have seen among the most recent cohorts of women compared with those born a few decades ago at the same age will persist throughout their life cycle. In practice, our estimated returns will not be dramatically affected by what happens to employment rates of individuals later in life, as earnings are discounted and hence earnings towards the end of people's working lives will have a smaller impact on net lifetime earnings than earnings at the start of their careers.

Finally, Figure 7 shows median earnings over the life cycle only for those with positive earnings. The broad patterns are the same as in Figure 5, although the main difference is that the medians continue to grow – particularly for graduates – right up to retirement age, and the drop in earnings among non-HE-educated women in their 30s is much less pronounced. This suggests that the drop in median earnings from age 50 (men) or 60 (women), and the drop in earnings of female non-graduates in their 30s, are primarily driven by individuals dropping out of employment altogether, rather than purely by reductions in hours or hourly wages.[43]

[42] One caveat to this is that, due to data limitations, we also treat as workless those who leave the country or die, the propensity for which may differ among our four groups.

[43] Our data unfortunately do not allow us to look at hours worked directly.

Figure 7: Real and simulated median earnings profiles for graduates and non-graduates



Note: Median earnings in 2018 prices. Does not include zero earnings. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

4.2 Net lifetime earnings

In this section, we present lifetime earnings net of the tax and student loans system.[44] In order to increase the relevance for current policy, we have calculated the net figures using the tax and student loan system as of 2019. To capture real earnings growth since the 2002 GCSE cohort attended university, we have adjusted pre-tax earnings in line with earnings growth for the whole economy in the period between 2005 and 2019. To generate net earnings, we have subtracted income tax, National Insurance and student loan repayments from our simulated gross earnings, and included maintenance loan receipts.[45] In our main results, we do not include benefits.[46]

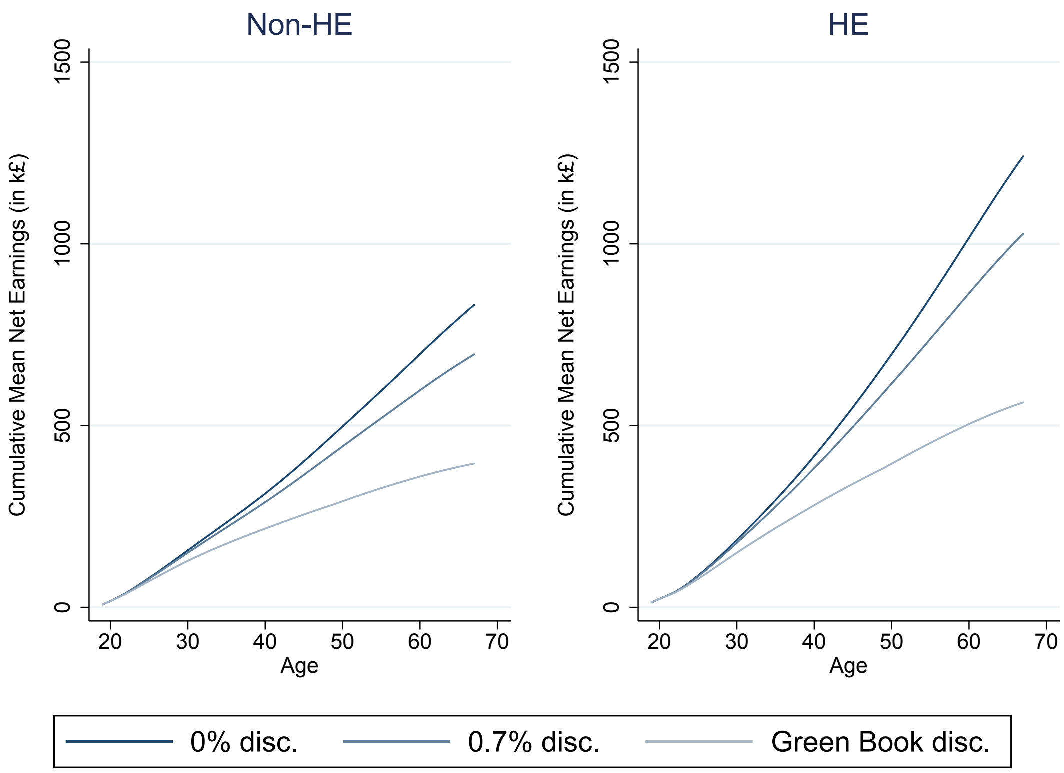
[44]By lifetime earnings, we mean earnings between the ages of 19 and 67. We make no attempt to model either pensions or pension saving apart from National Insurance contributions, which are treated like a tax.

[45]We make some minor simplifications in order to keep our tax calculation tractable. First, in order to avoid the complexities of the tax system for the self-employed, we treat self-employment earnings as if they were earnings from employment. Second, as we do not observe any information about spouses, we disregard the marriage allowance.

[46]As benefits are calculated at the household level, and the LEO data set does not contain any information about individuals' families, any benefits calculation is subject to a large amount of uncertainty because family formation has to be simulated. Graduates are, on average, less likely to receive benefits due to their higher earnings, but this effect will be small and unlikely to alter our results meaningfully. Rough estimates of the likely impact of undergraduate degrees on benefit receipt are provided in the online appendix.

Figure 8 shows the predicted cumulative net earnings over the course of the life cycle for women, split by HE status. We are now showing the mean rather than the median, to be comparable to our estimates in subsequent sections and to previous literature. In each of the panels, we show the cumulative estimates using three different ways of discounting future earnings: 0% (no discounting), 0.7% and Green Book discounting. This highlights just how dramatic the impact of discounting is. Without discounting, the present value of lifetime earnings for HE (non-HE) women is around £1.2m (£850k), while the equivalent figure with Green Book discounting is around £550k (£400k) respectively.

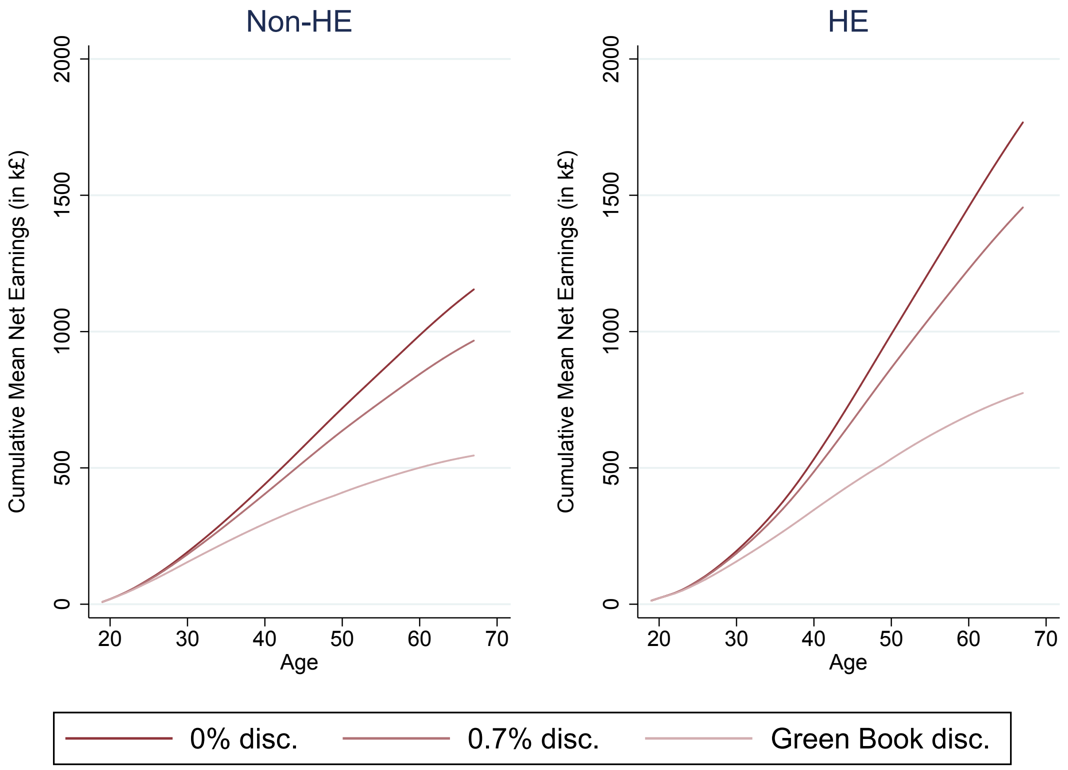
Figure 8: Average net present value of cumulative net earnings of women over the life cycle



Note: Cumulative lifetime earnings are discounted as shown and are in 2018 prices. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 9 is the equivalent figure for men. Again, the cumulative net earnings change dramatically depending on the discount rate: without discounting, HE men earn around £1.8m over their working lives on average, while with Green Book discounting the figure is around £750k. For non-HE men, the equivalent figures are £1.2m and around £550k.

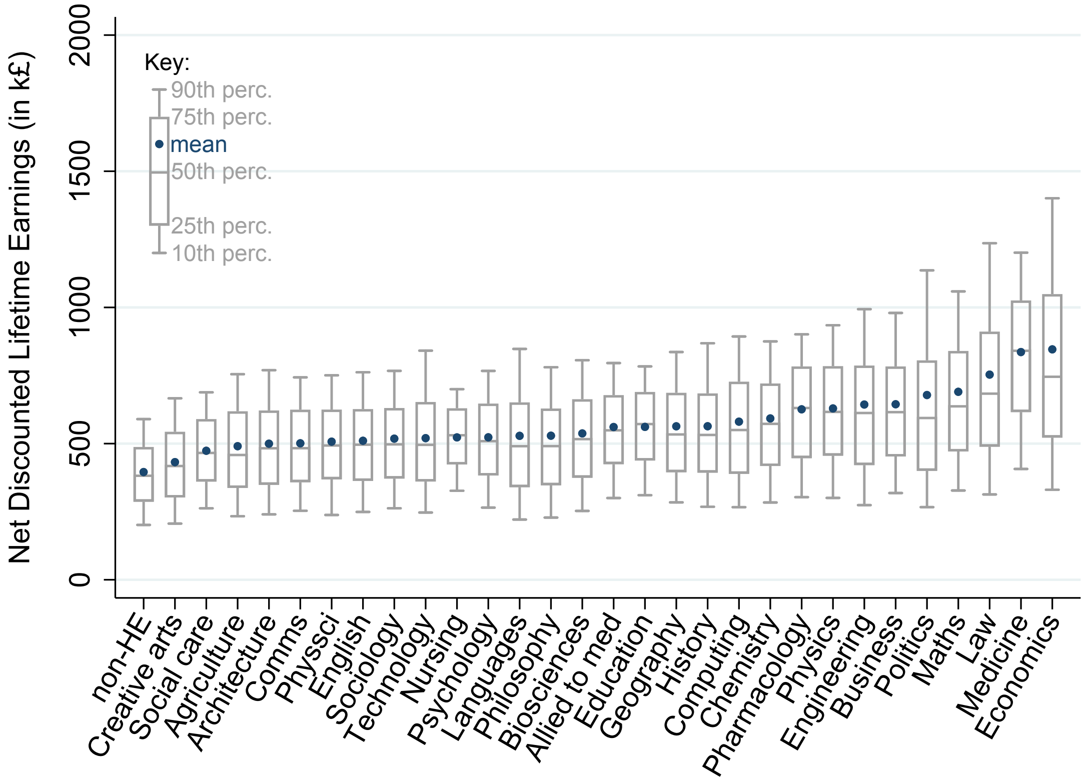
Figure 9: Average net present value of cumulative net earnings of men over the life cycle



Note: Cumulative lifetime earnings are discounted as shown and are in 2018 prices. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 10 shows the distribution of projected lifetime earnings (with Green Book discounting) disaggregated by subject, with those who did not attend university included as a separate category. Projected average lifetime earnings are the highest for women who studied economics, but median lifetime earnings are higher for women who studied medicine, reflecting the fact that there are more very-high-earning women who studied economics. As might be expected, non-HE women are projected to earn less on average than women who studied any subject at university, but the difference from the least lucrative university subjects is small. Furthermore, there is substantial overlap, in the sense that there are non-HE women who will see higher lifetime earnings than many women who went to university. Inequality in net lifetime earnings is smaller than in gross earnings, reflecting the effect of the progressive tax and student loan system.

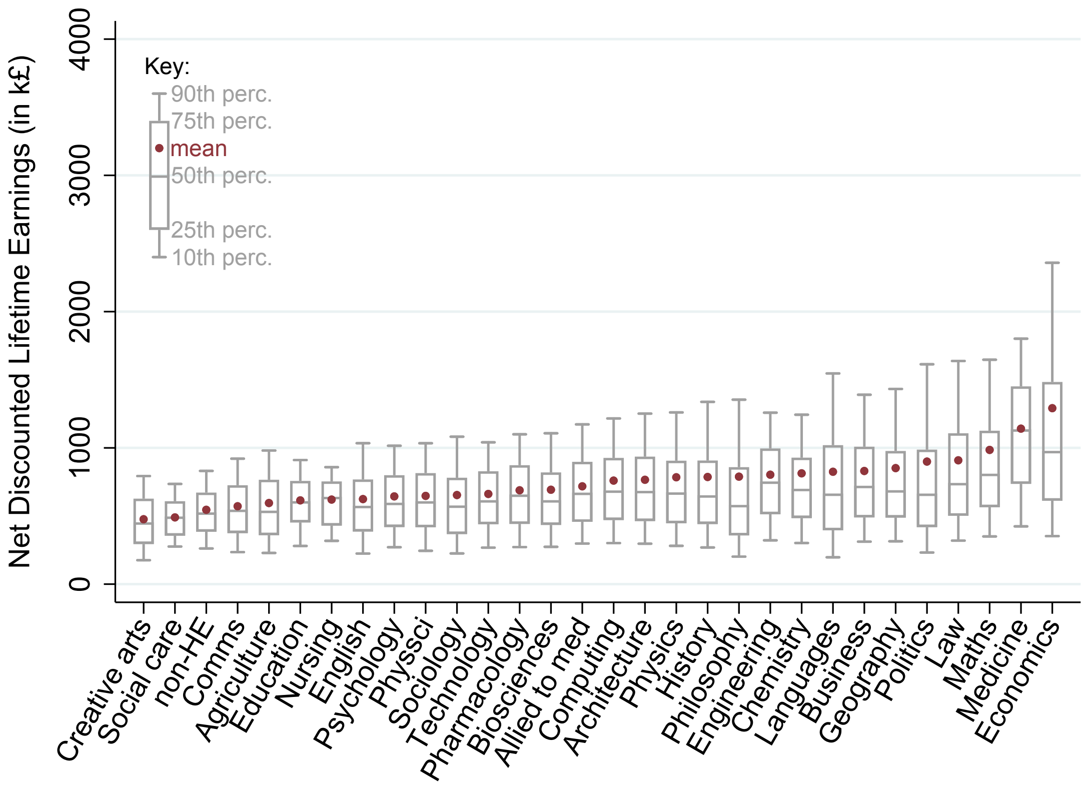
Figure 10: Net lifetime earnings of women by subject



Note: Lifetime earnings are in 2018 prices and are discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 11, the equivalent for men, shows a similar pattern, with creative arts and social care at the bottom and medicine and economics at the top. However, there are some notable differences. First, overall lifetime earnings are much higher for men, as we saw above. Second, the spread in lifetime earnings is much larger than for women; for men who studied economics, someone at the 10th percentile of earnings is projected to earn a net discounted lifetime income of well below £400k, whereas someone at the 90th percentile is expected to earn in excess of £2.3m. Third, we project that men who choose not to go to university will actually earn *more* on average net of tax and the student loan system than those who studied social care or creative arts.

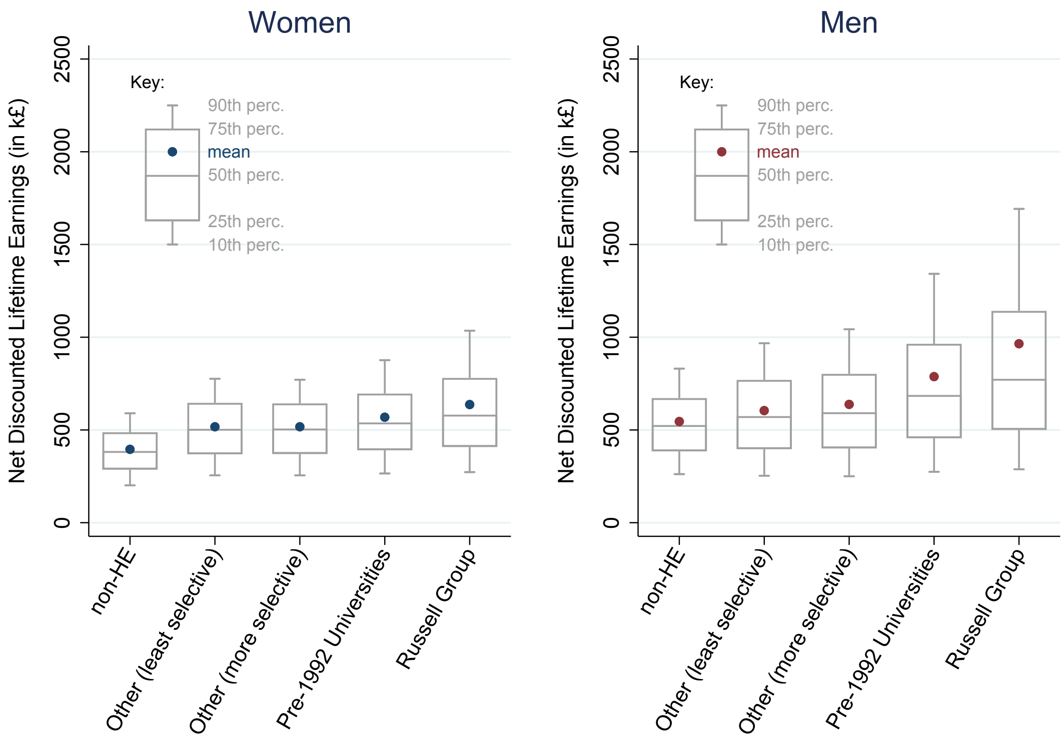
Figure 11: Net lifetime earnings of men by subject



Note: Lifetime earnings are in 2018 prices and are discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 12 shows the projected distribution of net lifetime earnings by institution type, with people who did not attend university again included as a separate category. Those who did not attend university have lower expected lifetime earnings on average than those who did attend, for both men and women, although for men the difference between those not attending HE and those attending the least selective universities is small. Conversely, the difference in lifetime earnings between the different university types is much greater for men than for women, with men who went to Russell Group universities on average earning nearly £400k more over their lifetimes in discounted present value terms than those who attended the least selective universities. Notably, the differences between university types are much larger near the top of the earnings distribution of each group than near the bottom, especially for men.

Figure 12: Net lifetime earnings by HEI type



Note: Lifetime earnings are in 2018 prices and are discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

5 Returns at different ages

We now move on from the more descriptive aspects of our analysis to consider the *returns* to higher education, using the methodology described in Subsection 3.3.1. We start by looking at percentage returns at different ages, which means we are trying to estimate the effect of HE on gross annual earnings at different points in the life cycle. We first look at average returns to attending higher education, before disaggregating by subject and institution type.[47]

5.1 Overall returns by age

Figure 13 shows how our estimated returns change with age. These estimates are analogous to our previous work (Belfield et al., 2018*b*), where we estimated gross earnings returns of 26% for women and 6% for men for those in work at age 29.[48] Figure 13 shows the magnitude of our age

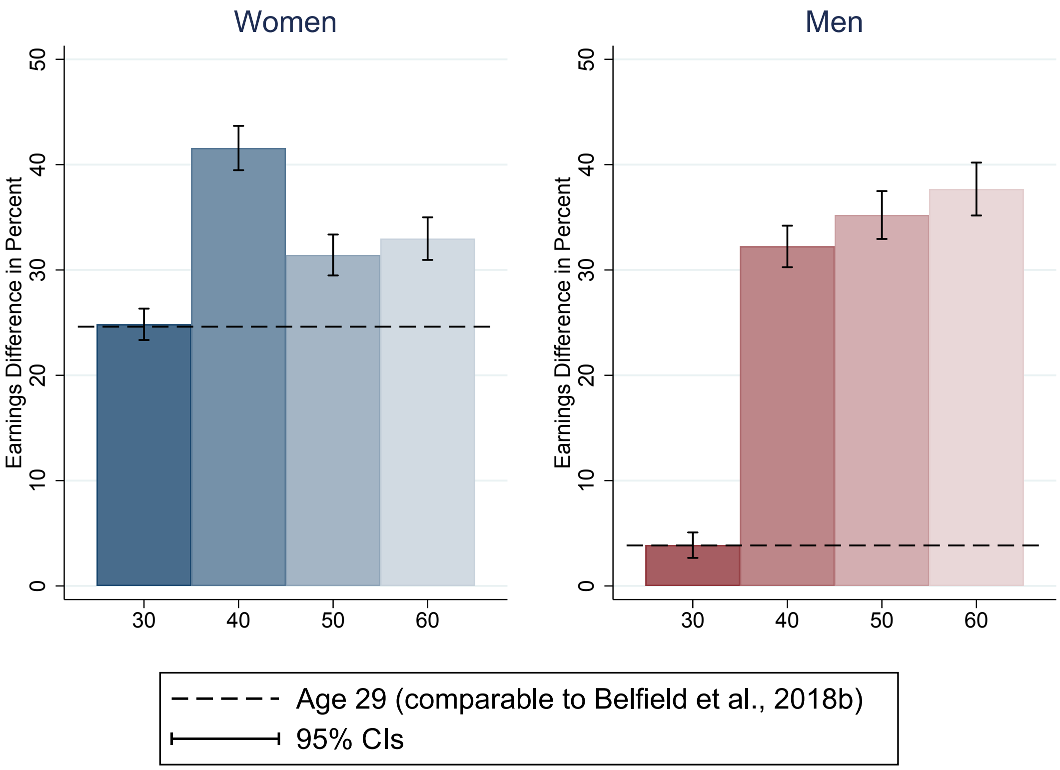
[47]It should be noted that all of our returns estimates presented here also include the returns to any postgraduate qualifications students may choose to pursue after their undergraduate degrees.

[48]In fact, the most directly comparable estimates are the OLS estimates reported in column 4 of table 7 in Belfield et al. (2018*b*), as due to our relatively small sample size we do not use IPWRA weighting in this report. At 26% for

29 estimates with a black dashed line, alongside returns at ages 30, 40, 50 and 60.

Our age 29 estimates are reassuringly similar to those reported in Belfield et al. (2018*b*) despite differences in methodology and sample selection, and nearly identical to our age 30 estimates. We estimate that at age 30, the gross earnings returns are 25% for women and 4% for men. For women, we see that the return increases to 42% at age 40 before settling back to between 30% and 35% thereafter. This variation is likely driven at least in part by differential selection into and out of the labour market. For men, we see that the age 30 returns are dramatically lower than those in later life, as we predicted in Belfield et al. (2018*b*). Average returns increase to more than 30% at age 40 and climb further to 38% at age 60. These returns estimates are in line with those of Walker and Zhu (2013) and other previous literature on the pre-tax returns to undergraduate degrees over the life cycle.

Figure 13: Returns to HE for those in work by age



Note: All results are estimated from separate OLS regressions, where the non-HE group only includes those with at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level. The impact of initial conditions is fixed at age 30 to help deal with the fact that the later-life estimates are based on simulated data. The dashed line shows the returns at age 29, in line with the estimates in Belfield et al. (2018*b*). The 95% confidence intervals only capture sampling uncertainty regarding the difference in conditional means between HE and non-HE groups; they do not account for simulation uncertainty or uncertainty in the estimation of the dependence of earnings on initial conditions.

women and 4% for men, these OLS estimates differ slightly from the headline IPWRA estimates reported in Belfield et al. (2018*b*), and are nearly identical to the age 29 estimates we report here.

These findings are unsurprising given the overall patterns in earnings we saw in Figure 7. There we saw that the gap in median earnings between male graduates and non-graduates still increased dramatically after age 30, as the earnings of male graduates increased at a much faster rate than those of non-graduates. For women, we saw that the gap at age 30 is much closer to the gap at later ages. However, we re-emphasise that these findings are based on an extrapolation of patterns in historical earnings data, which may not persist in the future.

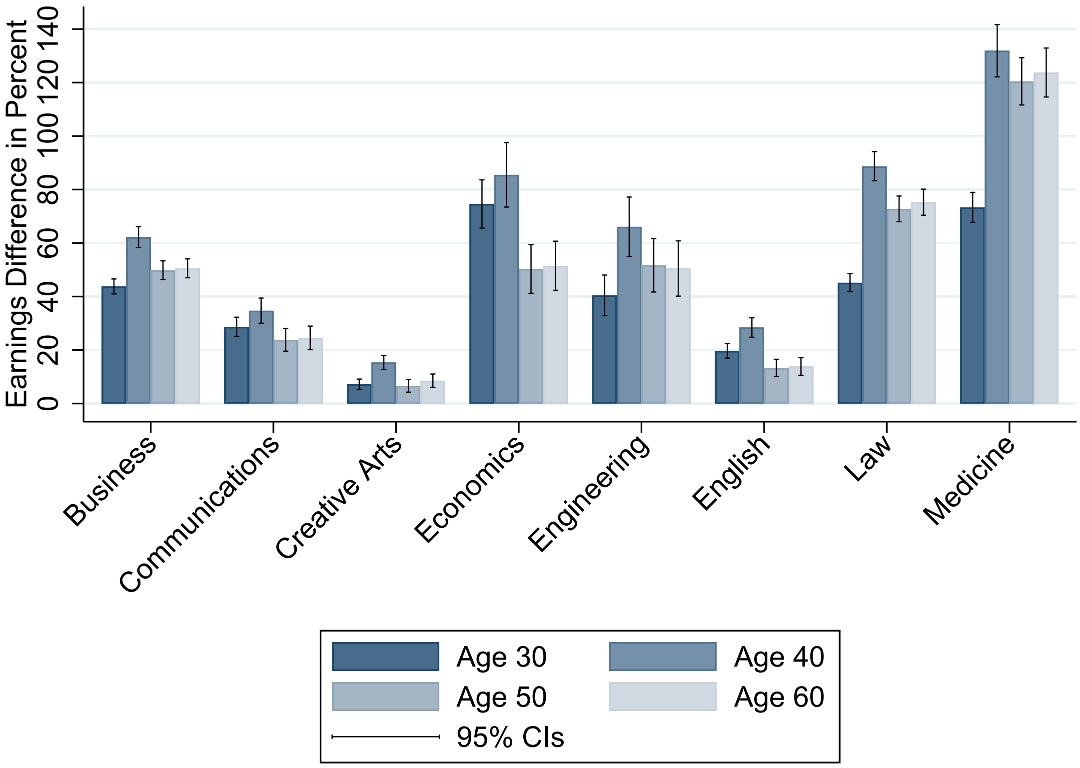
5.2 Subject returns by age

We now investigate returns at different ages broken down by subject studied at university. Figures 14 and 15 do this for women and men respectively for a selected set of subjects. The full set of results is presented in Table 8 in Appendix D.

For women, we see that average returns are positive for all subject areas that we show. Most of the subjects show very similar patterns to the overall results, whereby the returns at age 30 are broadly reflective of the longer run, with a small uptick in returns at age 40. The exceptions are law and medicine, for which returns grow considerably after age 30 and settle at age 40, and economics, for which returns are actually quite a lot lower at 50 and 60 than at 30.[49] However, broadly speaking, the ordering at 30 is very similar to the ordering at 50 and 60, with creative arts and English at the bottom (but still with positive returns of around 10% and 20% respectively) and law, economics and medicine at the top. Medicine in particular appears to be an excellent option for women, with returns well in excess of 100% (i.e. earnings being more than twice as high compared with not attending HE) from age 40.

[49]For economics in particular, however, these results should be treated with some caution, as they are based on a relatively small sample of late-career women economists in the Labour Force Survey. Furthermore, the labour market for economists appears to have changed considerably over the past few decades, making a long-term forecast difficult.

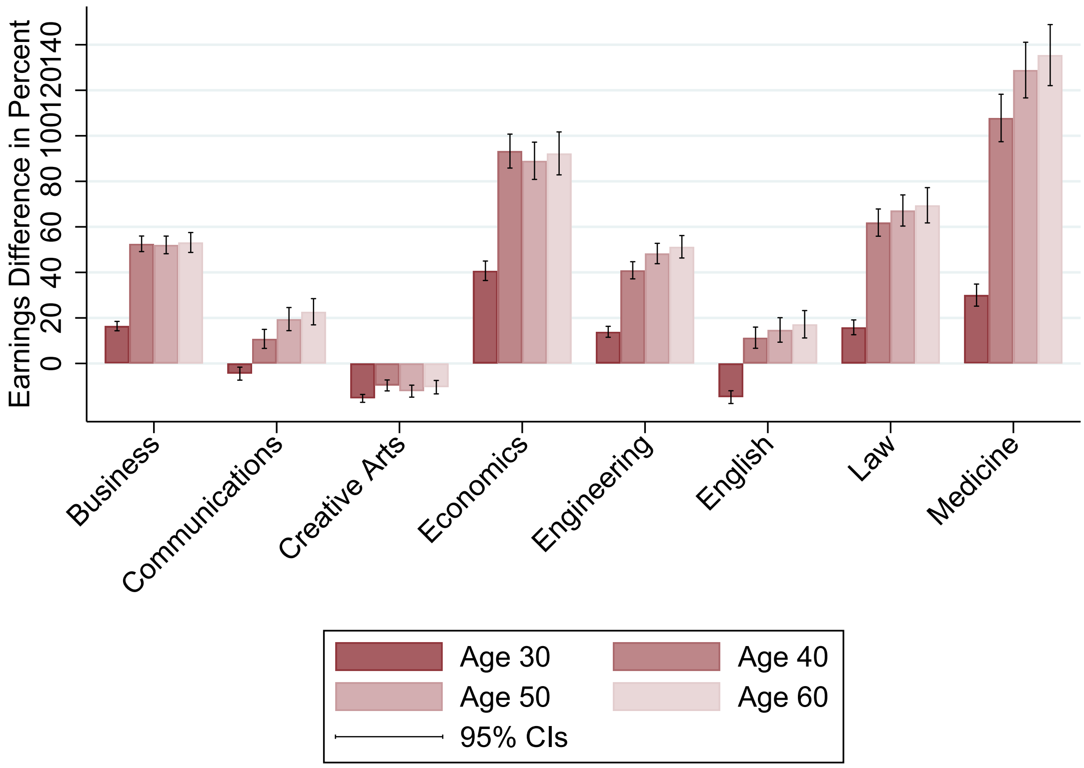
Figure 14: Returns to HE for women in work by subject and age



Note: All results are estimated from separate OLS regressions, where the non-HE group only includes those with at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level. The impact of initial conditions is fixed at age 30 to help deal with the fact that the later-life estimates are based on simulated data. The 95% confidence intervals only capture sampling uncertainty regarding the difference in conditional means between graduates of a given subject and the non-HE group; they do not account for simulation uncertainty or uncertainty in the estimation of the dependence of earnings on initial conditions.

For men, the overall pattern is similarly replicated across the subjects that we show. That is, we typically see a large jump in the returns between 30 and 40 followed by negligible or much slower growth subsequently. In particular, business, economics, law and medicine all see very large increases in their returns between the ages of 30 and 40. Again, medicine is the highest performer at later ages, with an earnings boost of around 130%. At the lower end of the scale, English and communications see their negative return estimates flip in sign, resulting in later-life returns of around 20%. The same is not true, however, for creative arts, for which the average returns are negative at all ages.

Figure 15: Returns to HE for men in work by subject and age



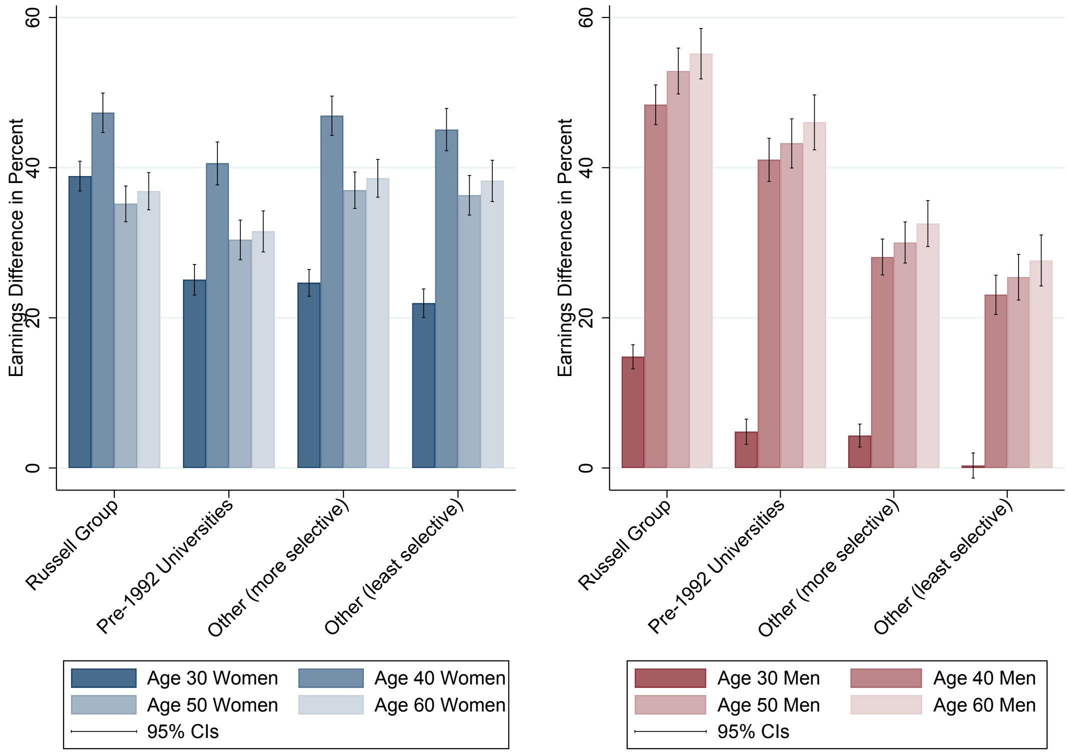
Note: All results are estimated from separate OLS regressions, where the non-HE group only includes those with at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level. The impact of initial conditions is fixed at age 30 to help deal with the fact that the later-life estimates are based on simulated data. The 95% confidence intervals only capture sampling uncertainty regarding the difference in conditional means between graduates of a given subject and the non-HE group; they do not account for simulation uncertainty or uncertainty in the estimation of the dependence of earnings on initial conditions.

5.3 HEI returns by age

We now turn to estimating the return by higher education institution (HEI). As before, we group the institutions into four groups: the Russell Group, pre-1992 universities, other (more selective) and other (least selective). Although it would be possible to estimate the return at university level, we felt that grouping universities together was appropriate and would give more robust results given the relatively small sample sizes combined with the speculative nature of the estimation.[50]

[50]It is also more consistent with the simulation procedure, given that dynamics were estimated at this level.

Figure 16: Returns to HE by university type and age



Note: All results are estimated from separate OLS regressions, where the non-HE group only includes those with at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level. The impact of initial conditions is fixed at age 30 to help deal with the fact that the later-life estimates are based on simulated data. The 95% confidence intervals only capture sampling uncertainty regarding the difference in conditional means between graduates of a given institution type and the non-HE group; they do not account for simulation uncertainty or uncertainty in the estimation of the dependence of earnings on initial conditions.

Figure 16 shows the estimated returns for each age for both women (on the left) and men (on the right). The patterns are quite stark. For women, we see that although the Russell Group dominates at age 30, the same is not true at later ages, with the two 'other' groups catching up, and indeed overtaking, in terms of returns. For men, we see dramatic growth in returns between 30 and 40 for all four HEI types, with the 'other (least selective)' group growing from around zero at 30 to more than 20% at 40 and more than 25% at later ages.

One concern with the positive results for the 'other' universities is that they might be driven by our assumptions about the relative importance of age, period and cohort effects. By estimating earnings growth based on how different cohorts compare within the same year, we are essentially assuming that cohort effects are small. This might be a problem if universities of this type have expanded considerably, as the younger cohorts might be doing worse at a given time in the labour market than the older cohorts because they have worse labour market prospects, rather than because there are large age effects. However, as seen in Table 3, all university types expanded quite significantly during this period, allaying this concern to some extent.

6 Net lifetime returns

In this section, we look at the average net lifetime return of pursuing an undergraduate degree from the point of view of the student.[51] As discussed in Section 3, this is the sum of the increase (or decrease) in earnings associated with attending university at each age, plus the value of maintenance loans received and minus the value of any student loan repayments and taxes paid, all discounted. In our main results, we do not include any impact on benefit receipt.[52]

The results in this section should be interpreted as the average lifetime gain from enrolling in a particular course for students who actually enrolled in those courses. It cannot be inferred from these calculations what the returns would have been for students who did not enrol in those courses. Nor can it be inferred what would have happened if certain degrees had not been offered at all, as students would have redistributed in complex ways across subjects and universities, and the labour market would have adjusted. In general, it should be noted that this and the following two sections are the most speculative parts of the report.

6.1 Overall lifetime returns

With this caveat in mind, we estimate that the overall average discounted present value (DPV) of enrolling in an undergraduate degree is around £100k for women and £130k for men. In percentage terms, this represents an gain in average net lifetime earnings of around 20% for both men and women.[53] These findings are in line with the previous literature on lifetime returns in the UK.[54]

Figures 17 and 18 demonstrate how we arrive at these figures. In these 'waterfall charts', darker bars indicate additions and lighter bars indicate subtractions. The charts are to be read from left to right. We start with the difference in gross earnings among people with at least five A*–C GCSEs and a Key Stage 5 record, between those who started an undergraduate degree and

[51] Estimates of *median* net lifetime returns are presented in Appendix C.

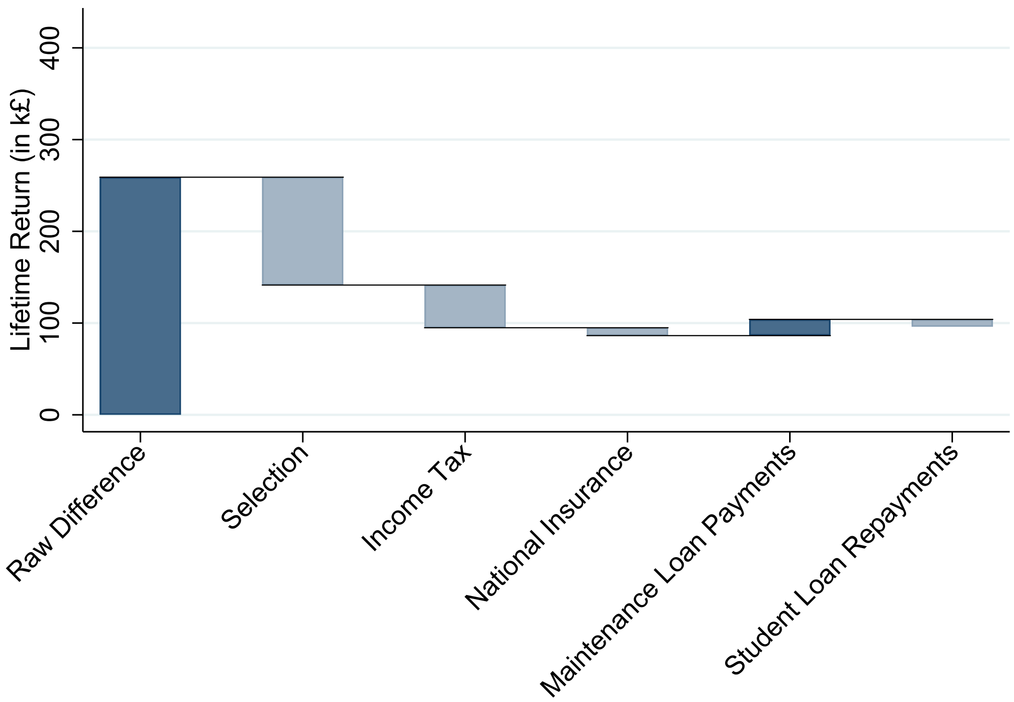
[52] As benefits are calculated at the household level, and the LEO data set does not contain any information about individuals' families, any benefits calculation is subject to a large amount of uncertainty because family formation has to be simulated. Graduates are, on average, less likely to receive benefits due to their higher earnings, but this effect will be small and unlikely to alter our results meaningfully. Rough estimates of the likely impact of undergraduate degrees on benefit receipt are provided in the online appendix.

[53] This percentage represents the average gain as a share of counterfactual earnings. This is very different from an average over individual percentage gains and losses.

[54] Our net lifetime returns estimates are similar to those of Conlon and Patrignani (2011). Although our gross percentage returns estimates are similar to those of Walker and Zhu (2013), our net lifetime returns estimates are much smaller. These differences appear to be primarily driven by the large differences in employment rates they found between graduates and non-graduates, especially for women, whereas we have found the differences in employment rates to be minor. Besides large differences in overall methodology, a number of particular factors may explain the differences between the survey and administrative data. First, labour force participation among non-HE women has increased over time, and our estimates rely on data from more recent cohorts. Second, Britton, Shephard and Vignoles (2019) show that survey earnings measures systematically understate low earnings, especially for non-graduates. Finally, in contrast to Walker and Zhu (2013), we count émigrés as workless, as we cannot distinguish between emigration and worklessness in the HMRC tax data; this is likely to overstate worklessness rates for graduates more than for non-graduates.

those who did not. Then we subtract what we estimate to be the effect of selection, i.e. the fact that those who got to university are, on average, from wealthier backgrounds and achieved higher marks in secondary school. We then account for the effects of the tax system and of the student loans system. The bottom of the final bar represents our estimate of the average net lifetime return.

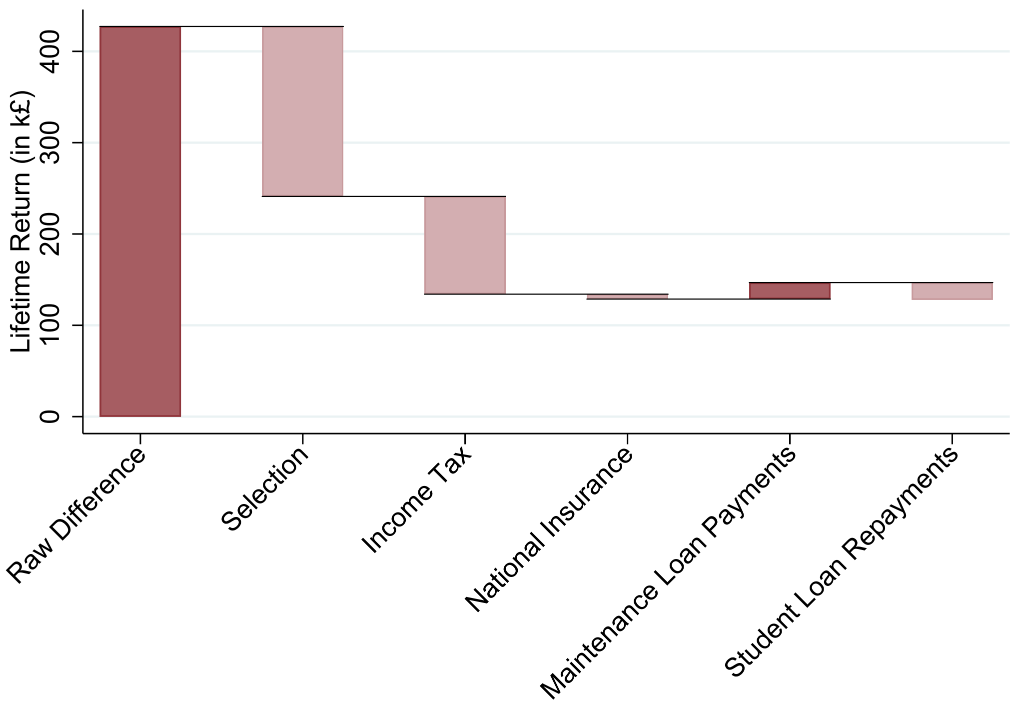
Figure 17: Overall average DPV lifetime returns to HE for women



Note: All figures are shown in 2018 prices and are discounted using Green Book discounting. The first bar shows the difference in raw earnings between those who did not attend HE, but have a KS5 record and at least five A*–C GCSEs, and those who started an undergraduate degree. The second bar shows how much of this difference in earnings is accounted for by differences in prior attainment and background characteristics. We then account for the extra income tax and National Insurance payments from graduates. The penultimate bar adds on the net present value of the maintenance loans payments received by students, and finally the last bar takes into account the net present value of student loan repayments over the life cycle. Dark blue bars indicate additions and light blue bars reductions.

For women, the predicted pre-tax difference in discounted lifetime earnings between those who go to university and those who do not is around £260k. However, we estimate that nearly half of that difference arises from selection into HE; hence women who go to university would have made only around £140k less if they had not gone to university. Accounting for tax and National Insurance payments on the extra income from doing a degree takes off roughly another £55k of the returns. Including the student loan system takes the return up to £100k as women actually pay back less, on average, in overall student loan repayments than they receive in maintenance loans.

Figure 18: Overall average DPV lifetime returns to HE for men

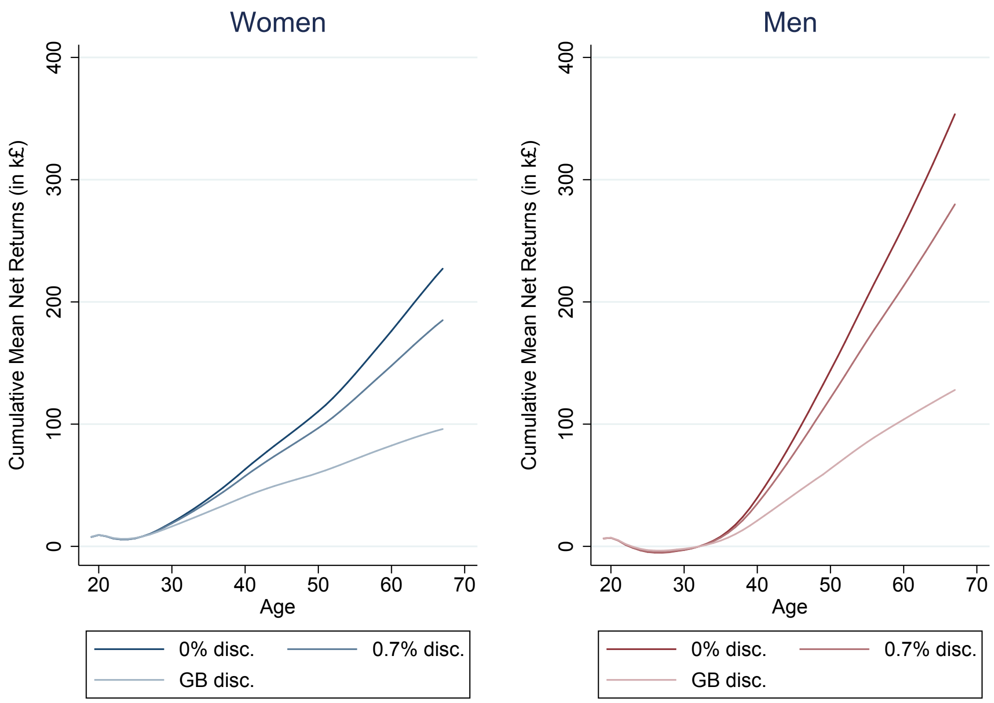


Note: All figures are shown in 2018 prices and are discounted using Green Book discounting. The first bar shows the difference in raw earnings between those who did not attend HE, but have a KS5 record and at least five A*–C GCSEs, and those who started an undergraduate degree. The second bar shows how much of this difference in earnings is accounted for by differences in prior attainment and background characteristics. We then account for the extra income tax and National Insurance payments from graduates. The penultimate bar adds on the net present value of the maintenance loans payments received by students, and finally the last bar takes into account the net present value of student loan repayments over the life cycle. Dark red bars indicate additions and light red bars reductions.

The predicted pre-tax discounted earnings difference between men who attend university and those who do not is much greater than that for women, at around £430k. However, the estimated selection effect is also proportionately bigger, taking the pre-tax return to around £240k. As much of the additional income will be earned at the higher rate of tax, and the lost income earlier in life will mostly have been taxed at lower rates, the difference in income tax for men is large and reduces the return by more than £100k. The difference in National Insurance payments is small, due to many of these men earning above the National Insurance upper earnings limit. The student loan system only has a negligible effect, leaving a total lifetime return of around £130k for men.

However, these averages hide substantial heterogeneity. We expect the 10% of women with the highest returns to gain more than £350k on average, but around 15% of women not to get a positive return from their degree at all. For men the differences are even larger: we estimate that the 10% of men with the highest returns will gain more than £700k on average, but around a quarter of men will have negative returns. As shown in Figure 43 in Appendix C, *median* net lifetime returns to undergraduate degrees are around £70k for both women and men.

Figure 19: Overall average cumulative private DPV returns to HE by age



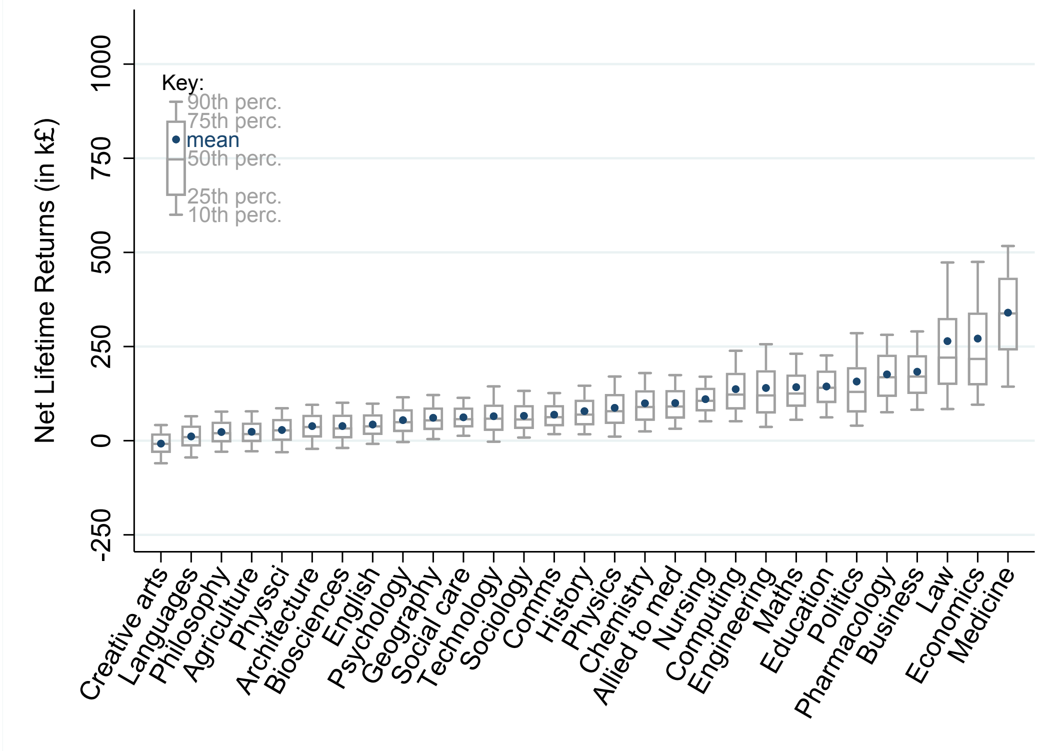
Note: Cumulative returns are shown in 2018 prices and are discounted as shown. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Figure 19 shows cumulative average returns by age. Three aspects of the graphs are notable. First, as for the raw earnings differences between non-HE and HE groups, the size of the estimated cumulative returns figure is dramatically influenced by the choice of discount rate. Second, men's projected lifetime returns in £ terms exceed those of women, with a larger difference at lower discount rates. Third, while the cumulative discounted returns to women from attending university are positive on average at all ages, for men this is only true from roughly the mid 30s. The main reason for this appears to be that men would have had much higher earnings in their 20s had they not gone to university; for women, on the other hand, counterfactual earnings are small.

6.2 Lifetime returns by subject

Figure 20 presents returns results disaggregated by subject studied for women. Estimated discounted average returns range from roughly zero for creative arts and languages to more than £250k for law, economics and medicine. The estimated range of individual returns is larger for subjects that have higher average returns. Notably, almost all women who studied social care are projected to achieve positive returns despite the average return being relatively low.

Figure 20: DPV cash returns to HE for women by subject

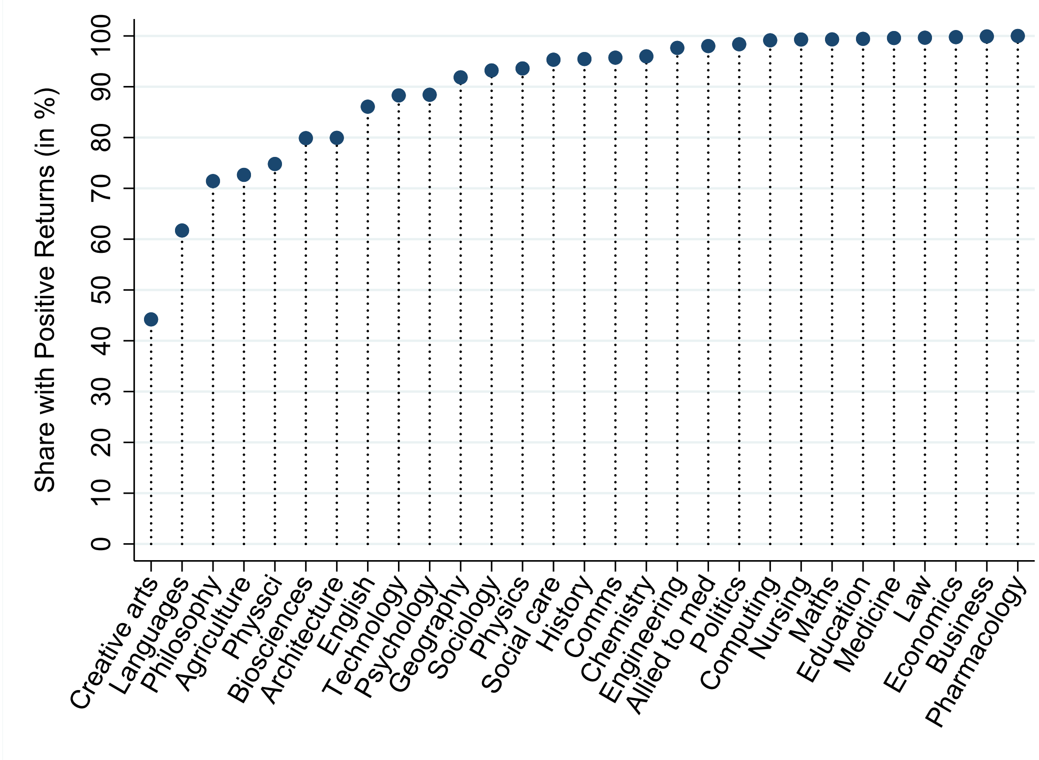


Note: Lifetime returns are shown in 2018 prices in £k and are discounted using Green Book discounting. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Figure 21 presents another way to highlight the individual-level heterogeneity in returns within each subject. It shows the share of women whom we expect to get a positive return from going to university compared with not going. This share ranges from less than half of women for creative arts to essentially all women who study high-return subjects such as pharmacology, business, economics, law or medicine. Two subjects that have relatively low returns but a high share of positive returns are nursing and education: while these subjects are not the most lucrative on average, they see very little variation in average earnings and offer solid returns to essentially all women who study them.[55]

[55]However, it should be noted that our methodology only allows us systematically to account for heterogeneity in returns based on the observable characteristics of individuals. To the extent that there is also heterogeneity in returns among observationally identical individuals (e.g. due to differences in motivation for a specific subject), we are likely to understate the true individual-level heterogeneity in returns. As a result, our estimates of the share of students with positive returns are likely to be somewhat overstated for the 'safest' subjects.

Figure 21: Estimated share of female students getting positive net returns by subject



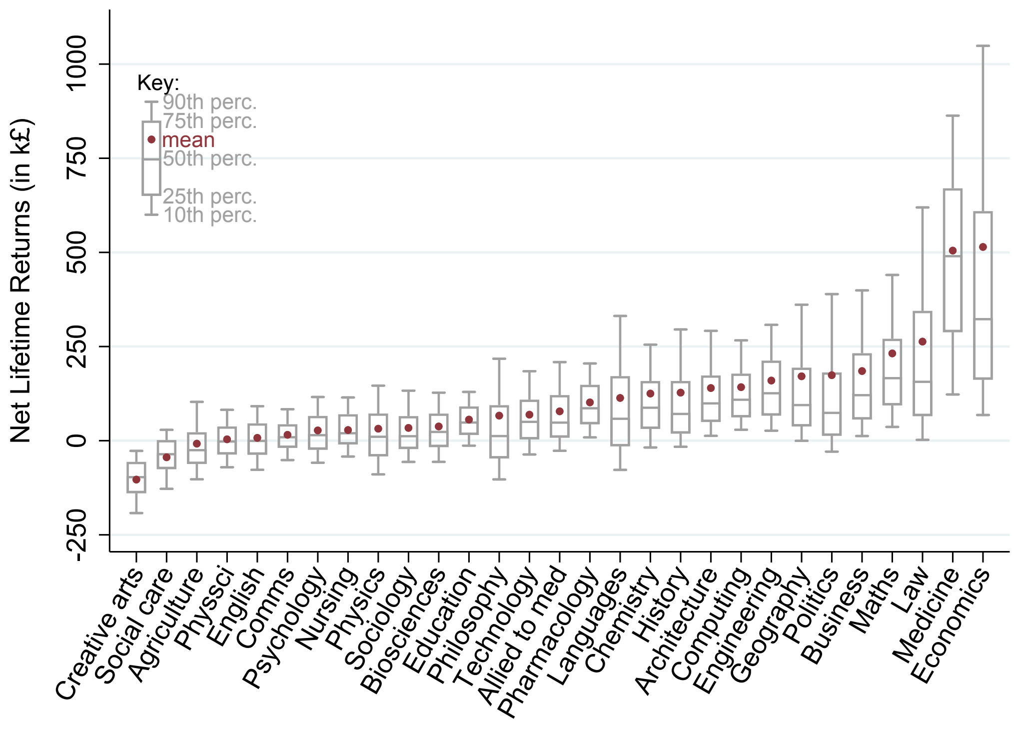
Note: Figure shows the estimated share of graduates of each subject who will receive a positive net discounted return to their degree. Returns are discounted using Green Book discounting, and take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Figure 22 shows the distribution of net lifetime returns by subject for men, calculated using Green Book discounting. Overall, returns vary more by subject for men, with creative arts and social care exhibiting strongly negative returns on average,[56] while those who studied medicine or economics have average net returns of around £500k. Average net lifetime returns for agriculture, English, physical sciences[57] and communications are around zero. In many subjects, returns differ a lot across individuals, with more than 10% of those who studied economics expected to get a discounted return of more than £1m and the bottom 10% expected to see returns below £70k.

[56]However, the estimate for social care should be treated with caution, as relatively few men study social care and even fewer studied it in earlier cohorts.

[57]Note that according to the CAH2 subject classification that we use, physical science does not include chemistry, physics or astronomy (which is classed as physics). Instead, it comprises the remainder of physical science such as materials and earth science.

Figure 22: DPV cash returns to HE for men by subject

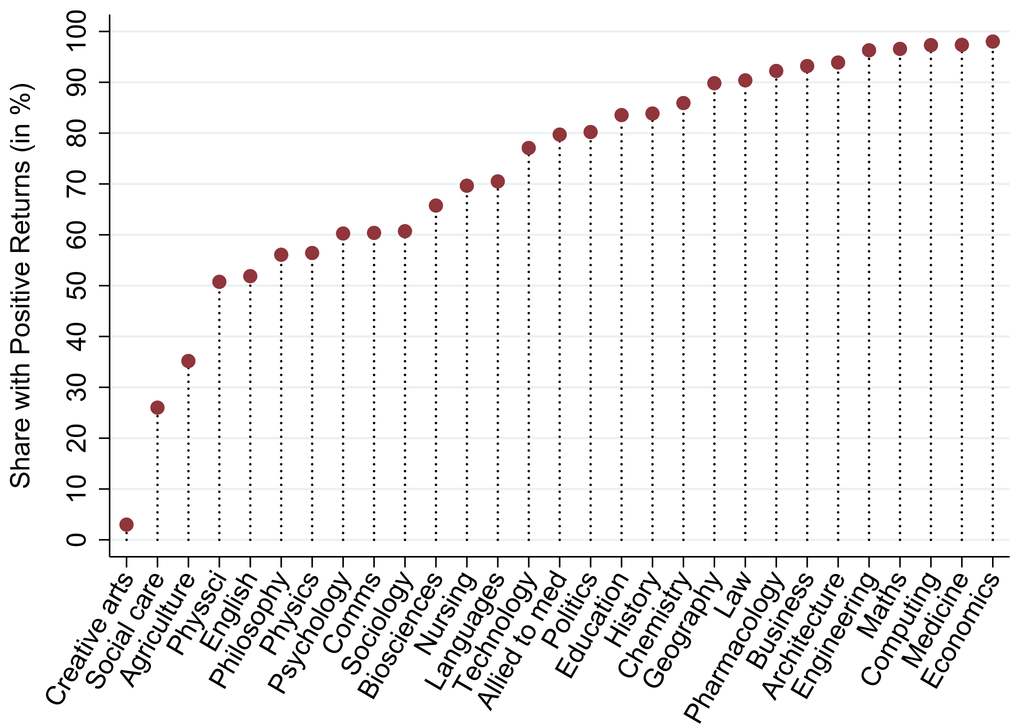


Note: Lifetime returns are shown in 2018 prices in £k and are discounted using Green Book discounting. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

As for women, subjects that are associated with higher earnings do not necessarily have higher returns, because students of some subjects have more favourable background conditions than others, which determine the incomes they could have earned had they chosen not to go to university. For example, physics has a lower average return than most subjects, even though the earnings of men who study physics are higher than those for most other subjects. The reason is that men studying physics have among the most favourable background conditions of all subjects behind only economics and maths. Much the same is true, at a lower level of earnings, for students of physical sciences: while their net lifetime earnings are just below average, given their background we would expect them to have roughly the same net lifetime earnings if they had not gone to university. The opposite is true for education, which offers solid returns for most despite the comparatively low earnings of education graduates.[58]

[58] Table 9 in Appendix E shows average returns by subject with different discount rate assumptions. Returns are generally smaller in magnitude with Green Book discounting than with the other discounting schemes shown, because higher discount rates imply that the distant future counts for less in present value terms.

Figure 23: Estimated share of male students getting positive net returns by subject



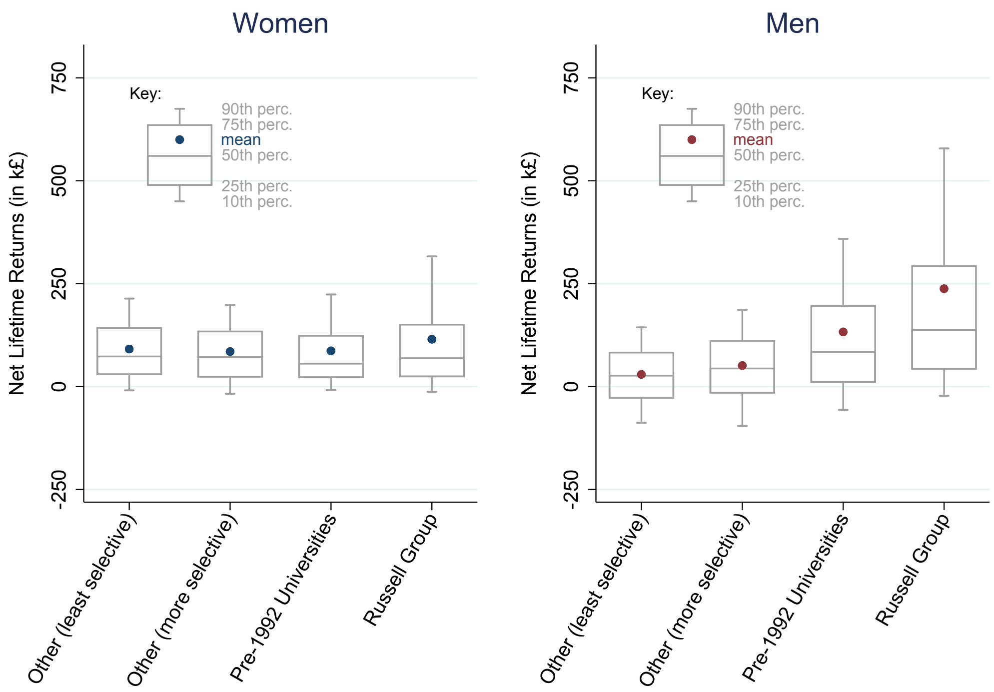
Note: Figure shows the estimated share of graduates of each subject who will receive a positive net discounted return to their degree. Returns are discounted using Green Book discounting, and take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Figure 23 shows the share of men studying different subjects achieving positive returns from their degrees. We expect almost no men who studied creative arts and few who studied social care to achieve positive returns from their degrees in discounted present value terms; even for agriculture, physical sciences and English, we project the share of students with positive returns to be no more than half. At the other end of the spectrum, maths, computing, medicine and economics offer positive returns to almost all men who study them.[59]

[59] Again, however, it should be noted that as we cannot fully capture heterogeneity in returns among observationally identical individuals (e.g. due to differences in motivation for a specific subject), we are likely to understate the true individual-level heterogeneity in returns. As a result, our estimates of the share of students with positive returns are likely to be somewhat understated for creative arts and overstated for the 'safest' subjects.

6.3 Lifetime returns by university type

Figure 24: Returns to HE by HEI type



Note: Lifetime returns are shown in 2018 prices in £k and are discounted using Green Book discounting. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Figure 24 disaggregates net lifetime returns by university type. There is little difference between average lifetime returns across university types for women. Within all types, a large majority of women benefit from attending HE. Only the top end of the distribution of women attending Russell Group universities can expect higher lifetime returns from going to university than women who attended universities elsewhere.

The picture is somewhat different for men, where there is a clear ordering: men who go to Russell Group universities have high returns on average, with pre-1992 universities coming second and other universities third. While average returns for men who studied at Russell Group universities are high at almost £250k on average, a sizable minority of men who attend non-Russell-Group universities will see negative returns in discounted net present value terms.[60]

[60]Table 10 in Appendix E shows average returns for men and women disaggregated by university type. Discounting has a very large impact on absolute returns, but relative returns across university types are essentially unchanged. Discounting has a larger impact for men than for women, because men have higher returns later in life.

7 Exchequer returns

We now turn to estimating the returns to the exchequer, i.e. from the point of view of the taxpayer. These consist of the increase in discounted lifetime tax and National Insurance receipts, minus any losses on student tuition fee and maintenance loans. In our main results, we do not include effects on VAT payments[61] or on benefit payments.[62]

The results in this section should be interpreted as the average gain to the exchequer from people enrolling in the courses that they did in fact enrol in, compared with not going to university at all. As in the previous section, it cannot be inferred from these calculations what the exchequer returns would have been for students who did not enrol in those courses. We also do not consider 'general equilibrium' effects, which may be an important determinant of the overall exchequer return to higher education. It may well be the case, for instance, that graduates compete for the same jobs with non-graduates, who they merely displace.[63] In this case, we might estimate a positive exchequer return to HE, even though the overall exchequer return would be negative.

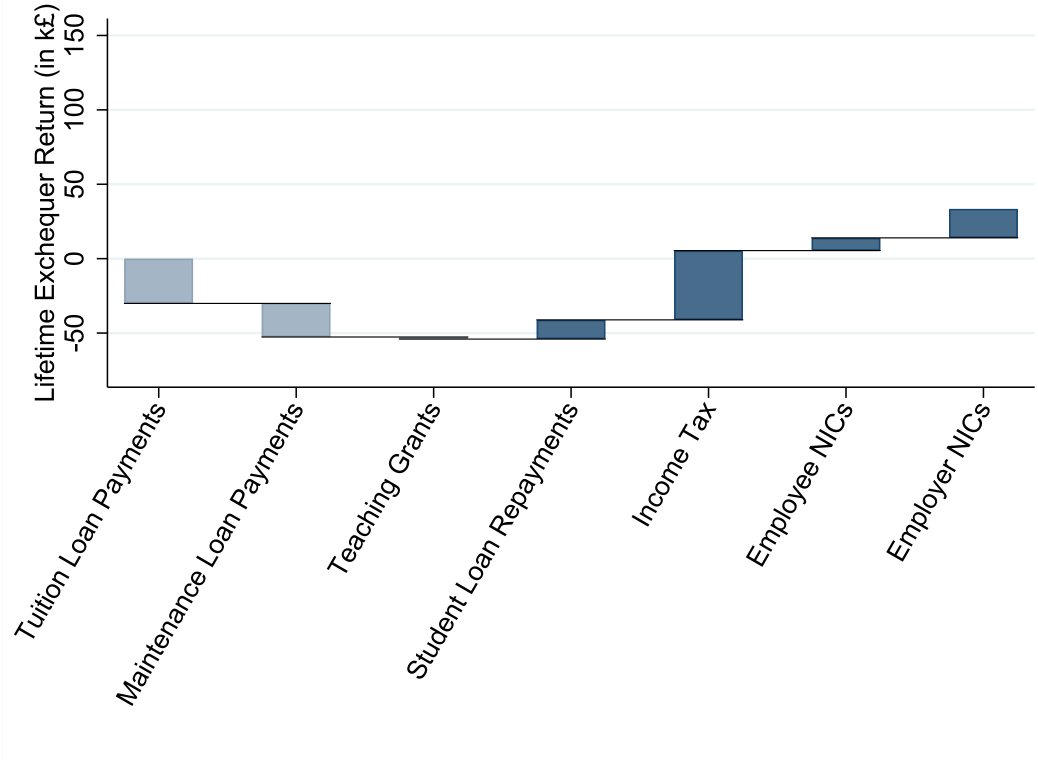
With these caveats in mind, we arrive at lifetime exchequer returns of around £30k for women and around £110k for men. While average discounted exchequer returns for women are thus less than a third of private returns, exchequer returns for men are roughly the same magnitude as private returns. This reflects the progressivity of the tax and student loan system. Men earn more on average, and men who go to university have particularly uneven earnings profiles over the life cycle. Both of these factors lead to a situation in which, for men, nearly half of the lifetime return of attending university accrues to the exchequer.

[61] This is done to ensure that net returns and exchequer returns add up to total returns. As part of net income is spent on VAT, the sum of exchequer returns and net returns would otherwise include VAT payments twice.

[62] As benefits are calculated at the household level, and the LEO data set does not contain any information about individuals' families, any benefits calculation is subject to a large amount of uncertainty because family formation has to be simulated. Graduates are, on average, less likely to receive benefits due to their higher earnings, but this effect will be small and unlikely to alter our results meaningfully. Rough estimates of the likely impact of undergraduate degrees on benefit receipt are provided in the online appendix.

[63] This might be true, for example, if degrees did nothing to increase students' labour productivity, but employers interpreted a degree as a signal of pre-existing productivity.

Figure 25: Overall average DPV lifetime exchequer returns to HE by component for women

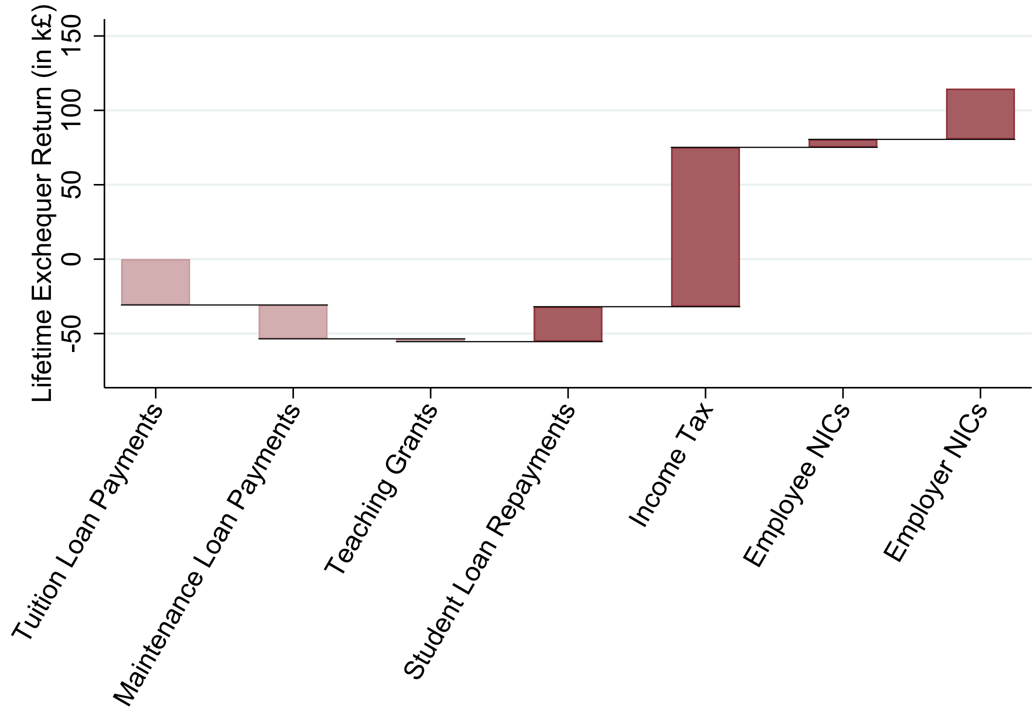


Note: All figures are shown in 2018 prices in £k and are discounted using Green Book discounting. The first two bars show the net present value of the tuition and maintenance loan payments to students. The next bar shows the net present value of teaching grants for high-cost subjects. Subsequent bars then show the net present value of government receipts in terms of student loan repayments and higher income tax and National Insurance payments over the life cycle from graduates compared with non-graduates. Dark blue bars indicate additions and light blue bars reductions.

Figure 25 shows the different components of exchequer outlays and returns for women. Financing an undergraduate degree costs the exchequer around £50k in tuition and maintenance loan payments and teaching grants.[64] Women will only pay back a small fraction of that cost in student loan repayments, but will more than make up for it through increased income tax payments alone. Adding the additional employee and employer National Insurance contributions (NICs) leads to the overall figure for the average taxpayer return to HE for women of around £30k per student.

[64]'Teaching grants' only includes high-cost subject funding, which makes up roughly half of the university funding disbursed by the Office for Students. We do not model spending on 'targeted allocations', the National Collaborative Outreach Programme or any non-recurrent university funding. As direct funding through the Office for Students is a relatively minor part of overall government expenditure on higher education, these omissions do not materially affect our results.

Figure 26: Overall average DPV lifetime exchequer returns to HE by component for men



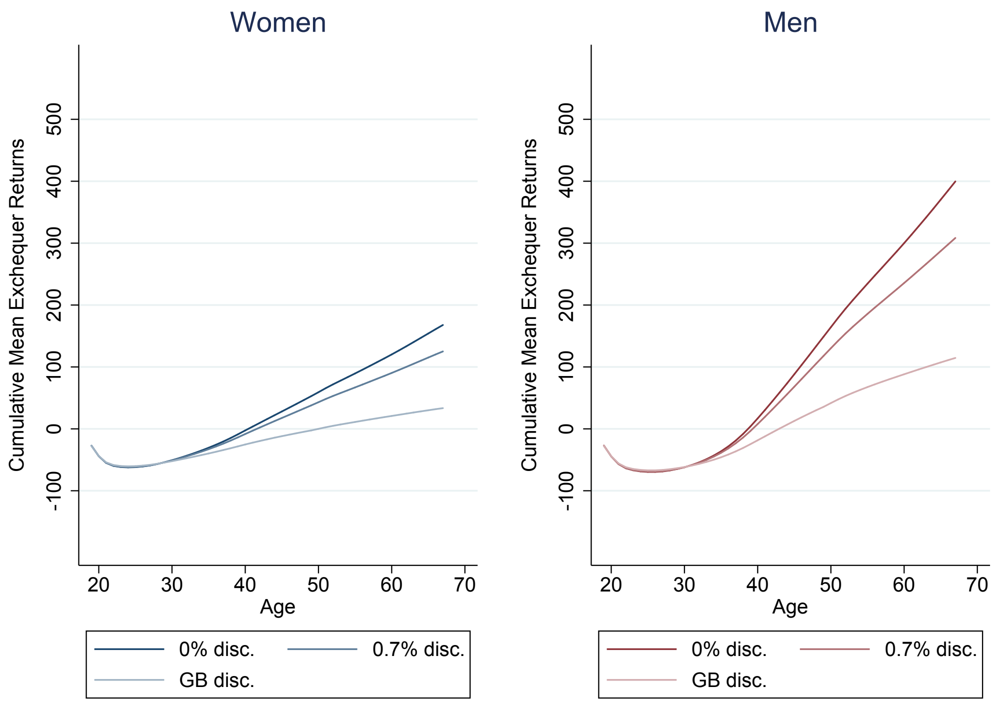
Note: All figures are shown in 2018 prices in £k and are discounted using Green Book discounting. The first two bars show the net present value of the tuition and maintenance loan payments to students. The next bar shows the net present value of teaching grants for high-cost subjects. Subsequent bars then show the net present value of government receipts in terms of student loan repayments and higher income tax and National Insurance payments over the life cycle from graduates compared with non-graduates. Dark red bars indicate additions and light red bars reductions.

Figure 26 is the equivalent plot for men. Financing a degree costs essentially the same but, due to their higher average earnings, men are expected to pay back a larger fraction of that cost in student loan repayments.[65] As for women, the difference in income tax payments as a result of a degree is the most important part of the exchequer return for men. Additional receipts of employee and employer NICs lead to a sum for the average taxpayer return to HE for men of around £110k per student.

However, these averages conceal even more heterogeneity than for private returns due to the progressivity of the tax and student loans system. We expect the 10% of women with the highest exchequer returns on average to generate an extra £300k for the exchequer as a result of going to university, but around half of all women to generate negative returns. For men, we estimate that the 10% with the highest returns will on average contribute and extra £790k to the exchequer as a result of attending HE, but the exchequer will make an overall loss on the undergraduate degrees of around 40%.

[65] The fraction of tuition and maintenance loans not paid back through the student loan system is analogous to but not the same as the 'RAB charge', which is determined using a discount rate of 0.7% and therefore substantially lower for both men and women.

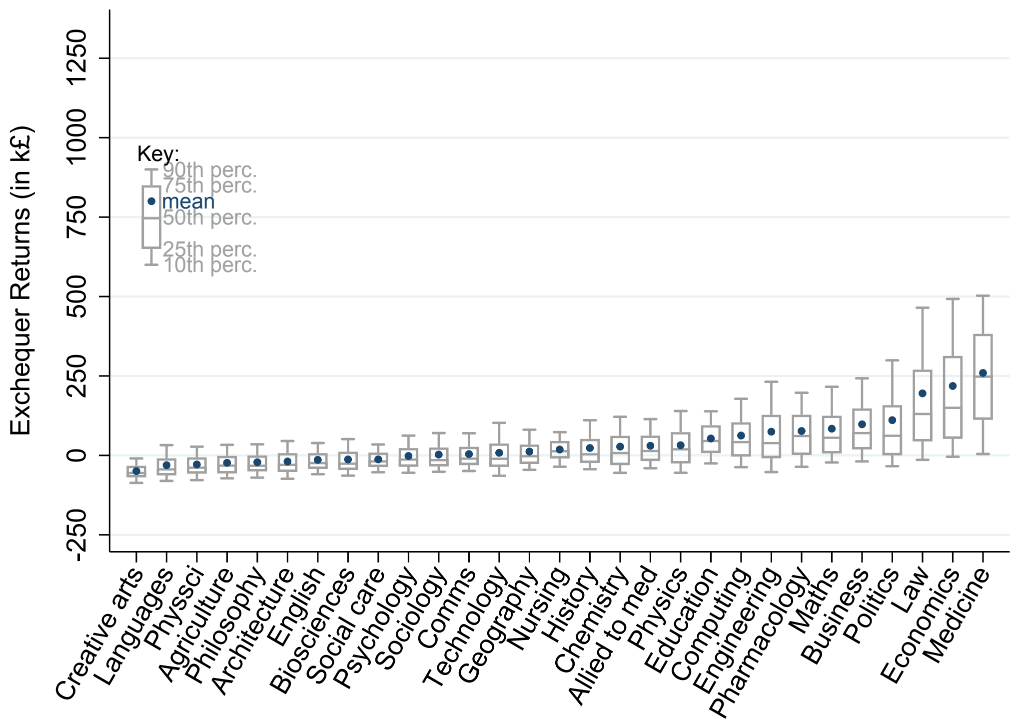
Figure 27: Overall cumulative DPV exchequer returns to HE by age



Note: Discounted cumulative exchequer returns are shown at different ages, using three different discount rates. These numbers are shown in 2018 prices in £k and include the impact of tuition and maintenance loan payments, as well as teaching grants, and any student loan repayments and tax and National Insurance payments.

Figure 27 shows the exchequer returns by age and highlights that, depending on the discount rate, the lifetime exchequer returns to degrees are between twice and three-and-a-half times as large for men as for women. In contrast to the private cumulative returns to degrees, the exchequer returns are negative for a significant part of the life cycle for both genders, because the exchequer bears almost all of the up-front cost of pursuing a degree. Exchequer returns only turn positive in the early 40s for men and around age 50 for women.

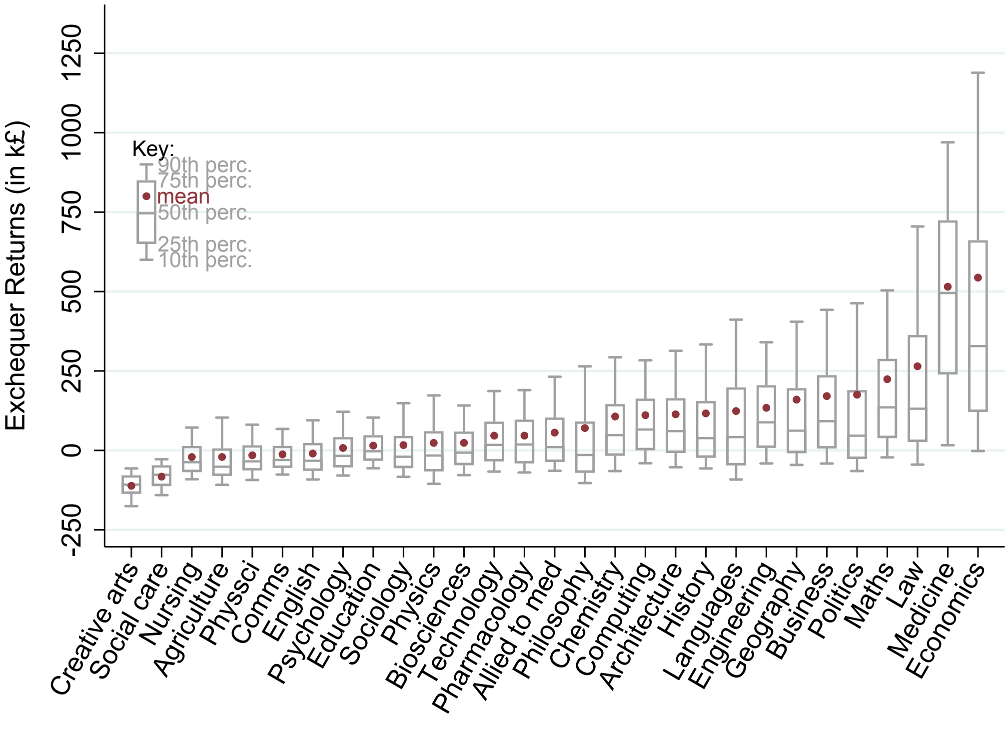
Figure 28: DPV exchequer returns to HE for women by subject



Note: Discounted lifetime exchequer returns are shown in 2018 prices in £k using Green Book discounting. These numbers include the impact of tuition and maintenance loan payments, as well as teaching grants, and any student loan repayments and tax and National Insurance payments.

As with private returns to HE, we show how the taxpayer returns to HE differ across subjects in Figure 28. While the ordering of subjects is very similar to that for private returns, average exchequer returns are negative for around a third of all subjects for women, whereas average private returns were negative for only one (creative arts). Almost all women who study creative arts generate negative exchequer returns. This again is due to the very large up-front costs of a degree, which are borne by the government.

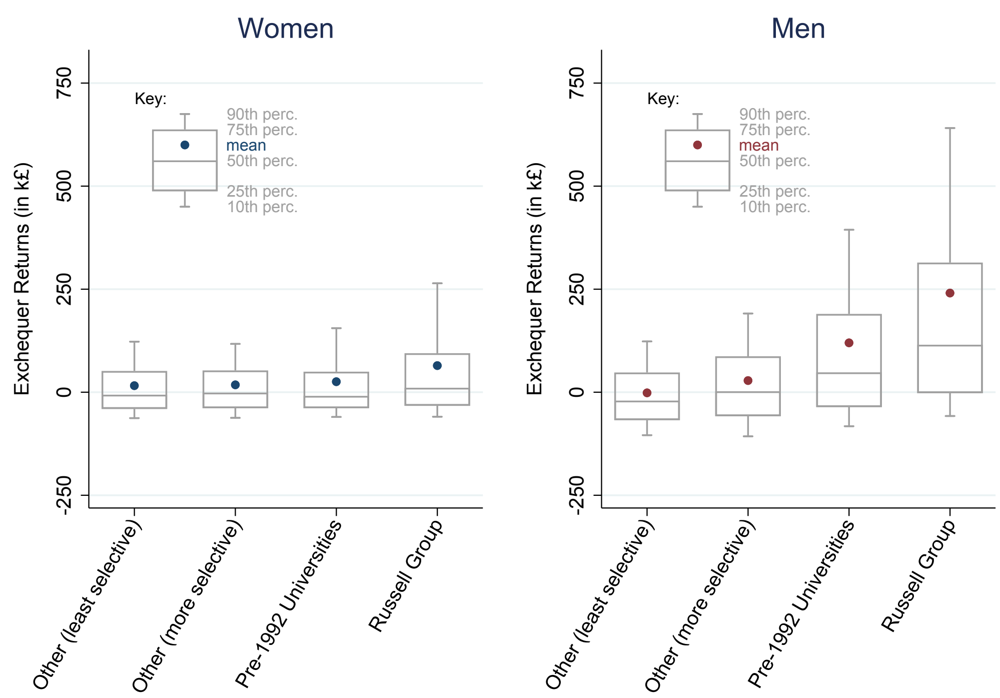
Figure 29: DPV exchequer returns to HE for men by subject



Note: Discounted lifetime exchequer returns are shown in 2018 prices in £k using Green Book discounting. These numbers include the impact of tuition and maintenance loan payments, as well as teaching grants, and any student loan repayments and tax and National Insurance payments.

Figure 29 is the equivalent figure for men. Whereas three subjects have negative average private returns for men, average exchequer returns are negative for seven subjects. The progressivity of the student loan and tax system is reflected in very high lifetime exchequer returns for the 90th percentile of economists of around £1.2m.

Figure 30: DPV exchequer returns to HE by HEI type



Note: Discounted lifetime exchequer returns are shown in 2018 prices in £k using Green Book discounting. These numbers include the impact of tuition and maintenance loan payments, as well as teaching grants, and any student loan repayments and tax and National Insurance payments.

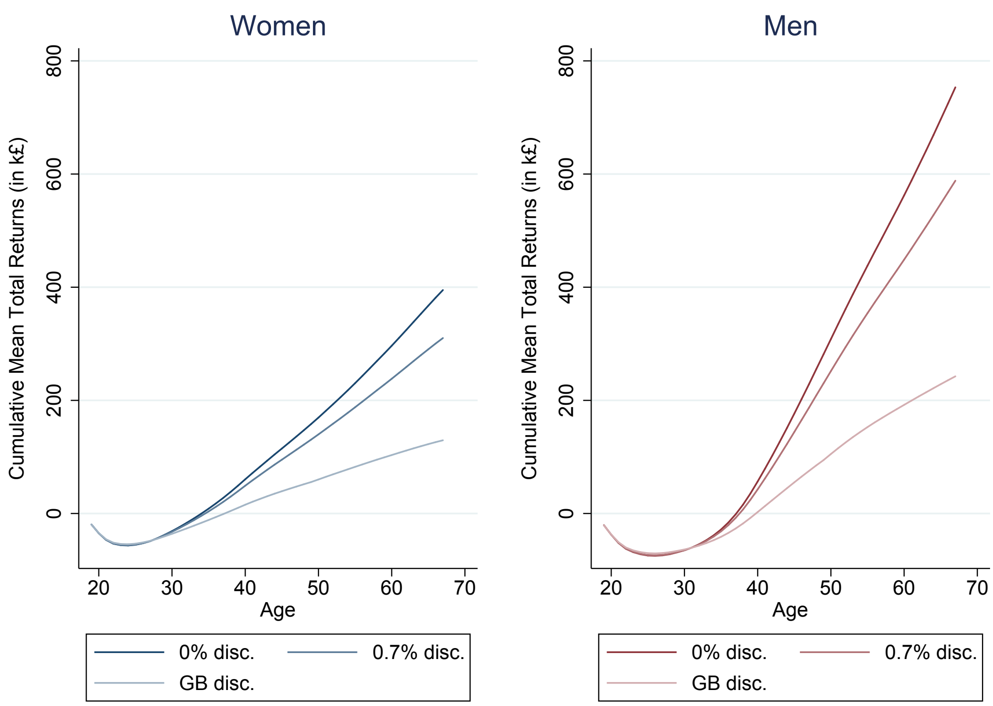
The progressivity of the tax and student loan system also leads to a larger spread of exchequer returns within and across university types. Figure 30 shows that the exchequer returns of roughly half of women at all university types are negative, but the top 10% of earners among women who went to Russell Group universities contribute an additional £250k on average. For men, the picture is very much split by university type. While exchequer returns are positive for about three-quarters of men who went to Russell Group universities, the same figure for the least selective universities is less than half. On average, we estimate that the lifetime exchequer return for men who go to Russell Group universities is around £240k per student, while the same figure for men who go to the least selective universities is roughly zero.

8 Total returns

In this section, we briefly discuss the *total* returns to undergraduate degrees, by which we mean the sum of net returns and exchequer returns discussed in the previous sections. Total returns can be thought of as the overall earnings impact of undergraduate degrees, irrespective of to whom these earnings accrue. This is a similar concept to the gross earnings return, but not the same. First, it includes the effect of undergraduate education on employer National Insurance contributions, which would not be included in gross returns. Second, it takes into account the cost of providing higher education.

The average total return per student in discounted present value terms is around £130k for women and around £240k for men. As Figure 31 shows, these numbers crucially depend on the discount rate: undiscounted total returns are around £400k for women and £750k for men. Total returns for both genders only turn positive in the late 30s, reflecting the high up-front cost of degrees both in terms of the cost of provision and in terms of forgone earnings.

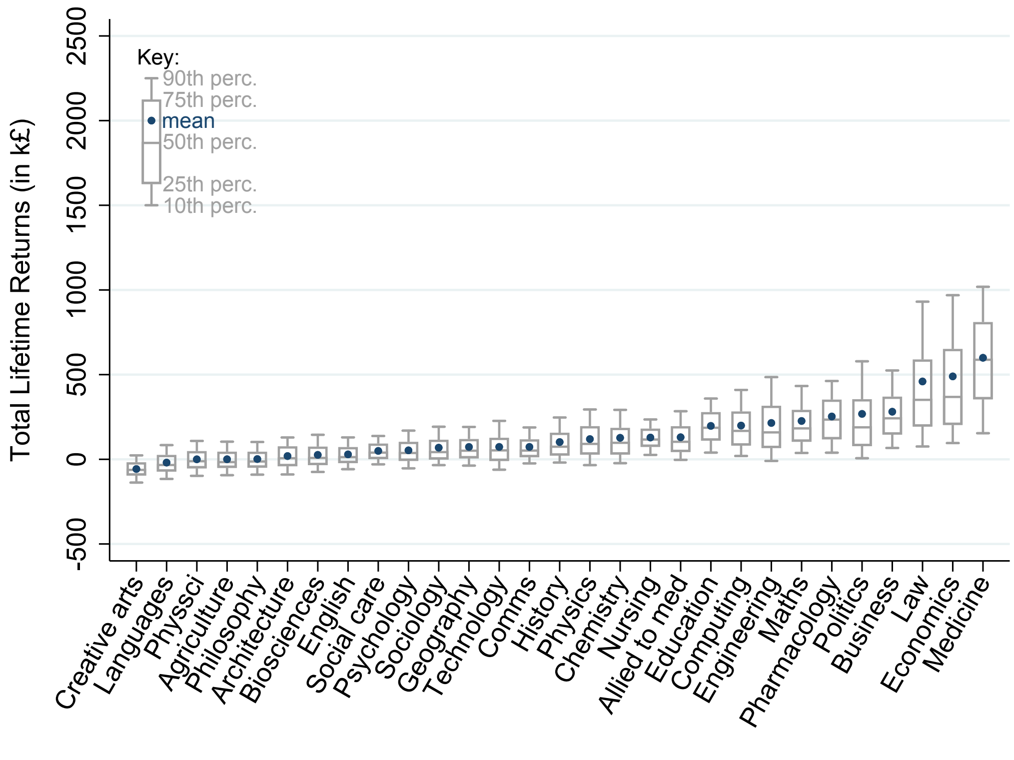
Figure 31: Overall cumulative DPV total returns to HE by age



Note: Discounted cumulative total returns are shown at different ages, using three different discount rates. These numbers are shown in 2018 prices in £k.

These averages once again hide substantial heterogeneity: seen over the whole lifetime, we estimate that total returns will be negative for around 30% of both men and women. As for net private returns and exchequer returns, one driver of this heterogeneity is the very different returns to different university subjects.

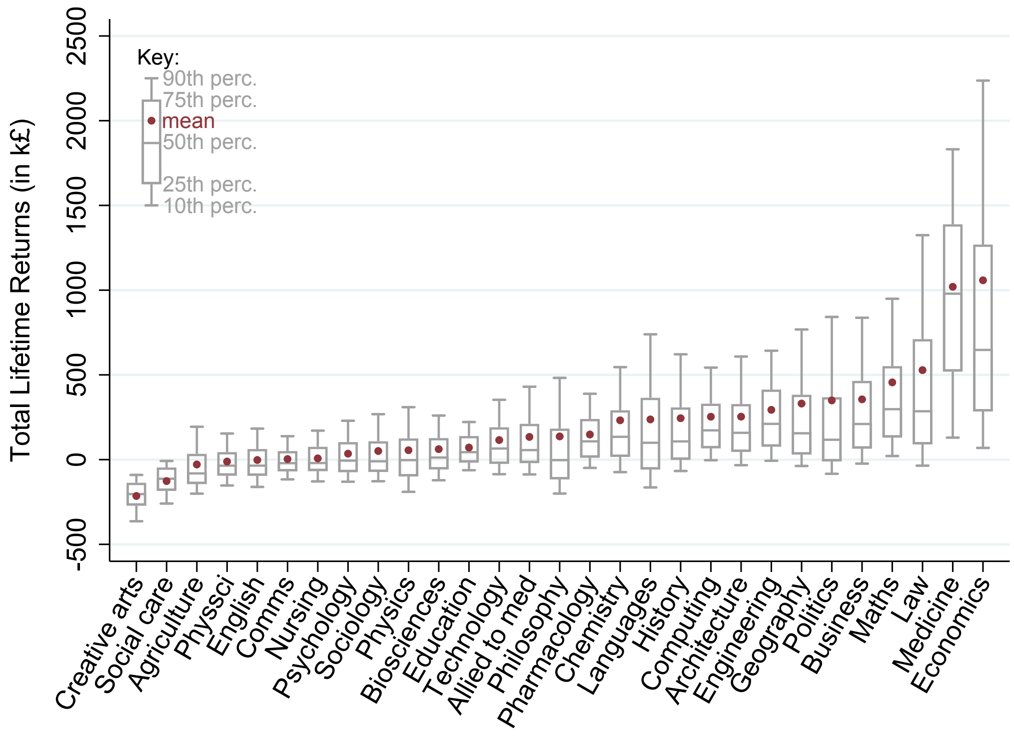
Figure 32: DPV total returns to HE for women by subject



Note: Lifetime total returns are shown in 2018 prices in £k and are discounted using Green Book discounting.

Figure 32 shows discounted lifetime total returns for women by subject. A large number of subjects have negative or near-zero average total returns, including not only arts and humanities subjects such as creative arts, languages and philosophy, but also STEM subjects such as physical sciences and biological sciences. At the other end of the spectrum, average total returns for law, economics and medicine are around £500k. For a large number of subjects, we estimate that more than 90% of students achieve positive total returns.

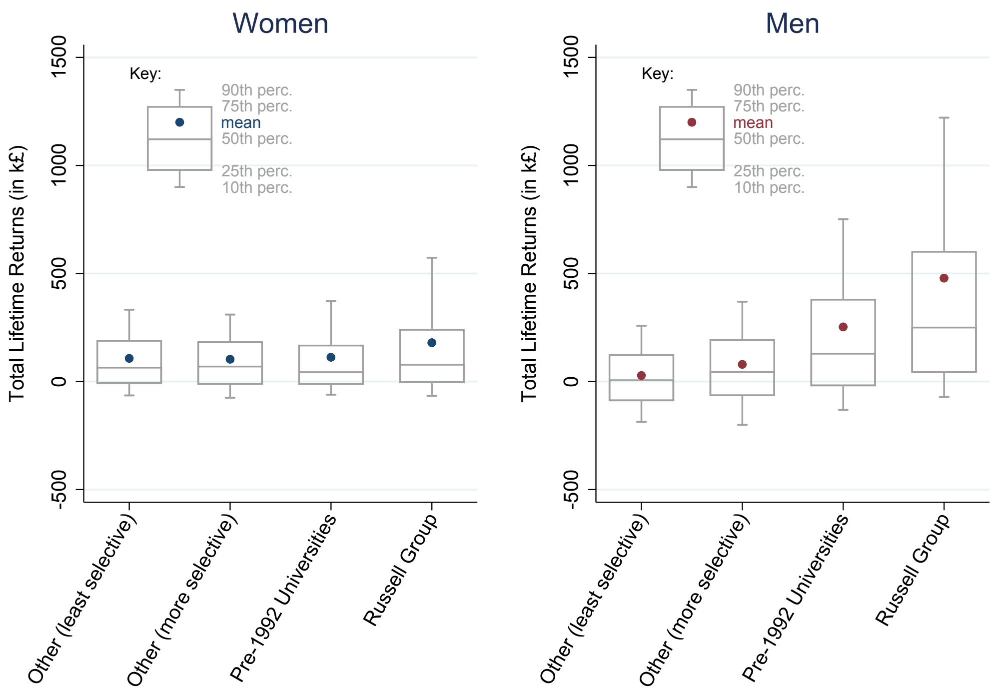
Figure 33: DPV total returns to HE for men by subject



Note: Lifetime total returns are shown in 2018 prices in £k and are discounted using Green Book discounting.

Figure 33 is the equivalent figure for men. Total returns are negative for a large majority of creative arts and social care students, but also for more than half of all students of agriculture, physical sciences, English and a number of other subjects. Average total returns in medicine and economics are in excess of £1m.

Figure 34: DPV total returns to HE by HEI type



Note: Lifetime total returns are shown in 2018 prices in £k and are discounted using Green Book discounting.

Figure 34 shows discounted lifetime total returns by HEI type. Returns for women are relatively constant across institution types. We estimate that, at all types of institutions, around three-quarters of women have positive returns. For men, there is a clear ordering, with Russell Group students achieving the highest total returns at around £480k on average and students at the least selective universities achieving the lowest average total returns at just above zero. Differences between university types are more pronounced at the top end of the distribution than at the bottom end.

9 Conclusion

We show that even once we account for HE students having higher prior attainment and coming from more advantaged backgrounds on average than those who did not attend HE, lifetime earnings returns to attending HE are considerable for both men and women. We estimate that the average earnings return for men grows dramatically over the life cycle, from around 5% at age 29 to almost 40% at age 60. For women, returns increase from around 25% at age 29 to more than 40% by age 40, but then drop back down to between 30% and 35% at ages 50 and 60 as we expect non-HE women's earnings to grow faster in their 40s.

While getting an undergraduate degree is worthwhile financially for most students, there is significant variation across subjects. Some subjects, such as medicine, law and economics, offer a springboard to very lucrative careers. Others, such as computing, pharmacology and education, are safe choices with acceptable returns for almost anyone. However, a significant minority of mostly men are likely to not see positive returns as a result of going to university. These students are largely concentrated in a small number of subjects; even though male returns increase considerably after age 30 for all subjects, lifetime earnings returns remain low or negative for subjects such as creative arts and English.

Returns to undergraduate degrees also vary by university type. Over the life cycle, returns for men are highest for Russell Group graduates, followed by pre-1992 universities. For women, the differences between university types are less stark: while Russell Group graduates have higher returns at age 30, women from 'other' universities overtake them at later ages, leading to similar net lifetime returns overall. These results should be interpreted with some caution, however, as due to the large expansion of, in particular, the more selective 'other' universities, younger cohorts at these institutions may fare differently in the labour market from how previous cohorts did.

Over the lifetime, we estimate that the overall average discounted present value of enrolling in an undergraduate degree is around £100k for women and £130k for men. While the raw earnings differences between graduates and non-graduates are much larger than this, much of the difference is accounted for by differences in characteristics and attainment. The progressive tax system reduces the returns further, as part of the increase in pre-tax earnings from HE is lost in the form of higher taxes or National Insurance contributions. Further accounting for maintenance loans received and student loan repayments slightly increases returns for women, and has only a negligible effect for men, as women repay less in discounted present value terms than they receive in maintenance loans, whereas men repay roughly the same. It should be noted, however, that these figures are highly sensitive to the discount rate used, as a higher discount rate means that, in particular, earnings later in the life cycle are valued much less. Our main estimates use Green Book discounting; using a lower discount rate of 0.7%, as used in student loan accounting, would roughly double those estimates.

The differences in subject returns at each age translate into substantial differences in lifetime returns. Average subject returns for women vary from close to no return to more than £300k. For men, the difference is even larger, ranging from negative returns for creative arts and social care to returns of around £500k for medicine and economics.

These averages obscure important individual heterogeneity in returns. For most subjects with low returns, the spread in returns is limited. Notably, for subjects such as education and nursing, while the average return is low, nearly all women studying those subjects do receive a positive return. On the other hand, many high-return subjects such as economics see huge variation in their returns, with 10% of male economics graduates having returns of close to £1m, while another 10% have returns of less than £70k.

Policymakers may care not only about the private financial return to HE, but also about the taxpayer returns to different degrees. While the government only gets back part of the money it gives out in tuition fee and maintenance loans, as a large share of student loans is written off, this loss is more than made up for by the higher income taxes HE graduates pay. Increases in employee and employer NICs further increase the taxpayer benefit to HE, resulting in overall exchequer returns of around £30k for women and £110k for men. For women, these exchequer returns are around a third of the private returns; for men, they are nearly the same magnitude as the private returns. This pattern reflects the progressivity of the tax and student loan system. Due to the higher earnings of graduate men, as well as their particularly uneven pattern of earnings over the life cycle, nearly half of their lifetime benefits to HE accrue to the taxpayer.

As with the private returns, there are important differences in exchequer returns across subjects. Due to the high cost of financing HE, and the progressive student loan system, the taxpayer on average incurs a net loss on a handful of subjects for both men and women, even though the private earnings returns to some of those subjects are positive. This reflects the substantial subsidy of higher education by the government, mostly through the student loan system, which for these subjects is only partially compensated by higher tax payments. At the other end of the spectrum, taxpayer returns to medicine and economics are around £250k per student for women and more than £500k per student for men.

These results provide an important insight into the benefits of pursuing an undergraduate degree for individuals and the taxpayer. Not only will this provide valuable information to students making their choice of whether to go to university and what to study, but also provide policymakers with important information on the value for money of different degrees. However, two important caveats should be kept in mind. First, this report relies on an extrapolation of historical patterns in earnings growth over the life cycle that may not persist in the future. Second, this report only addresses financial returns to HE, and does not take into account any non-financial benefit to HE such as improved health or happiness, nor any wider returns to society such as increases in the productivity of other workers or lower crime.

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Appendix

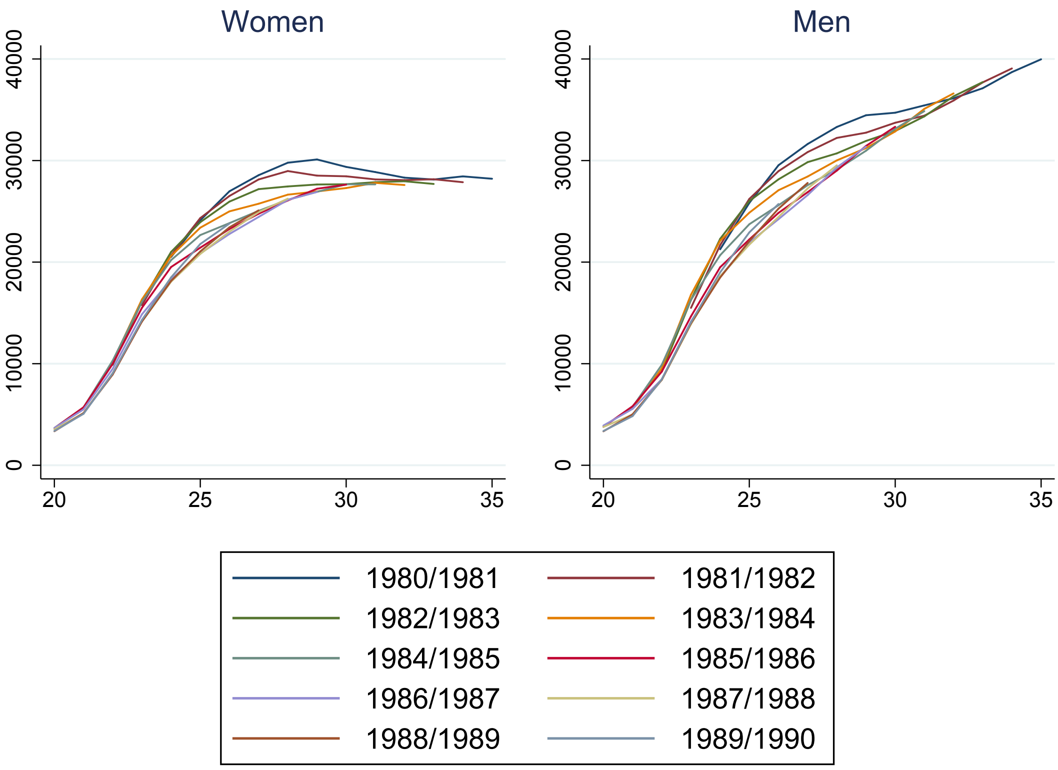
A More on the HESA data

Table 5: Percentage of students of each subject in different university groups

Subject	Russell Group	Pre-1992	Other (more selective)	Other (least selective)
Agriculture	0.8%	0.9%	1.3%	0.7%
Allied to med	3.1%	2.2%	3.3%	3.0%
Architecture	1.1%	1.2%	3.8%	2.0%
Biosciences	7.1%	6.7%	4.5%	3.4%
Business	4.1%	9.8%	16.4%	20.3%
Celtic	.	0.3%	.	.
Chemistry	2.9%	2.2%	0.8%	0.6%
Combined	2.1%	1.2%	2.3%	8.7%
Comms	0.4%	0.9%	3.1%	2.6%
Computing	2.8%	3.6%	5.5%	6.0%
Creative arts	3.7%	5.1%	17.5%	13.0%
Economics	3.4%	3.3%	1.4%	1.3%
Education	1.8%	1.9%	5.8%	3.8%
Engineering	7.2%	8.8%	5.0%	5.1%
English	4.6%	4.9%	3.5%	1.9%
Geography	4.0%	4.1%	2.4%	1.9%
History	6.7%	5.8%	2.4%	1.9%
Humanities n.s.	0.2%	.	0.1%	.
Languages	7.8%	7.5%	2.4%	2.2%
Law	5.2%	3.7%	2.6%	4.4%
Maths	4.2%	3.1%	1.2%	0.8%
Medicine	5.5%	1.1%	.	.
Nursing	0.4%	0.3%	0.7%	1.0%
Pharmacology	1.5%	1.2%	0.6%	0.3%
Philosophy	2.4%	1.3%	1.0%	0.8%
Physics	2.9%	1.6%	0.2%	0.2%
Physsci	2.3%	2.1%	2.5%	1.7%
Politics	2.5%	3.4%	1.3%	1.3%
Psychology	2.9%	3.8%	1.9%	3.7%
Social care	.	0.2%	0.5%	0.3%
Sociology	3.4%	4.2%	3.9%	4.4%
Sportsci	.	.	.	.
Technology	0.8%	1.1%	1.0%	0.9%
Vetsci	0.6%	0.2%	.	.
Unknown	1.0%	2.4%	1.0%	1.4%
Total	46,256	29,965	46,231	30,591

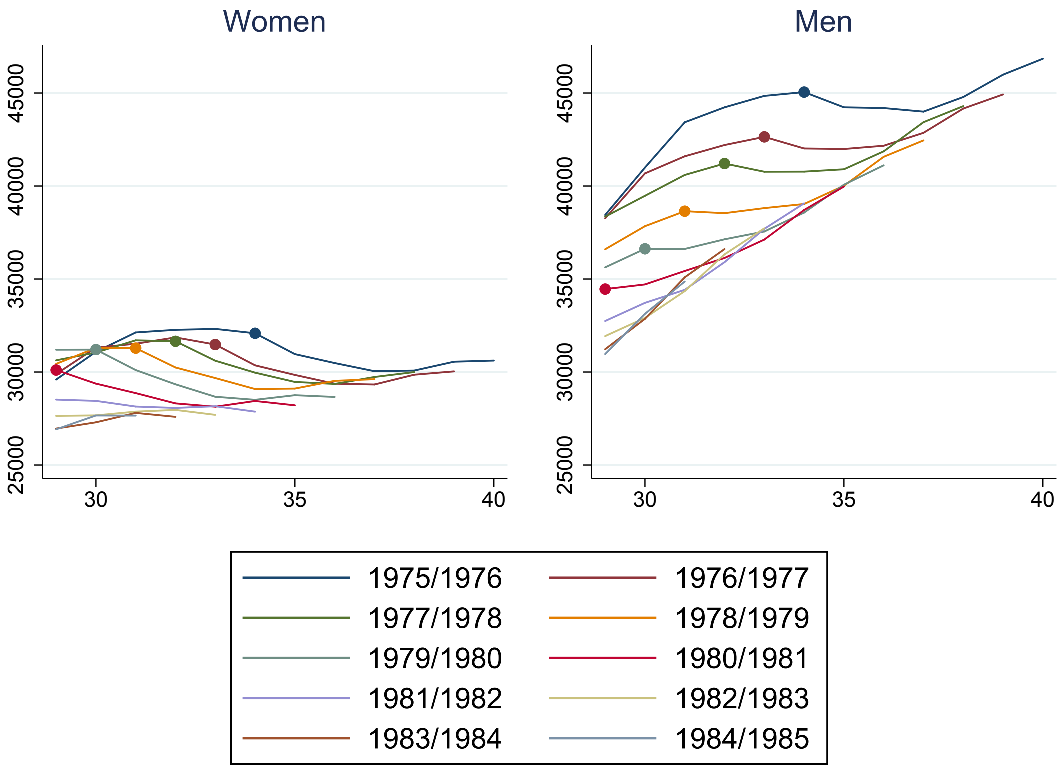
Note: Percentage of students studying each subject at each institution group is shown for the 1975/76 birth cohort. A dot indicates where sample sizes are too small to be shown for statistical disclosure purposes.

Figure 35: Median PAYE earnings of HE attendees by age: recent cohorts



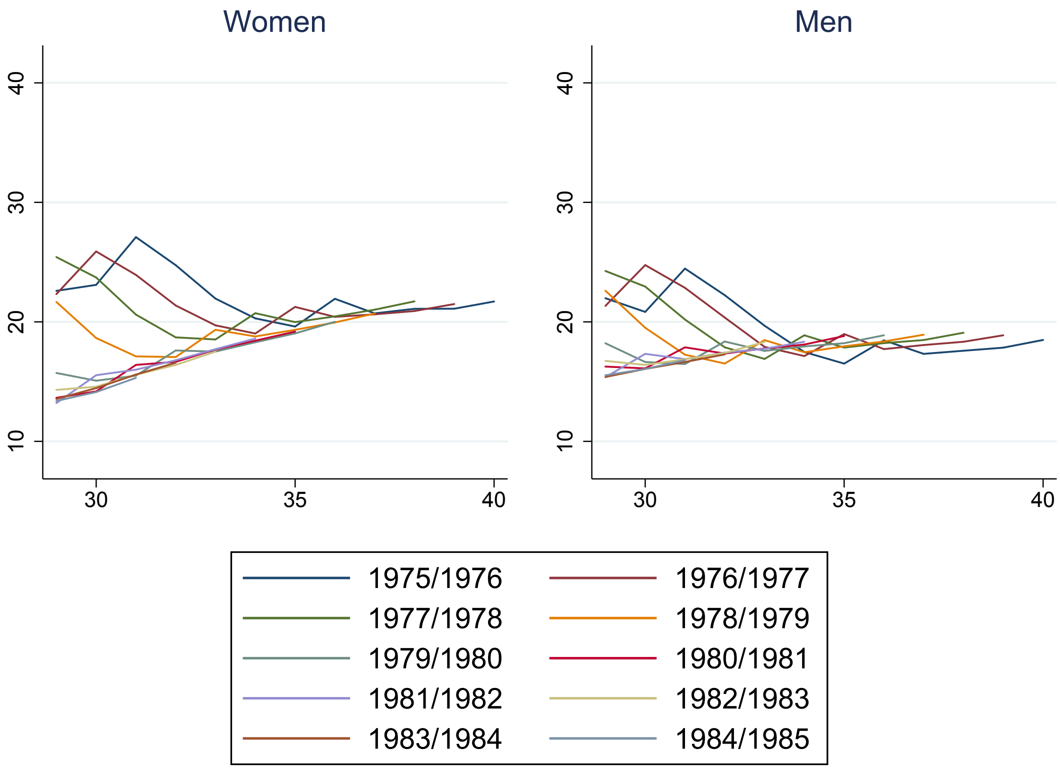
Note: Median PAYE earnings for the 1980/81 to 1989/90 cohorts by age. HE attendees with positive earnings only. Earnings are in 2018 prices. Analysis cohort marked in bright red.

Figure 36: Median PAYE earnings of HE attendees by age: earliest cohorts



Note: Median PAYE earnings for the 1975/76 to 1984/85 cohorts by age. HE attendees with positive earnings only. Earnings are in 2018 prices. Dots indicate the year of the Global Financial Crisis (2008).

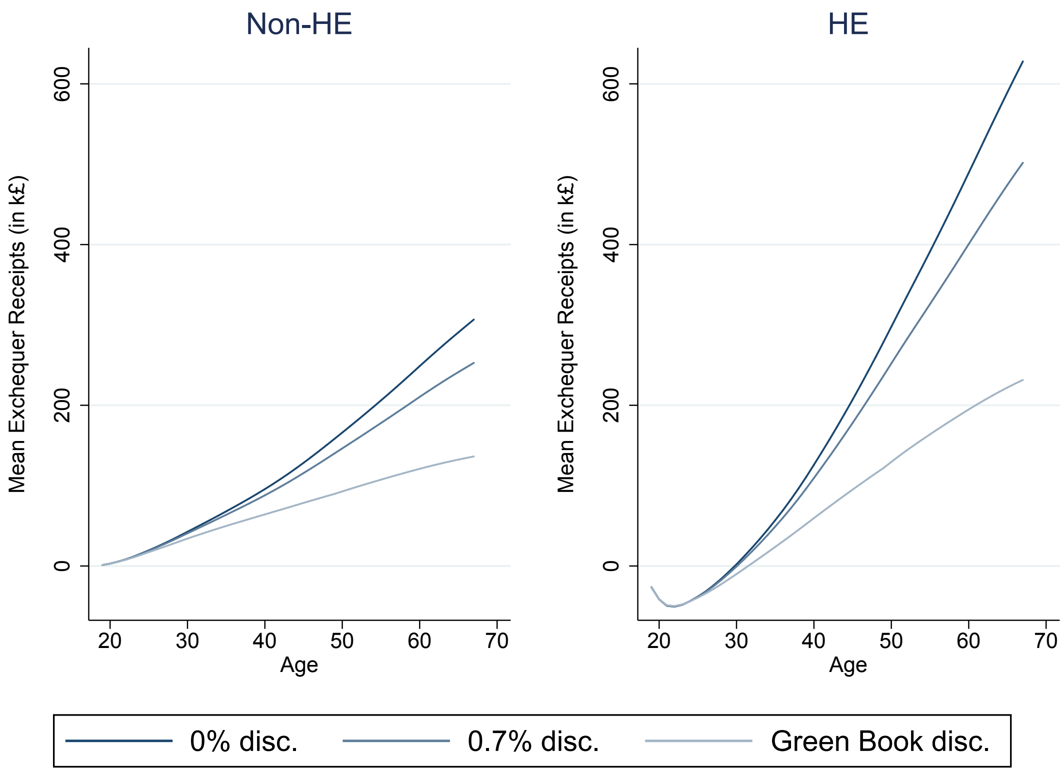
Figure 37: Non-employment of HE attendees by age



Note: Percentage non-employment of HE attendees, by birth cohort and by age, defined as zero PAYE earnings. Those who are purely self-employed, out of the country or dead are all counted as workless, as all register as zero PAYE earnings in our data.

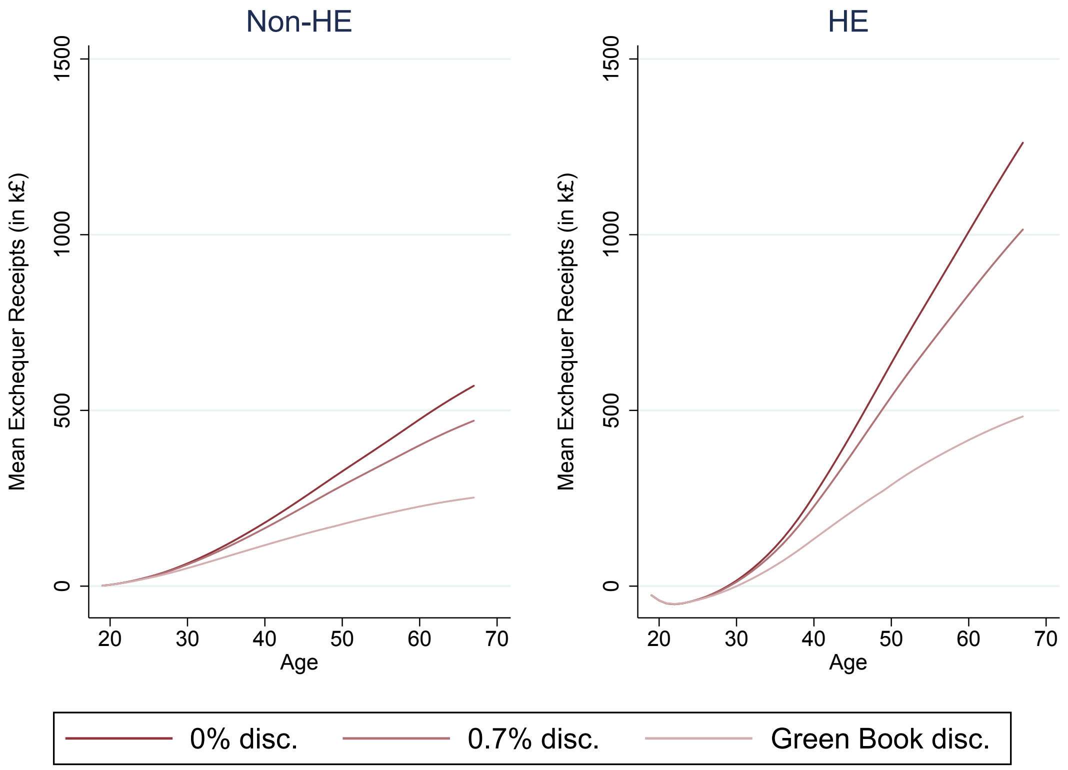
B Lifetime exchequer receipts

Figure 38: Cumulative exchequer receipts from women over the life cycle



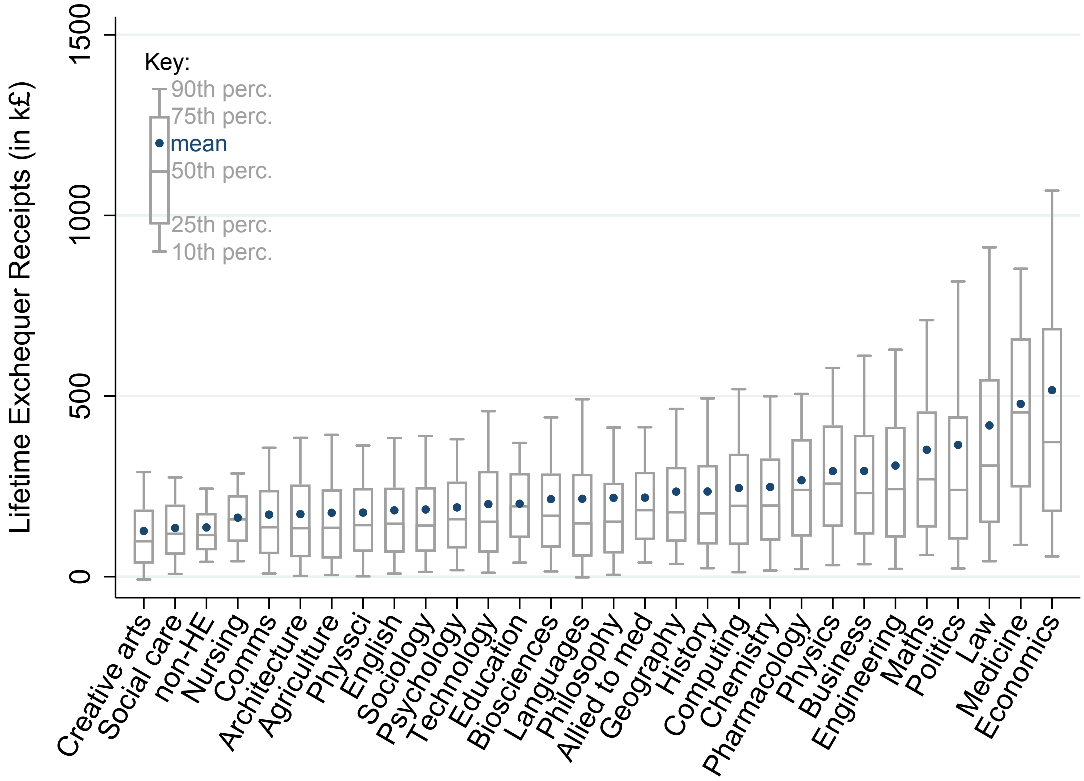
Note: 2018 prices. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 39: Cumulative exchequer receipts from men over the life cycle



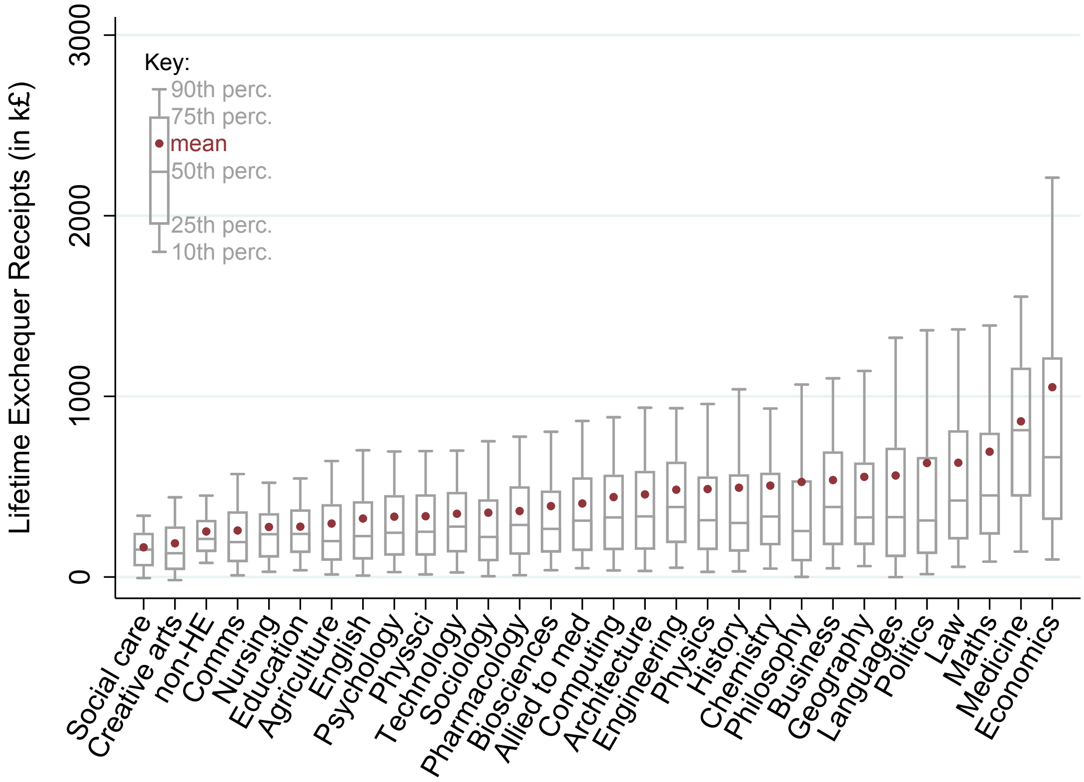
Note: 2018 prices. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 40: Lifetime exchequer receipts from women by subject



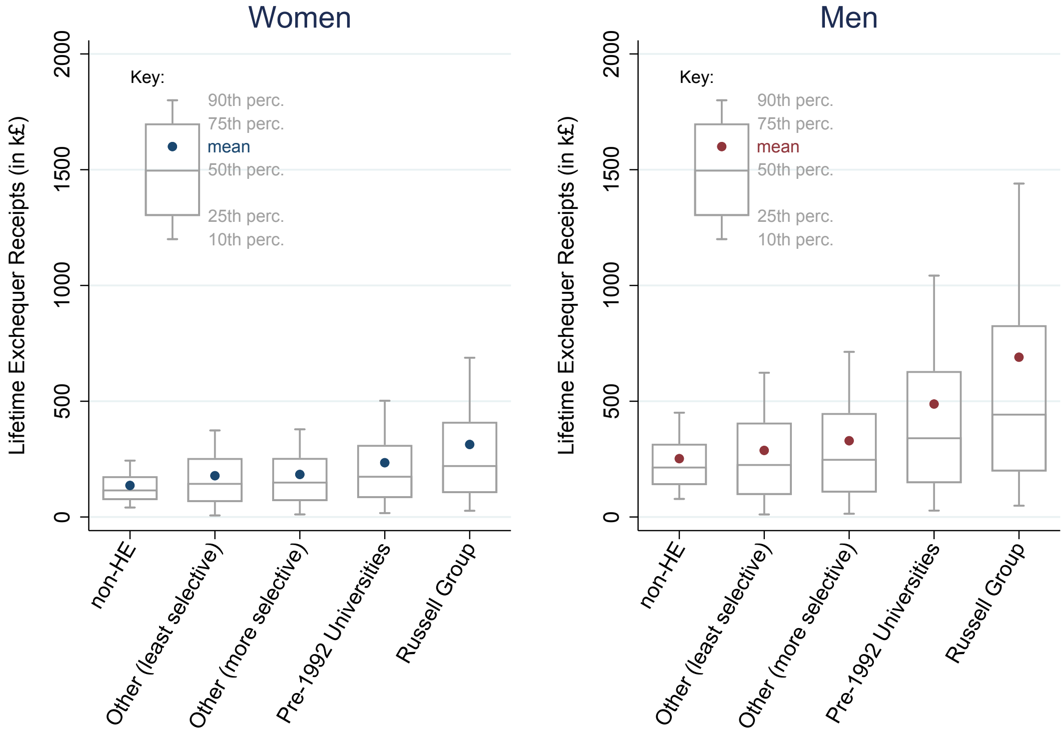
Note: 2018 prices, discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Figure 41: Lifetime exchequer receipts from men by subject



Note: 2018 prices, discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

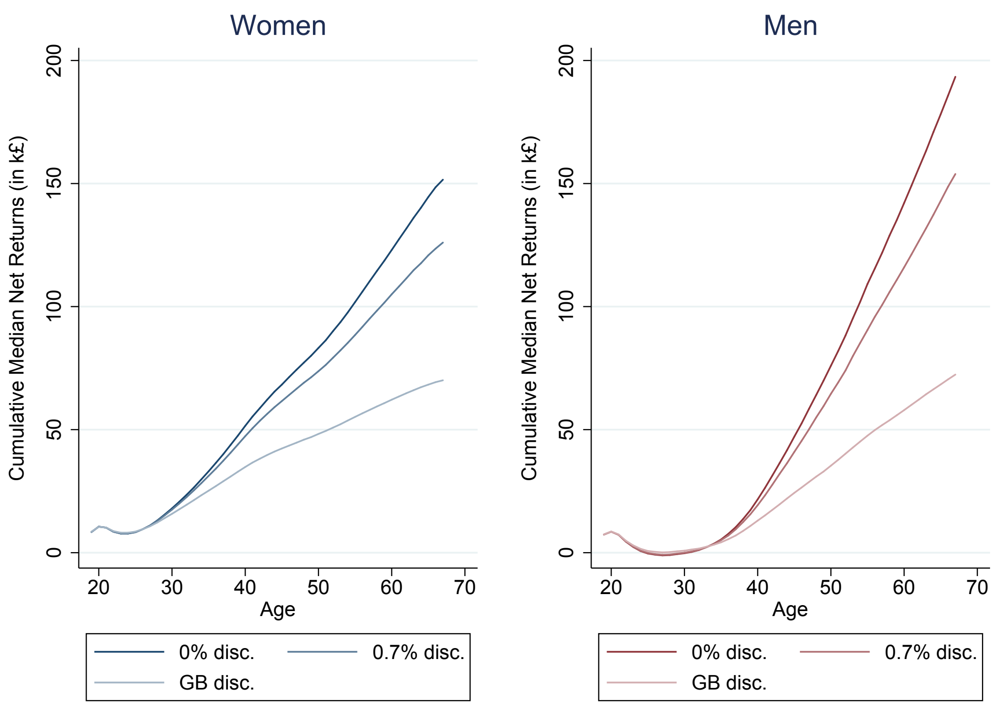
Figure 42: Lifetime exchequer receipts by HEI type



Note: 2018 prices, discounted using Green Book discounting. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

C Median net lifetime returns

Figure 43: Overall median cumulative private DPV returns to HE by age



Note: 2018 prices. 'Non-HE' conditions on having at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level.

Table 6: Median lifetime returns (in £k) by subject and gender

	Women			**Men**		
Subject	**0% disc.**	**0.7% disc.**	**GB disc.**	**0% disc.**	**0.7% disc.**	**GB disc.**
Agriculture	43	37	21	-22	-25	-22
Allied to med	204	169	94	157	121	51
Architecture	79	68	39	272	218	102
Biosciences	72	61	36	116	85	26
Business	408	332	173	298	243	124
Chemistry	217	176	93	277	211	91
Comms	138	115	65	46	34	12
Computing	277	230	126	282	226	112
Creative arts	-10	-9	-5	-201	-169	-94
Economics	497	410	220	787	638	326
Education	350	283	144	139	110	51
Engineering	265	218	123	334	267	129
English	79	67	41	31	22	2
Geography	115	98	57	276	218	98
History	166	137	72	219	171	74
Languages	20	18	13	213	165	61
Law	573	460	224	404	325	159
Maths	256	218	128	416	334	169
Medicine	821	667	341	1,294	1,036	493
Nursing	219	186	109	55	40	23
Pharmacology	364	302	172	206	165	89
Philosophy	43	37	23	73	54	15
Physics	199	162	81	81	57	13
Physsci	52	45	31	39	25	1
Politics	327	263	133	217	172	77
Psychology	120	98	52	77	56	18
Social care	132	109	60	-68	-56	-33
Sociology	131	108	59	54	41	15
Technology	130	110	62	169	132	53

Note: Median lifetime returns are shown in 2018 prices in £k and are discounted at different discount rates. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Table 7: Median lifetime returns (in £k) by university type and gender

	Women			Men		
Subject	**0% disc.**	**0.7% disc.**	**GB disc.**	**0% disc.**	**0.7% disc.**	**GB disc.**
Russell Group	151	126	71	359	288	140
Pre-1992 universities	121	101	58	230	183	86
Other (more selective)	166	137	74	128	101	46
Other (least selective)	161	134	75	80	63	29

Note: Median lifetime returns are shown in 2018 prices in £k and are discounted at different discount rates. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

D Full subject results by age

Table 8: Subject returns by age

	Women				Men			
Subject	**Age 30**	**Age 40**	**Age 50**	**Age 60**	**Age 30**	**Age 40**	**Age 50**	**Age 60**
Agriculture	14.1	28.1	14.1	12.8	-11.2	9.3	16.8	19.3
	[7.6, 20.5]	[19.0, 37.2]	[5.9, 22.2]	[4.4, 21.2]	[-18.2, -4.2]	[-1.6, 20.3]	[4.0, 29.7]	[4.6, 33.9]
Allied to med	24.7	47.5	39.9	41.8	0.4	17.7	28.3	33.6
	[21.5, 27.9]	[42.8, 52.2]	[35.4, 44.3]	[37.2, 46.5]	[-3.6, 4.4]	[11.7, 23.7]	[20.9, 35.7]	[25.4, 41.8]
Architecture	32.2	30.3	21.8	20.9	15.0	38.1	45.3	48.3
	[25.5, 38.9]	[21.9, 38.6]	[14.1, 29.5]	[12.9, 28.8]	[11.5, 18.5]	[32.7, 43.5]	[38.9, 51.7]	[41.3, 55.4]
Biosciences	17.9	31.7	18.2	18.5	-9.8	17.5	27.4	27.5
	[14.6, 21.2]	[27.1, 36.3]	[14.1, 22.3]	[14.2, 22.7]	[-12.5, -7.1]	[13.1, 22.0]	[21.9, 32.9]	[21.5, 33.5]
Business	43.8	62.2	49.8	50.5	16.4	52.6	52.1	53.1
	[41.0, 46.6]	[58.4, 66.1]	[46.3, 53.3]	[47.0, 54.1]	[14.4, 18.5]	[49.1, 56.0]	[48.2, 55.9]	[48.8, 57.5]
Chemistry	32.5	47.9	35.9	34.3	-0.7	37.6	41.0	44.1
	[25.1, 39.8]	[37.8, 58.0]	[26.7, 45.2]	[24.9, 43.7]	[-5.1, 3.8]	[29.9, 45.4]	[31.9, 50.1]	[34.2, 53.9]
Comms	28.7	34.7	23.8	24.5	-4.5	10.8	19.5	22.7
	[25.1, 32.3]	[30.0, 39.4]	[19.6, 28.1]	[20.1, 28.9]	[-7.3, -1.6]	[6.6, 15.0]	[14.4, 24.6]	[17.0, 28.5]
Computing	45.3	58.3	49.7	55.6	13.0	41.9	44.5	46.5
	[38.0, 52.5]	[48.4, 68.2]	[40.4, 59.0]	[45.6, 65.6]	[10.5, 15.5]	[37.9, 45.9]	[39.8, 49.1]	[41.5, 51.6]
Creative arts	7.2	15.3	6.6	8.6	-15.3	-9.7	-12.2	-10.4
	[5.3, 9.2]	[12.7, 17.9]	[4.3, 9.0]	[6.1, 11.0]	[-17.1, -13.6]	[-12.1, -7.3]	[-14.8, -9.5]	[-13.4, -7.5]
Economics	74.6	85.5	50.3	51.5	40.7	93.3	89.0	92.3
	[65.6, 83.6]	[73.4, 97.6]	[41.2, 59.5]	[42.3, 60.7]	[36.4, 45.0]	[85.8, 100.7]	[80.8, 97.2]	[82.8, 101.7]
Education	23.7	65.7	60.6	63.2	6.3	25.9	28.6	32.0
	[20.8, 26.6]	[60.9, 70.5]	[55.9, 65.3]	[58.3, 68.1]	[1.1, 11.5]	[18.2, 33.7]	[19.7, 37.5]	[21.8, 42.2]
Engineering	40.4	66.1	51.7	50.5	13.9	40.9	48.3	51.3
	[32.9, 48.0]	[55.0, 77.2]	[41.7, 61.7]	[40.2, 60.8]	[11.5, 16.3]	[37.2, 44.7]	[43.8, 52.8]	[46.3, 56.2]
English	19.7	28.4	13.3	13.8	-14.8	11.3	14.7	17.2
	[17.0, 22.4]	[24.8, 32.1]	[10.1, 16.5]	[10.6, 17.1]	[-17.6, -12.0]	[6.7, 16.0]	[9.3, 20.1]	[11.2, 23.2]
Geography	27.3	32.1	24.8	23.4	2.7	35.0	41.2	44.0
	[23.2, 31.5]	[26.8, 37.4]	[19.7, 29.9]	[18.1, 28.6]	[-0.4, 5.8]	[29.9, 40.1]	[35.2, 47.1]	[37.3, 50.6]
History	25.3	37.4	27.2	28.5	-2.0	29.6	34.0	38.4
	[22.0, 28.5]	[33.0, 41.8]	[23.2, 31.3]	[24.3, 32.7]	[-4.5, 0.5]	[25.4, 33.8]	[29.2, 38.8]	[32.9, 43.9]
Languages	21.2	23.9	7.7	6.9	-8.4	35.6	36.2	40.2
	[18.0, 24.5]	[19.9, 28.0]	[4.2, 11.2]	[3.4, 10.4]	[-11.7, -5.0]	[29.5, 41.8]	[29.5, 43.0]	[32.7, 47.8]
Law	45.2	88.7	72.8	75.3	15.9	61.9	67.2	69.5
	[41.8, 48.5]	[83.3, 94.2]	[68.0, 77.6]	[70.4, 80.2]	[12.6, 19.1]	[55.9, 67.8]	[60.3, 74.0]	[61.7, 77.2]
Maths	40.0	51.2	33.8	33.6	14.7	47.6	42.8	44.3
	[34.0, 46.1]	[43.3, 59.2]	[26.6, 40.9]	[26.2, 41.0]	[11.0, 18.5]	[41.6, 53.6]	[36.3, 49.3]	[37.2, 51.4]
Medicine	73.3	131.9	120.5	123.8	30.0	107.8	128.9	135.5
	[67.7, 78.9]	[122.1, 141.7]	[111.6, 129.3]	[114.6, 132.9]	[25.2, 34.9]	[97.4, 118.2]	[116.6, 141.1]	[122.0, 148.9]
Nursing	33.9	43.5	41.1	41.6	5.8	18.8	17.7	19.0
	[29.1, 38.7]	[37.1, 49.8]	[34.7, 47.5]	[34.8, 48.3]	[-7.9, 19.4]	[0.0, 37.5]	[-3.8, 39.2]	[-4.6, 42.5]
Pharmacology	36.9	64.0	54.5	55.4	0.4	24.6	23.4	22.5
	[29.9, 43.8]	[53.7, 74.4]	[44.7, 64.4]	[45.0, 65.7]	[-5.3, 6.1]	[15.7, 33.6]	[13.3, 33.6]	[11.5, 33.5]
Philosophy	13.2	26.2	10.3	9.9	-11.2	17.2	17.4	24.1
	[8.4, 18.0]	[19.4, 32.9]	[4.5, 16.1]	[4.0, 15.8]	[-15.1, -7.3]	[10.6, 23.9]	[10.2, 24.6]	[15.7, 32.5]
Physics	19.7	49.2	34.4	33.0	-7.3	15.9	19.0	20.7
	[9.4, 30.0]	[33.8, 64.5]	[20.9, 48.0]	[19.0, 47.0]	[-11.0, -3.5]	[10.0, 21.9]	[12.2, 25.8]	[13.3, 28.2]
Physsci	24.3	26.8	13.9	16.1	-6.0	13.5	14.8	18.2
	[18.6, 30.0]	[19.7, 33.9]	[7.4, 20.4]	[9.3, 23.0]	[-10.2, -1.8]	[7.0, 19.9]	[7.3, 22.2]	[10.0, 26.5]
Politics	36.8	68.3	54.2	59.3	0.1	41.0	38.6	41.3
	[30.8, 42.7]	[59.2, 77.5]	[46.1, 62.3]	[50.8, 67.8]	[-3.2, 3.5]	[35.0, 47.0]	[32.1, 45.2]	[33.9, 48.6]
Psychology	12.8	33.0	29.2	31.9	-9.6	12.9	21.7	26.9
	[10.3, 15.2]	[29.4, 36.7]	[25.6, 32.8]	[28.1, 35.7]	[-13.2, -5.9]	[7.1, 18.7]	[14.7, 28.8]	[18.9, 34.8]
Social care	13.4	23.9	27.2	31.7	-7.3	-12.2	-4.9	-0.5
	[8.3, 18.5]	[17.0, 30.8]	[19.9, 34.4]	[24.0, 39.4]	[-19.1, 4.4]	[-25.9, 1.6]	[-22.2, 12.4]	[-20.7, 19.7]
Sociology	19.4	35.0	26.5	28.4	-1.2	23.1	21.8	22.0
	[16.4, 22.4]	[30.7, 39.2]	[22.6, 30.5]	[24.2, 32.5]	[-5.0, 2.6]	[17.1, 29.1]	[15.1, 28.5]	[14.5, 29.5]
Technology	30.5	37.1	24.7	27.8	-1.2	37.1	39.2	43.3
	[21.3, 39.8]	[24.8, 49.3]	[13.8, 35.6]	[16.1, 39.5]	[-6.4, 3.9]	[28.0, 46.2]	[28.8, 49.6]	[31.6, 54.9]

Note: All results are estimated using separate OLS regressions by age, where the non-HE group only includes those with at least five A*–C GCSEs and a Key Stage 5 record and excludes those with other HE below undergraduate level. The impact of initial conditions is fixed at age 30 to help deal with the fact that later-life estimates are based on simulated data. 95% confidence intervals given in square brackets should be taken as a lower bound on true uncertainty as they do not reflect uncertainty from either the simulation of earnings or the estimation of the dependence of earnings on background conditions.

E Average net lifetime returns with different discount rates

Table 9: Average net lifetime returns (in £k) by subject and gender

	Women			Men		
Subject	**0% disc.**	**0.7% disc.**	**GB disc.**	**0% disc.**	**0.7% disc.**	**GB disc.**
Agriculture	53	44	24	38	20	-8
Allied to med	222	183	100	240	185	78
Architecture	78	66	39	386	305	140
Biosciences	83	70	39	167	123	38
Business	438	355	183	460	373	185
Chemistry	237	194	99	392	304	125
Comms	149	124	69	67	49	16
Computing	300	248	137	369	295	142
Creative arts	-11	-10	-8	-220	-184	-103
Economics	614	505	271	1,270	1,030	514
Education	351	284	144	157	124	56
Engineering	319	263	140	427	339	160
English	88	74	43	68	46	8
Geography	126	106	61	488	384	171
History	188	153	78	367	289	128
Languages	22	19	11	373	286	113
Law	681	544	264	682	547	263
Maths	293	247	142	594	477	232
Medicine	827	670	340	1,350	1,072	505
Nursing	224	189	110	81	64	28
Pharmacology	378	314	176	243	197	102
Philosophy	48	41	23	231	176	67
Physics	220	178	87	156	113	32
Physsci	55	47	28	63	42	4
Politics	408	326	157	492	388	174
Psychology	128	104	55	122	88	27
Social care	142	117	62	-100	-82	-44
Sociology	152	125	66	115	88	34
Technology	145	120	65	226	173	69

Note: Average lifetime returns are shown in 2018 prices in £k and are discounted at different discount rates. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.

Table 10: Average net lifetime returns (in £k) by university type and gender

	Women			**Men**		
Subject	**0% disc.**	**0.7% disc.**	**GB disc.**	**0% disc.**	**0.7% disc.**	**GB disc.**
Russell Group	268	219	115	635	506	238
Pre-1992 universities	203	165	87	370	293	133
Other (more selective)	207	168	85	157	122	51
Other (least selective)	215	175	91	95	73	30

Note: Average lifetime returns are shown in 2018 prices in £k and are discounted at different discount rates. Figures take into account the impact of selection into HE, taxes paid and student loan repayments as well as maintenance loans received.