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The labour market returns to graduation: reconciling administrative and survey data estimates

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ABSTRACT

This paper contributes to the literature on the earnings returns to university graduation. Recent evidence using administrative earnings data from England suggests a zero return to graduation for men and positive returns to graduation for women in annual earnings at age 26. We show that once hours worked are taken into account – typically not available in administrative tax data – returns to graduation in hourly wages are considerably smaller for women than returns in annual wages at this age. Graduate women work more hours than comparable non-graduate women; thus, not taking hours worked into account leads to overestimating returns to graduation for women by more than two-fold. This highlights the importance of using both survey and administrative data sources when estimating the returns to university graduation.

1. Introduction

The labour market value of higher education is a topic of keen public and policy debate in many advanced economies. This is in part due to the nature of the public investment and there being both public and private returns which arise from it. A range of literature has highlighted the positive returns to the individual from completing a university degree – from higher earnings (Britton et al., 2022; Maurin & McNally, 2008; Webber, 2016), to better health (Herd et al., 2007; Raghupathi & Raghupathi, 2020), to positive assortative mating (Elsayed & Shirshikova, 2023; Hu & Qian, 2016) – see Oreopoulos & Petronijevic (2013) for a review. This has raised concerns about how higher education should be funded and the debate has been particularly salient in England where participation in higher education has increased markedly from around 15 % in 1990 to just over 53 % in 2019/20 (Office for National Statistics (ONS), 2021; Walker & Zhu, 2013). This expansion has been accompanied first by the introduction of tuition fees (1998) and then sharp increases in them (2006, 2012) to fund the extra supply of places, with fees now standing at £9250 per year for a full-time undergraduate course (Wyness, 2010). For most students, these fees and maintenance costs are paid for up-front by government loans that are then repaid by graduates once they are in the labour market and earning above a certain salary threshold.

This rebalancing of higher education costs towards the individual has invigorated the research literature on the estimated value of university graduation to graduates, who are now expected to repay the cost of their tertiary education. The most recent research on the topic in England (Belfield et al., 2018) has exploited newly available earnings data from tax records, linked with administrative information on higher education participation, prior educational attainment and family background, to estimate the returns to higher education.[1] This type of rich administrative data is increasingly being made available to researchers in England and elsewhere. A limitation with this data, however, is that earnings information comes from tax records, which are calculated annually, and therefore reflect both hourly earnings and annual hours worked. This issue is common to estimates of returns to higher education using administrative data in numerous other countries too (Zimmerman, 2019; Kirkeboen et al., 2016; Hastings et al., 2013).

For women in particular, differences in annual hours between graduates and non-graduates can distort the apparent graduate premium. While on average, women work fewer hours and are more likely to work part-time than their male counterparts (European Commission, 2013), this is not necessarily true among graduates. Furthermore, graduate women are less likely to work part-time compared to

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[1] This linked administrative data resource is known as the Longitudinal Education Outcomes (LEO) dataset.

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non-graduate women (Department for Education, 2023), hence estimating returns to graduation for women without observing hours worked would lead to overestimation compared to hourly earnings. As such, recent estimates on the returns to university graduation that do not account for hours worked may present an incomplete picture and lead to incorrect policy conclusions on the gender differences in the returns to graduation.

In this paper, we use data from an English longitudinal cohort study linked with administrative schooling data and self-reported higher education and hourly wage information to estimate the hourly earnings returns to graduation. We find that, as per the recent literature, in annual earnings at age 25/26 there is a positive premium for women (13 %), but none for men. When we take hours worked into account, the return to graduation in hourly wages falls to 4.8 % and is only significant on a 10 % level for women (and stays around zero and insignificant for men). This is due to graduate women working 2.3 hours more per week on average than comparable non-graduate women while among men, graduates do not work more hours than non-graduates. Our findings are robust across a series of robustness checks and highlight the continuing importance of using survey data to complement studies undertaken using administrative data.

2. Recent literature

The positive association between higher education and a wide range of later life outcomes, and the extent of causation in these relationships, is the subject of an extensive literature in economics and the social sciences more generally, see Oreopoulos & Petronijevic (2013) and Hout (2012) for comprehensive reviews. The most populous sub-division within the literature on the returns to higher education focuses on estimating the impact of an undergraduate (bachelor's) degree on labour market earnings. This literature has in recent years been reinvigorated by the increasing availability of linked administrative datasets that provide accurate measures of background characteristics, prior educational attainment, university subject and institution, and crucially earnings from national (or state) tax registers.

In the US this has seen several recent papers exploiting state-level administrative datasets to both estimate the return to a higher education degree and look at returns to specific college majors and how they vary according to the quality of match between the student and the course. Andrews et al. (2022) exploit earnings data from Texas, linked with school and college information, to show the return to different majors and how the subject of major also affects earnings growth and variability. Similarly, Mountjoy & Hickman (2021) exploit administrative data from Texas to estimate the value-added of the state's public universities, and how this varies by college selectivity and student characteristics. This follows earlier work by Dale & Krueger (2014) exploring the relationship between college selectivity and earnings returns. They use the College and Beyond survey linked to Social Security Administrative earnings data and find that while there is a high return to college selectivity, once the student choice sets were controlled for, these selectivity returns fall to zero, albeit with some large returns remaining for Hispanic and black students. Liu et al. (2015) use state-level administrative data and estimate returns to community college qualifications, up to and including bachelor's degrees, attained in the North Carolina Community College system, showing that while the returns to certificates and diplomas were low, there were strong returns for associate's and bachelor's degrees, with returns for females being higher than for males.

Outside the US, numerous studies have used administrative data to examine the returns to degrees and the importance of institutional selectivity and/or quality, subject of major, and individual characteristics in determining the return. Hastings et al. (2013) find large positive effects of enrolment on selective degree programs and for particular subjects (Health, Sciences and Social Sciences) in Chile, with little variation in returns to selectivity by students' socio-economic status. Conversely, focusing more narrowly on elite business-focused degrees, Zimmerman (2019) finds that the large returns associated with these particular programs in Chile are completely driven by males from high-tuition, private secondary schools, with zero returns for females or males from other school types. For Norway, Kirkeboen et al. (2016) find that returns to selectivity are low relative to the variation related to subject of major, with Sciences, Technology, Business and Law consistently providing high returns. In England Belfield et al. (2018) were the first to exploit the availability of linked administrative registers to estimate the return to an undergraduate degree, and how this varies by subject and institution. They find an overall earnings return at age 29 of 26 % for women and 6 % for men but with substantial variation around this by both choice of subject and institution.

However, the common feature of this recent literature from around the world exploiting linked administrative datasets, is that earnings are recorded on an annual or quarterly basis and have no adjustment for hours worked. This is problematic given the consistent finding in the literature that part of the return to (higher) education works via the impact on working hours. For example, Card (1999) summarised that in the US approximately one-third of the return to education in annual earnings is attributable to the effect of education on annual hours. For higher education specifically, Marcotte et al. (2005) used data from the National Education Longitudinal Survey to show that for degrees earned in community college, male returns in annual earnings are around 50 % higher than returns in hourly earnings, while for women annual earnings returns are 80 % higher than hourly returns, suggesting the impact of higher education on hours worked is even greater for women. For the UK, using Labour Force Survey data Devereux & Fan (2011) exploit the expansion in the number of higher education institutions in the early 1990s to estimate returns to education, finding a return in weekly earnings that is around 6 % higher than the return in hourly wages for men, but around 25 % higher for women. Indeed, this limitation of using administrative data that lacks information on hours worked is particularly acute for women, given their greater likelihood of part-time work (Blau & Kahn, 2017), and presents an additional issue when looking at graduate premia given differences in hours worked between graduate and non-graduate women. In this paper, we overcome this widespread issue by using information on hours worked as well as annual earnings to compare the returns to a degree in annual and hourly earnings, highlighting the importance of this more detailed information for returns estimates and the policy implications that derive from them.

3. Data and methods

We use Next Steps, a longitudinal study which follows a cohort born in 1989/1990 and comprises eight waves of data up to the age of 25/26 (University College London, 2024). Next Steps has been linked with the National Pupil Database (NPD), which provides a census of pupils attending schools in England, allowing us to access their school exam results. This includes compulsory, high-stakes, end of secondary school (GCSE) exams, and the exams typically necessary for university entry (A-level exams).

Next Steps is the closest English cohort study in age that matches the administrative data used in Belfield et al. (2018). The young people in their analysis took their GCSEs between 2002-07, while the young people in Next Steps took their GCSEs in 2005-06. This means we should be able to broadly replicate their results with our sample.

The eighth wave of Next Steps covers 7707 individuals, however, following Belfield et al. (2018), we restrict the sample to those who have at least 5 A*-C GCSEs (this is usually the minimum attainment threshold for progression to study university entry qualifications), and are in sustained employment, i.e. had paid employment at the time of data collection, and worked for at least five of the previous six months. Our sample consists of 1220 men and 1658 women.

We look at three outcome variables: log annual wage, log hourly wage, and hours worked, all observed on average at age 26 (Fig. A1 in the Appendix). This is slightly younger than the primary age examined by Belfield et al. (2018), who look at annual earnings at age 29; however, they also produce earlier age estimates for this cohort (see Table 12 in Belfield et al., 2018). Following their methods, we control for the following characteristics:

- demographic and family background: age in months, mother's and father's social class (NS-SEC), region, ethnicity;
- early and pre-university educational attainment: GCSE and A-level (age 18) raw scores, indicator variables for A-level subjects (Math, Sciences, Social Science, Humanities, Arts, Languages and Other), a binary variable for having vocational qualifications, a binary variable capturing whether the individual attended a private (fee paying) secondary school at age 13/14.

Within our analytical sample, the only missing values are for A-level scores; hence we turn these to quintiles and include an extra category for those who did A-levels, but their scores are not observed. The rest of the variables have no missing values in our sample.

Descriptive statistics for the sample are shown in Appendix Tables A1 and A2 by gender. Among men, 47 % (Table A1), while among women (Table A2), 46 % obtained university degrees in the sample by age 26, which gives us confidence that most of the individuals who attend higher education will have completed by this point.[2] Both men and women select into higher education on the basis of pre-university characteristics. Male graduates in particular are much more likely to be from higher social class than non-graduates: for 52 % of graduates their father is in the highest social class (NS-SEC groups 1-2) compared to 39 % for non-graduates, with corresponding figures of 42 % v 30 % for mother's social class. Graduates also have higher attainment at age 16: average GCSE points are 509 (509) for male (female) graduates versus 463 (466) for male (female) non-graduates. Those who do not go on to attain a university degree are much more likely to study a vocational qualification at level 3, particularly amongst males (39 % vs. 27 %), and for those who do study A-levels, non-graduates are more likely to be in the lower quintiles of attainment at A-level and less likely to be in the highest quintiles. These differences highlight the importance of controlling for background characteristics and prior attainment when estimating the returns to graduation. The raw figures in Table A1 show that amongst men, graduates and non-graduates work approximately the same average weekly hours (41.58 vs. 41.34) with hourly wages slightly higher for graduates (£13.35 vs. £12.48). For females, hourly wages see a greater raw graduate premium (£12.65 vs. £10.98) but weekly hours are notably higher for female graduates than non-graduates (40.17 vs. 36.99), underlining the importance of taking work hours into account.

Our methods follow Belfield et al. (2018) since we are firstly aiming to replicate their estimates for annual earnings before going on to examine the impact on returns when we account for hours worked. We estimate standard Mincer-type wage models using ordinary least squares (OLS), separately by gender:

$$ln\, y_i = \alpha + X_i'\beta + \gamma Grad_i + \varepsilon_i \tag{1}$$

in which y_i is either annual earnings, hourly wage, or weekly hours, X_i is the vector of the control variables listed above, $Grad_i$ is an indicator for being a graduate, and ε_i is a well-behaved error term. Standard errors are clustered at the school level.

In Model 1, we look at the raw wage difference between graduates and non-graduates. In Model 2, we control for all variables listed above. Lastly, in model 3 we apply inverse probability weighting regression adjustment (IPWRA) (Wooldridge, 2007), which reweights the sample so that the first moments of the control variables do not differ between graduates and non-graduates. We operationalize the IPWRA approach using *teffects ipwra* in Stata (StataCorp, 2013)[3]. We document the details of this method in the Online Appendix. We show the estimated logit selection models for men and women in Tables OA 1. Figure OA 1 plots the estimated propensity scores, the inverse of which are used as the IPWRA weights. The predictive power of the estimated selection models is acceptable, with area under the ROC curve measures of 0.7595 for men and 0.7446 for women. We also test the common support assumption and find that all observations in the analytical sample fall within the common support. However, as the plotted propensity scores show a slight imbalance at the two tails of the propensity score distribution between the treated and control groups, we provide a robustness check (Robustness check 1) in which we drop the top and bottom 5 % of the propensity score distribution from the sample, see Table OA R1 in the Online Appendix.

We provide three further robustness checks in the Online Appendix. Robustness check 2 re-estimates the main estimates (Model 3) without controlling for A-levels and vocational qualifications (Table OA R2) while in robustness check 3 we drop those from the analytical sample who did not have A-levels (Table OA R3). Lastly, in robustness check 4, we also control for the length of the current employment spells of individuals (Table OA R4) as a proxy for work experience (which we do not observe in the data).

We also provide a sensitivity analysis to our main models in the Online Appendix to challenge the unconfoundedness assumption following the method of Masten et al. (2024), operationalized using *tesensitivity* in Stata. Here we test how the estimated returns to graduation coefficients would change in the presence of an unobserved variable correlated with both graduation and labour market outcomes. This also includes a sensitivity test of our model specification as it shows how missing one control variable at a time would change our IPWRA estimates.

The procedure of Masten et al. (2024) introduces the concept of conditional partial independence and a framework in which a single parameter c captures how far we would deviate from the unconfoundedness assumption in the presence of omitted variable bias under certain conditions. The value of parameter c ranges from 0 to 1. When c=0, the unconfoundedness assumption perfectly holds. For any c>0, the conditional independence assumption only partially satisfied, meaning that the "true" values of estimated parameters cannot be determined. Instead, we can only establish lower and upper bounds for the parameters. Masten et al. (2024) describe these bounds as a function of c, where smaller values of c lead to narrower while higher values of c lead to wider bounds. Furthermore, the method estimates a *breakdown* value of c which would cause the estimated coefficient to flip sign. Using the *tesensitivity* package, we estimate c-values for our three main outcome variables by gender, and investigate 1) the breakdown c-value of a potential unobserved omitted variable (Table OA S1), 2) the breakdown c-values of our observed variables as points of comparison (Table OA S2), and 3) how our main coefficient would change if we left out each observed variable in turn as if it was unobserved (Table OA S3).

Using this method, we conclude that our estimates are fairly insensitive to omitted variable bias if the estimated breakdown c-values are at least moderately large, and leaving out observable characteristics with similar breakdown c-values would only cause a small change in the estimated coefficients. Thus, we report the estimated breakdown c-

[2] These proportions are similar to the proportions of graduates aged 25 with at least one A*-C GCSE exam in the 2015 Annual Population Survey (APS) (Office For National Statistics, 2019). In the APS 2015, 39.7% of men and 42.3% of women aged 25 with at least one A*-C GCSE exam have a university degree. This leads to a small gender gap in favor of women of 2.6pp, which is not dissimilar in magnitude to our gender gap of –1.0pp.

[3] We estimate the IPWRA weights separately by gender, using the following control variables: age, ethnicity, region, father's and mother's social class, private school, GCSE and A-level (age 18) raw scores, indicator variables for A-level subjects (Math, Sciences, Social Science, Humanities, Arts, Languages and Other), and having a vocational qualification.

Table 1
Returns to graduation: log annual earnings and hourly wages.

	(1) Men	(2)	(3)	(4) Women	(5)	(6)
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Outcome: log annual earnings						
Returns to graduation	0.076**	-0.008	-0.005	0.238***	0.098***	0.122***
	(0.031)	(0.033)	(0.029)	(0.028)	(0.029)	(0.029)
	NR	9.113***	10.088***	NR	8.392***	9.825***
Constant		(0.967)	(0.021)		(0.870)	(0.021)
R-squared	0.006	0.121		0.051	0.179	
Outcome: log hourly wage						
Returns to graduation	0.071**	-0.015	-0.029	0.120***	0.041*	0.047*
	(0.028)	(0.030)	(0.029)	(0.023)	(0.024)	(0.026)
	NR	2.202***	2.428***	NR	0.127	2.296***
Constant		(0.844)	(0.019)		(0.708)	(0.016)
R-squared	0.007	0.136		0.020	0.109	
Outcome: hours worked per week						
Returns to graduation	0.146	0.214	0.907	3.846***	1.836***	2.298***
	(0.581)	(0.610)	(0.624)	(0.533)	(0.536)	(0.521)
	NR	22.140	41.752***	NR	54.889***	37.386***
Constant		(19.177)	(0.385)		(17.936)	(0.366)
R-squared	0.000	0.088		0.039	0.126	
Number of unweighted observations, control variables and weighting						
No. of obs.	1220	1220	1220	1658	1658	1658
Control variables		Yes	Yes		Yes	Yes
IPWRA weighting			Yes			Yes

Notes: Sample of those having at least 5 A*-C GCSE examinations and in sustained employment. Model 1 and 2: linear regression models estimated by OLS, weighted using wave 8 weights. Model 3: IPWRA-weighted regressions, also weighted using wave 8 weights. Robust standard errors clustered by sampling school are in parenthesis.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$. Control variables: Family background: age in months as a continuous variable, mother's and father's social class, region, ethnicity. Early and pre-university educational attainment: GCSE and A-level raw scores, indicator variables for A-level subjects as Math, Sciences, Social science, Humanities, Arts, Languages and Other, a binary variable for having vocational qualifications, a binary variable capturing whether the individual attended independent secondary school at age 13/14. NR = not reported due to UK Data Service Secure Lab rules. Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2024). Next Steps: Linked Education Administrative Datasets (National Pupils Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104, DOI: http://doi.org/10.5255/UKDA-SN-7104-6.

values of the potentially omitted variables in Table OA S1, the estimated breakdown c-values of the observed control variables in Table OA S2, and the provide the estimated coefficients when each observed control variables are excluded from the model in Table OA S3.

4. Results

Our results on the returns to graduation in terms of log annual earnings are similar to those of Belfield et al. (2018) using administrative data. Without controlling for any background characteristics or prior attainment, male graduates earn on average 7.9 % (0.076 log points, Table 1) more than their non-graduate peers, whereas for female graduates the average premium is 26.9 % (0.238 log points). This is similar to Belfield et al. (2018)'s pattern of findings at age 26 without any controls (Fig. 2, Belfield et al., 2018, p.16). Once we control for background characteristics and apply IPWRA, the estimated coefficients reduce to an insignificant -0.5 % (-0.005 log points) for men but a significant at 13 % (0.122 log points) for women. This again is similar to Belfield et al. (2018), who find -3 % returns to higher education for men and 14.9 % for women (results in their Table 12, p.63) at this age.[4] It is worth noting that our sample comprises those aged 25 and 26, which makes our estimates comparable to something between the age 24 and age 26 estimates of Belfield et al (2018), e.g. for women this would be between 0.04 log points and 0.13 log points, so close to our estimate of 0.12 log points. This broad congruence is reassuring given our earnings data is self-reported whereas Belfield et al. (2018) have access to administrative tax records.

Looking at log hourly wages (middle panel Table 1), however, reveals the importance of hours worked in generating these premia, in particular for women. In the uncontrolled regressions (Model 1) returns to graduation for women are about half as large as they are for annual wages (0.120 compared to 0.238). Once we control for individual characteristics (Model 2) and employ IPWRA (Model 3), returns to graduation become small (0.047) and only significant on a 10 % level for women while they stay around zero for men.

The last panel of Table 1 shows the same models, with hours worked per week as the outcome variable. Interestingly, it is only true for women that graduates work more hours than non-graduates. In the raw model, the difference is on average 3.8 hours per week; this reduces to 2.3 hours after controlling for characteristics and applying the IPWRA estimator. This relatively small difference in weekly working hours between graduate and non-graduate women is enough to reduce the magnitude of the graduation premium at this early career stage by almost two-thirds.

These results hold across all the above-detailed robustness checks as shown in Fig. 1. Our main finding shows that returns to graduation are more than two-times as large on annual wages than on hourly wages for women, but not for men. This is shown in Panel III of Fig. 1: across 15 IPWRA specifications, having only annual wages would lead to a 2-3-fold overestimation of returns to graduation among women. While some of this phenomenon goes through graduate women being more likely to work full-time than non-graduate women (Table OA F1 in the Online Appendix), even if we restrict the sample to those working full-time, annual wages for women would still overestimate returns to graduation 1.63-times (Table OA F2, 0.062/0.038=1.63).

[4] Belfield et al. (2018) estimate returns to HE attendance rather than graduation and so their estimates include those who drop-out as well as graduates; however, restricting to graduates only has little effect on their estimates, see Table 8, p. 38.

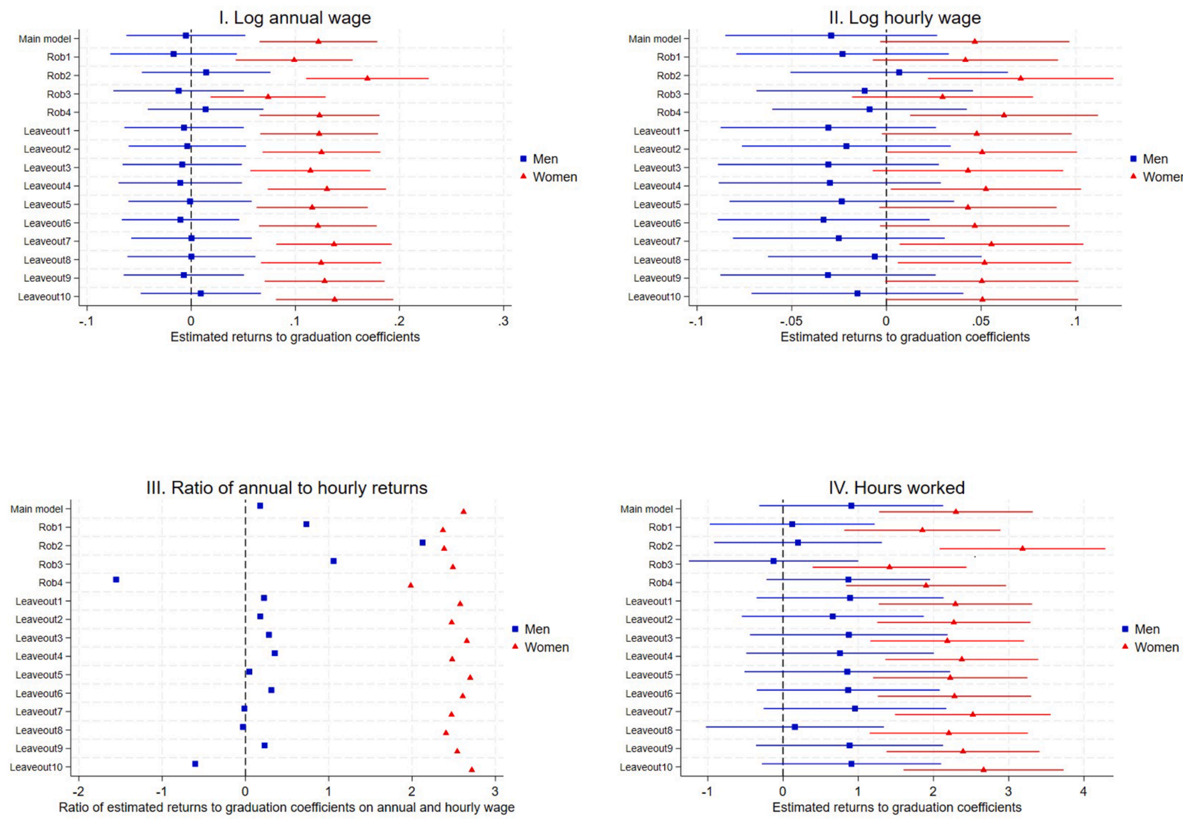

Fig. 1. Main results and robustness checks.
IPWRA model coefficients plotted along with their 95 % confidence intervals based on robust standard errors clustered by sampling units. Weighted by sample weights. No. of unweighted observations: men: 1220; women: 1658. "Ratio of annual to hourly returns" refers to the ratio of estimated coefficients on log annual and hourly wages. "Main model" refers to Model 3 in Table 1. Control variables: age in months, mother`s and father`s social class (NS-SEC), region, ethnicity, GCSE scores, A-level subjects, A-level total score quintiles, vocational qualifications, independent secondary school at age 13/14. Sample of those having at least 5 A*-C GCSE examinations and in sustained employment. Rob1-Rob 4 refers to Robustness tests 1-4 as detailed in Tables OA R1-OA R4. Leavout1- Leavout10 refers to leaving out each control variable in turn as detailed in Table OA S3. Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2024). Next Steps: Linked Education Administrative Datasets (National Pupils Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104, DOI: http://doi.org/10.5255/UKDA-SN-7104-6

As a final check, we examine returns by LFS subject classification and show that for men there are still zero returns across subjects and that for women there is some evidence of positive returns to Science, Technology, Engineering, and Mathematics (STEM), but that overall, the hourly wage premia for men and women across subject classifications remains either zero or small (Table OA F3). This is in line with similar estimates presented in Fig. 34 of Belfield et al. (2018), which also show zero or very small returns to STEM subjects compared to no university degree at age 29.

5. Discussion

The availability of administrative tax records linked to individual education and background information in numerous countries has allowed estimates of the return to graduating from university to be estimated on large samples, providing new insights on graduate premia. However, a widespread limitation in these studies is the lack of information on hours worked, hence these premia reflect both the productivity enhancement from higher education (hourly wage premia) and the effect on hours worked. Our results for England, using a smaller sample but with richer labour market information than is available from administrative records, show the importance of adjusting for hours worked when estimating returns to graduation, particularly for women where patterns of employment differ between graduates and non-graduates.

Estimating returns to graduation on annual as opposed to hourly wages severely overestimates these returns for women as graduate women work more hours than comparable non-graduate women. Some of this phenomenon goes through graduate women being less likely to work part time than non-graduate women. This has also been observed in other data sources. For example, in the UK Labour Force Survey, 31.2 % of female graduates worked part-time as compared to 46.8 % of female non-graduates in 2015, the year of data collection for Next Steps (Department for Education, 2023). In contrast, the difference in part-time working between male graduates and non-graduates was less than five percentage points (8.1 % and 12.7 % respectively). However, we find that it is also true among those working full-time that graduate women work more hours than non-graduate women, while among men, this does not hold. Overall, failing to take hours worked into account can result in the returns to graduation being heavily overestimated for women.

For both sexes the estimated hourly earnings premium for university graduation are close to zero at age 26. However, this is a relatively early stage in the labour market career of graduates who would typically have four or five years of labour market experience at this point, as compared with around eight years for their comparable peers who entered the labour market at age 18. This difference in experience is relatively large and plays a part in limiting the graduate premium at this point in the career. As further experience is gained, graduates tend to have a steeper earnings profile, with premia increasing into mid-career, resulting in positive lifetime returns to higher education for both men and women (Britton et al., 2020). As the graduates in Next Steps age, this will be something to explore in future work.

One important takeaway from our results is the robustness of self-reported earnings. In terms of magnitude, our annual earnings results broadly replicate findings from administrative data, which indicates a high degree of accuracy in self-reporting, at least for this cohort study. Previous work has highlighted that certain types of income are more accurately reported (e.g. regular, monthly sources of income) than others (Alwin et al., 2014). Given the relatively young age of the individuals in our sample, their primary source of earnings will be labour income, which is more likely to be regular and therefore easier for them to report accurately. This should assuage concerns around using self-reported earnings in survey data.

The misestimation of the returns to graduation due to ignoring hours worked has potentially important implications for governments and for individuals. Without including hours in the returns to graduation estimates for England, a policymaker could incorrectly assume that the zero return for men and large, positive return for women reflects a structural issue in the labour market. This could lead to incorrect policies to tackle discrimination against men, for example.

More broadly, governments should care about hourly wages because they are a measure of productivity. Our findings imply that there will be a limit on how much HE can improve national productivity, at least whilst graduates are in the early part of their career, if graduates' annual earnings are primarily being increased by increasing hours worked. Moreover, in England, where the government provides income contingent loans to fund students' higher education, there are earnings thresholds that specify whether/how much graduates pay back of their loan. As there are limits on the number of hours a person can work, productivity outcomes have fiscal consequences for the Exchequer not just through the tax take but also through the repayment of loans. Graduates, on the other hand, should care about their hourly wage because it is the price of leisure. While there may be higher lifetime earnings and increased hourly wages later in the lifecourse, it is important for them to be aware of the lack of impact on hourly wages in the early part of the career.

Our results further highlight the value of rich, longitudinal survey data. Despite smaller sample sizes and self-reported earnings data, we can replicate the returns to graduation for a cohort estimated using administrative data. The fact that administrative data lacks key variables (e.g. on hours worked or more nuanced measures of socioeconomic disadvantage) means that it cannot always provide more robust estimates. One potential solution to this problem is for tax authorities to start asking employers/employees to report contractual hours. Until then, combining administrative tax return data with rich, longitudinal survey data, is the best way forward to shed light on key policy debates.

Appendix

Fig. A1

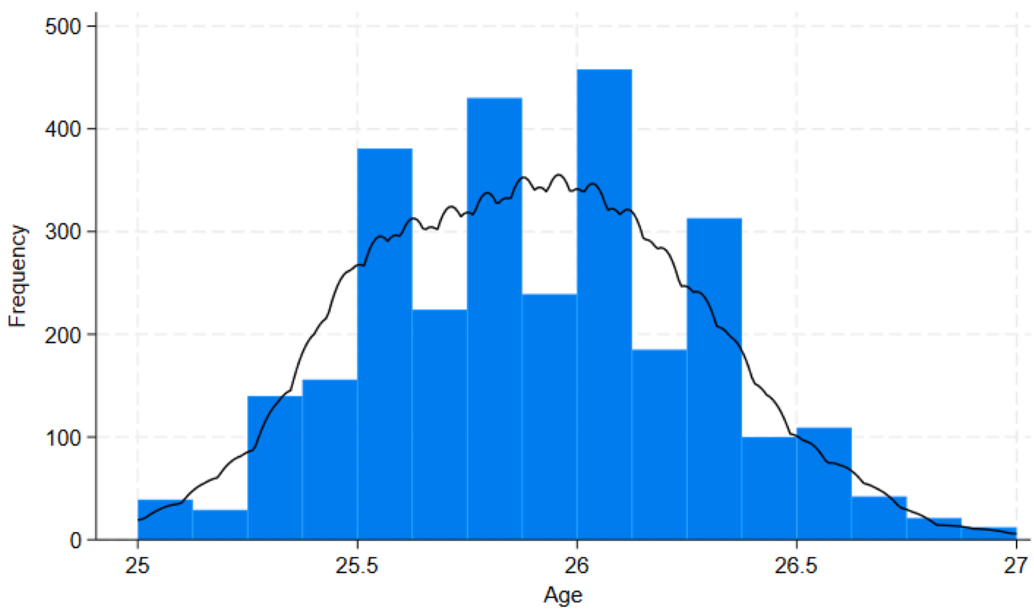

Fig. A1. This distribution of age of observation in the sample.
Notes: Number of unweighted observations: 2878. Sample of those having at least 5 A*-C GCSE examinations and in sustained employment. Unweighted results. Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2024). Next Steps: Linked Education Administrative Datasets (National Pupils Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104, DOI: http://doi.org/10.5255/UKDA-SN-7104-6

Table A1
Descriptive statistics: Men.

	Mean, non-grad	N, non-grade	Mean, grad	N, grad	Diff	p-value
Female	0.00	647	0.00	573	0.00	.
Graduation	0.00	647	1.00	573	-1.00	.
Age in months at the time of the interview	311.41	647	310.46	573	0.95	0.00***
White	0.79	647	0.72	573	0.07	0.01**
North East	0.05	647	0.03	573	0.02	0.03*

(continued on next page)

Table A1 (*continued*)

	Mean, non-grad	N, non-grade	Mean, grad	N, grad	Diff	p-value
North West	0.14	647	0.15	573	-0.00	0.82
Yorkshire and The Humber	0.09	647	0.12	573	-0.03	0.08
East Midlands	0.09	647	0.09	573	-0.00	0.85
West Midlands	0.13	647	0.12	573	0.00	0.87
East of England	0.12	647	0.11	573	0.01	0.44
London	0.14	647	0.14	573	-0.00	0.96
South East	0.14	647	0.17	573	-0.02	0.29
South West	0.10	647	0.08	573	0.02	0.20
Mother's NS-SEC: 1-2	0.30	647	0.42	573	-0.12	0.00***
Mother's NS-SEC: 3-5	0.30	647	0.27	573	0.03	0.20
Mother's NS-SEC: 6-7	0.29	647	0.20	573	0.08	0.00***
Mother's NS-SEC: missing	0.00	647	0.00	573	0.00	.
Father's NS-SEC: 1-2	0.39	647	0.52	573	-0.13	0.00***
Father's NS-SEC: 3-5	0.36	647	0.29	573	0.07	0.01**
Father's NS-SEC: 6-7	0.19	647	0.16	573	0.04	0.07
Father's NS-SEC: missing	0.00	647	0.00	573	0.00	.
Independent school	0.02	647	0.03	573	-0.00	0.74
GCSE test scores	462.65	647	508.99	573	-46.34	0.00***
Vocational qualification	0.39	647	0.27	573	0.12	0.00***
A-levels quintile, lowest	0.22	647	0.14	573	0.08	0.00***
A-levels quintile, lower-middle	0.15	647	0.23	573	-0.08	0.00***
A-levels quintile, middle	0.13	647	0.22	573	-0.09	0.00***
A-levels quintile, upper-middle	0.14	647	0.25	573	-0.12	0.00***
A-levels quintile, highest	0.18	647	0.14	573	0.04	0.08
A-level quintile missing	0.02	647	NR	573	NR	NR
No A-levels	0.17	647	NR	573	NR	NR
A-level in math	0.23	647	0.44	573	-0.21	0.00***
A-level in sciences	0.38	647	0.62	573	-0.24	0.00***
A-level in social sciences	0.14	647	0.20	573	-0.06	0.01**
A-level in art	0.13	647	0.14	573	-0.01	0.51
A-level in humanities	0.38	647	0.55	573	-0.17	0.00***
A-level in languages	0.07	647	0.16	573	-0.08	0.00***
A-level in other	0.49	647	0.72	573	-0.23	0.00***
Hours worked	41.34	647	41.58	573	-0.25	0.60
Annual wage	26,782.21	647	28,524.67	573	-1742.46	0.14
Log annual wage	10.06	647	10.15	573	-0.09	0.00***
Hourly wage	12.48	647	13.35	573	-0.87	0.11
Log hourly wage	2.41	647	2.50	573	-0.09	0.00***
Works full-time in wave 8	0.96	647	0.97	573	-0.01	0.28
No of months in employment	43.39	647	27.49	573	15.90	0.00***
No. of unweighted observations		647		573		1220

Sample of those having at least 5 A*-C GCSE examinations and in sustained employment. Unweighted results. NR = not reported due to low sample size in the underlying cell.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2024). Next Steps: Linked Education Administrative Datasets (National Pupils Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104, DOI: http://doi.org/10.5255/UKDA-SN-7104-6

Table A2
Descriptive statistics: Women.

	Mean, non-grad	N, non-grad	Mean, grad	N, grad	Diff	p-value
Female	1.00	893	1.00	765	0.00	.
Graduation	0.00	893	1.00	765	-1.00	.
Age in months at the time of the interview	310.56	893	310.46	765	0.10	0.63
White	0.76	893	0.67	765	0.09	0.00***
North East	0.04	893	0.07	765	-0.03	0.01*
North West	0.12	893	0.14	765	-0.01	0.39
Yorkshire and The Humber	0.10	893	0.10	765	0.01	0.72
East Midlands	0.10	893	0.09	765	0.00	0.82
West Midlands	0.14	893	0.12	765	0.03	0.09
East of England	0.11	893	0.09	765	0.02	0.26
London	0.14	893	0.21	765	-0.07	0.00***
South East	0.15	893	0.11	765	0.04	0.02*
South West	0.09	893	0.07	765	0.02	0.19
Mother's NS-SEC: 1-2	0.30	893	0.36	765	-0.06	0.02*
Mother's NS-SEC: 3-5	0.30	893	0.33	765	-0.03	0.19
Mother's NS-SEC: 6-7	0.28	893	0.19	765	0.09	0.00***
Mother's NS-SEC: missing	0.00	893	0.00	765	0.00	.
Father's NS-SEC: 1-2	0.40	893	0.50	765	-0.10	0.00***
Father's NS-SEC: 3-5	0.30	893	0.31	765	-0.00	0.87
Father's NS-SEC: 6-7	0.23	893	0.16	765	0.08	0.00***
Father's NS-SEC: missing	0.00	893	0.00	765	0.00	.
Independent school	NR	893	0.02	765	NR	NR
GCSE test scores	466.07	893	508.77	765	-42.71	0.00***

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Table A2 (*continued*)

	Mean, non-grad	N, non-grad	Mean, grad	N, grad	Diff	p-value
Vocational qualification	0.33	893	0.24	765	0.09	0.00***
A-levels quintile, lowest	0.20	893	0.13	765	0.07	0.00***
A-levels quintile, lower-middle	0.19	893	0.26	765	-0.07	0.00***
A-levels quintile, middle	0.16	893	0.25	765	-0.08	0.00***
A-levels quintile, upper-middle	0.12	893	0.23	765	-0.10	0.00***
A-levels quintile, highest	0.13	893	0.12	765	0.01	0.48
A-level quintile missing	0.02	893	NR	765	NR	NR
No A-levels	0.16	893	0.02	765	0.15	0.00***
A-level in math	0.11	893	0.26	765	-0.15	0.00***
A-level in sciences	0.35	893	0.57	765	-0.22	0.00***
A-level in social sciences	0.20	893	0.25	765	-0.05	0.01*
A-level in art	0.23	893	0.25	765	-0.02	0.25
A-level in humanities	0.46	893	0.61	765	-0.16	0.00***
A-level in languages	0.14	893	0.21	765	-0.07	0.00***
A-level in other	0.57	893	0.71	765	-0.14	0.00***
Hours worked	36.99	893	40.17	765	-3.19	0.00***
Annual wage	20,529.63	893	25,999.95	765	-5470.33	0.00***
Log annual wage	9.81	893	10.01	765	-0.21	0.00***
Hourly wage	10.98	893	12.65	765	-1.67	0.00**
Log hourly wage	2.29	893	2.40	765	-0.11	0.00***
Works full-time in wave 8	0.85	893	0.93	765	-0.08	0.00***
No of months in employment	36.97	893	24.91	765	12.06	0.00***
No. of unweighted observations		893		765		1658

Sample of those having at least 5 A*-C GCSE examinations and in sustained employment. Unweighted results. NR = not reported due to low sample size in the underlying cell.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2024). Next Steps: Linked Education Administrative Datasets (National Pupils Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104, DOI: http://doi.org/10.5255/UKDA-SN-7104-6

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econedurev.2025.102701.

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