

# Heterogeneities in the returns to degrees: evidence from the British Cohort Study 1970\*

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December 2008

## Abstract

Estimates of a high average return to a degree for UK graduates have provided a policy rationale for increasing the share of the costs of higher education borne by UK students over recent decades. We use evidence from a cohort of people born in 1970 to estimate hourly wage returns to a university degree. We analyse the extent of variations around average returns, focussing on heterogeneity in returns by factors such as: gender, degree subject studied, degree class awarded, student ability measures and family background. Among other results, we find substantial evidence of heterogeneous returns to a first degree according to subject area of study and class of degree awarded.

JEL: J3, J4, I2

Keywords: degree, return, subject, UK, university

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\*We would like to thank Martyn Andrews, Arnaud Chevalier, Luca Flabbi, Susan Harkness, Derek Leslie, Pedro Martins, Peter Sloane, Mark Stewart, Jan van Ours, Anna Vignoles, Ian Walker and participants at the ESPE 2005 Conference (Paris) and at seminars at CentER (Tilburg University) and the University of Pavia, for helpful comments and suggestions. The usual disclaimer applies.

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# 1 Introduction

Higher education policy in Europe is in flux, not least in the UK which has witnessed considerable and ongoing policy change in recent decades. One aspect of the UK experience has been a steady shift in the burden of funding higher education (HE) away from the taxpayer and towards students and their families. After a period of real decline, widespread maintenance grant provision was removed and replaced by a system of repayable loans from 1988. Furthermore, since 1998, uniform university tuition fees have been paid by all full-time UK university students from within the European Union. Since Autumn 2006, universities have been able to charge top-up fees up to a regulated maximum, differentiated by university and by course. Contemporaneously, there has been a significant expansion in the HE participation rate since the late 1980s, associated both with a reduction in the prior academic performance required for university admission and in the unit of resource in the teaching of university undergraduates.

In this context of ongoing policy change, it is important to have up-to-date estimates both of average private returns to HE and of the extent of systematic variations around average returns. When there is substantial variation around the average, reliance on the average return alone is potentially misleading. In the current paper, we exploit data for the 1970 birth cohort, BCS70. These individuals would, typically, have graduated in the early 1990s and have almost ten years labour market experience in 2000, when earnings data used in the current study were collected. Previous work based on cohort data has used data for the 1958 birth cohort from the National Child Development Study (NCDS). Estimates of HE returns for the 1958 birth cohort have been important and influential but are based on individuals who would have graduated in circa 1979, prior to: significant decline in public sector financial support to students; rapid expansion of student numbers; and significant skill-biased technical change (SBTC) during the last two decades of the twentieth century. It seems timely, therefore, to update our understanding of HE returns with estimates based on the more recent cohort.

The primary concern of the current paper is in the heterogeneity of returns to HE. We focus on heterogeneity according to a variety of characteristics, including: gender,

family background, ability measures and unobservables. Our main focus, however, concerns heterogeneity of returns by degree class awarded and by degree subject studied. Research on educational returns has tended to concentrate on average returns to qualifications: the question of variation according to level of performance, given qualifications, is surprisingly under-explored. Smith *et al.* (2000) find that the first destination outcomes of UK university students graduating in 1993 are associated with class of degree awarded. In the current paper, we are particularly interested in examining whether there is evidence of a wage premium associated with a ‘good’ degree performance for graduates of the 1970 birth cohort. In the UK degrees are typically classified, in descending order, as: first, upper second, lower second, third class, non-honour degrees, and fail. We follow the convention of referring to first and upper second class degrees as ‘good’ degrees. For our purposes, other classes are collectively referred to as ‘lower’ class degrees.

As we already said, variation in returns by class of degree has received very little attention in the literature. This is largely a consequence of the fact that few datasets contain adequate information on class of degree awarded. The issue is of interest, however, for two reasons. First, if there is significant variation by degree class around the average return to a degree, then the investment in HE could yield a low return to poor-performing students. Shifting the burden of university fees further towards students then risks generating a greater disincentive to HE participation than would be the case with relatively little variation around the average: a narrow focus on the average return may be inadequate for policy purposes.<sup>1</sup> Smith and Naylor (2001) analyse the determinants of students’ degree class outcomes and find that a more affluent family background is associated with a higher probability of obtaining a good degree class, holding constant other characteristics such as school background, prior academic performance, university attended and subject studied, *inter alia*. Second, it is of general interest to examine the extent to which the labour market rewards the graduate’s class of degree. Estimates of returns to education have tended to focus on years of schooling or on levels of qualifications. Yet, as there is substantial clustering of labour market entrants on both these

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<sup>1</sup>It is interesting to note that in 2006, following the introduction of top-up fees, there was a 5% fall in UK-based applications.

criteria, one would expect employers to discriminate between candidates on factors such as grades achieved: that is, on degree class awarded in the context of higher education in the UK. This itself is likely to vary over time with, for example, the proportion of a cohort investing in a university degree.

Variation in returns by degree subject has received more attention, as we discuss in detail below. Since the introduction of flat-rate fees, a number of authors have argued that there is a theoretical case for differentiating fees by subject (see, for example, Greenaway and Haynes, 2003). The strength of the case for differentiating fees depends in part on the strength of evidence that the return to a degree varies by subject studied and/or by institution attended. Our data do not enable us to estimate *ceteris paribus* variations in returns by institution of study. On this issue, see Chevalier and Conlon (2003).

The rest of the paper is organised as follows. Following a brief survey in section 2 summarising recent evidence on returns to HE in the UK, section 3 provides a description of the dataset and the sample selection procedure used in our analysis. In section 4, we discuss the issue of the endogeneity of educational qualifications and describe ways of addressing it, through the so-called *proxying and matching method* and under a control function approach. Section 5 reports estimates of the wage return to HE qualifications and to degree class and degree subjects. Section 6 uses propensity score matching to explore further the heterogeneity in wage returns to a first degree, by degree class and by degree subject. Finally, section 7 summarises the main findings and concludes.

## **2 Evidence on the returns to a degree in the UK**

An important paper on the estimation of the returns to a degree in Britain is that of Blundell *et al.* (2000). This study used data from the National Child Development Study (NCDS), an ongoing survey of all individuals born in Britain in a particular week in March 1958, to estimate the impact of different levels of HE on gross hourly wages at age 33. The study compares individuals with HE qualifications with those individuals who did not go on to HE but whose secondary school qualifications (A-levels) would

have permitted them admission to HE, and estimates the raw wage returns to a first degree to be 21% for men and 39% for women.<sup>2</sup> When the full set of controls is included in the estimation, the estimated wage returns to a first degree fall substantially in the case of men - to only 12% - and only slightly in the case of women - to 34%. In many ways, our analysis follows closely the approach of Blundell *et al.* (2000), updating their estimates for the more recent 1970 birth cohort, as well as providing a specific focus on heterogeneous returns. We must note, however, that inferences drawn from comparisons of estimated returns to HE across the two cohorts are inherently problematic for a number of reasons. A primary problem is that the control group of non-graduates across the two cohorts is likely to have changed substantially: both for reasons associated with the changing nature of pre-university qualifications and because of changing patterns of labour market and higher education participation, especially for women.

There have been a number of other studies using a variety of data sources in order to estimate the private return to a university first degree in the UK. Dearden (1999), also using NCDS, reports an estimated wage return to a degree of 17% for men and of 32% for women, based on OLS, and also finds that the conventional OLS estimates are reasonable approximations of the true causal impact of higher education on wages. Harkness and Machin (1999) examine changes in wage returns to education in the UK between 1974 and 1995 using data from the General Household Survey (GHS). They report time-varying estimates of the wage premium associated with various educational qualifications. For the period 1979-81, the estimated wage premia to a first degree, relative to A-level qualifications, are 14% for men and 21% for women. By the period 1993-95, these estimated premia have risen to 20% and 26%, respectively. Harkness and Machin (1999) conclude that despite a rise in the relative supply of workers who have a degree in the UK, the fact that the return to a degree was rising in the 1980s and 1990s suggests that relative demand - for example induced by SBTC - rose faster than relative

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<sup>2</sup>Heckman *et al.* (2006) stress that in estimating rates of return it is necessary to take account of, among other factors, the direct and indirect costs of schooling, taxes, and the length of working life. In what follows, we often use the term wage ‘return’ although it should be interpreted in the narrow sense of a log-wage premium.

supply. Walker and Zhu (2008), using Labour Force Survey (LFS) data from 1994-2006, estimate the average return to a degree to have been broadly constant for men and to have increased for women, though not significantly. Moffitt (2007) reports that the size of the graduate premium in the UK has been falling over a period in which the size of the graduating cohort has been rising, observing that this is consistent with the Becker Woytinsky Lecture hypothesis (see chapter 3 of Becker, 1975).

The differences in the estimates from different studies referring to the same period often stem from the specification adopted which in turn depends on the nature of the data used. Longitudinal studies, such as those based on the NCDS or BCS70, are rich in information on family background, ability-related and past educational variables, which are important for addressing the issue of ability bias and whose inclusion often results in a reduction in the estimated return to education (see Card, 1999). For this reason, studies using other data sources where these variables are not available (such as the LFS) estimate higher returns. Moreover, Heckman *et al.* (2006) discussing the differences between cross-sectional and cohort-based estimates of the return to education, suggest that the latter should be used when the purpose is to estimate historical returns and make comparisons over time, since cohort changes are likely to affect the cross-section estimates only slowly as they are diluted with the absorption of the cohort into the stock of all previous cohorts participating in the labour market.

A number of studies have investigated the extent to which returns to a university degree vary by subject studied. Because of problems of small cell size, most studies consider broad subject groups. Blundell *et al.* (2000) find that returns for men tend to be relatively low in Biology, Chemistry, Environmental Sciences, and Geography and for women tend to be relatively high in Education, Economics, Accountancy and Law and in ‘Other social sciences’. Lissenburgh and Bryson (1996) using the Youth Cohort Study estimate returns of 9% for Science relative to Arts and Social Sciences for both males and females combined. Harkness and Machin (1999) find that for men Social Sciences always give the highest wage premium with respect to A-level (25% in 1995) while Science ensures the highest premium for women (45%).<sup>3</sup> Walker and Zhu

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<sup>3</sup>Including controls for age, age squared, dummies for degree subject, teacher status, region and

(2001) use a quite disaggregated definition of subjects (13 in total), but based on their disaggregated estimates, for males (females) in 1999 the returns with respect to A-level are 19% (42%), 24% (46%) and 4% (21%) for Science, Social Science and Arts and Humanities, respectively.<sup>4</sup> Therefore, both males and females appear to obtain higher returns for Social Science degrees. Moreover, women have higher returns than men in all degree subjects, and in particular in Arts and Humanities.

Using follow-up surveys of samples of graduates, Dolton *et al.* (1990) analyse earnings data from the 1986 survey of one in six of the 1980 UK university graduates (5,002 graduates). Dolton *et al.* (1990) find significant earnings premia for Science and Social Science students compared to Humanities or Education students. A positive earnings premium for Mathematics-related degree courses is a common finding in studies using the graduate sample follow-ups: see Chevalier *et al.* (2002), Belfield *et al.* (1997), and Battu *et al.* (1999) for results pertaining to the 1996 follow-ups of the 1985 and 1990 graduate cohorts. Chevalier *et al.* (2002) analyse 1998 earnings data for a sample of 8,264 graduates from the 1995 graduate cohort. They report that relative returns are highest for Mathematics (at 29% for men and 19% for women), compared to Education studies. They make the important point that differences in relative returns across cohorts are to be interpreted with care given differences across cohorts in the method of classifying degree subjects. Chevalier *et al.* (2002) provide a comprehensive survey of estimates of returns to HE.

With respect to differences in returns to a degree according to the degree class obtained, Battu *et al.* (1999), using graduate cohort data, estimate a significant wage return associated with a first class over both upper second class and lower degree classes for graduate earnings 6 years after graduation. Naylor *et al.* (2008) match administrative data on the entire population of UK university students - as collected formerly by Universities' Statistical Record (USR) and now by the Higher Education Statistics industry.

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<sup>4</sup>Science includes Health, Nursing, Science, Maths, Engineering, Architecture. Social Science includes Economics, Law and Social Studies. Arts and Humanities includes Language, Education, Art and Combined degrees. Their specification includes controls for age, age squared and dummies for marital status, race, union status and region.

Agency (HESA) - to the information contained in the responses to the first destination survey of all 1993 graduates, and estimate an occupational earnings premium of 4% for a first class degree relative to an upper second class degree for both men and women. The premium for a first over a third class degree is estimated to be 14% for men and 9% for women; there is also strong evidence that the premium for a first class degree has been growing over time. One hypothesis for this is that as the population of graduates has grown, greater importance is attached by employers to the signal emitted by a graduate who has performed well at university. One focus of the current paper is to establish whether there is corroborating evidence on the extent of any degree class premium from a different data source. Using BCS70, our attention focuses on a cohort of young people who, typically, would have been graduating in the very early 1990s - the period of time for which Naylor *et al.* (2008) estimate significant relative premia for a good degree performance.

### 3 Data and sample selection

In this paper we use data drawn from BCS70, a dataset based on the cohort of 16,135 babies born in England, Wales, Scotland and Northern Ireland between the 5<sup>th</sup> and the 11<sup>th</sup> of April 1970. The data are particularly suitable for the estimation of returns to education as they are rich in information on family background and measures of cognitive ability. There are currently six complete follow-up surveys available: at periods 5, 10, 16, 26, 30 and 34 years after the original survey. We use data collected in the 30-year follow-up survey on gross hourly wages and highest educational qualification achieved, while family background and individual characteristics come from the 10-year follow-up survey.<sup>5</sup> Based on the sample of respondents to the 30-year follow-up survey (11,261 individuals), and in analogy with Blundell *et al.* (2000, p. F84), we select only individuals who have obtained at least A-level qualifications,<sup>6</sup> which is our population of interest, and analyse the wage return to HE qualifications with respect to those

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<sup>5</sup>We use the age 30 wage data rather than those for the age 34 follow up due to the high non-response rate in the last sweep. In related work we investigate the impact of attrition on estimated returns.

<sup>6</sup>Or an equivalent level of education such as a Scottish higher or sixth form college.



individuals who did not complete any form of HE. In order to check the sensitivity of the estimated wage returns to the selection of the comparison group, we produce separate estimates according to whether the control group consists of individuals with a highest educational qualification of (i) at least one A-level or (ii) at least two A-levels. We report here only the estimates for the group with at least two A-levels since our results are quite robust to changing the control group.<sup>7</sup>

Starting from the 14,875 individuals responding to the 10-year follow-up survey of BCS70, from which we obtain family background variables and proxies of ability, we select sequentially: those (10,397) individuals who also responded to the 30-year follow-up survey; those (3,802) with 2 or more A-levels or equivalent qualifications; those (3,781) with a mother figure at age 10;<sup>8</sup> those (3,098) who were full-time or part-time employees in the age 30 follow-up and who had non-missing wage information, producing a final sample of 2,919 individuals (1,497 men and 1,422 women). In order to maintain the sample size, unless otherwise specified, individuals with missing values in the covariates are kept in the dataset and missing value dummy variables included in the regressions.

From Table 1 we see that the mean hourly wage of male students with an undergraduate degree is £12.65; this is 20% higher than the average for those with two or more A-levels and no degree. For females, the mean wage rate is £10.81 for those with an undergraduate degree; 31% higher than for those with just two or more A-levels. This suggests that, on average, gender wage differences are less pronounced at the higher education level. Of those with an undergraduate degree, the raw data indicate a premium associated with having obtained a good, rather than a lower class of degree (that is, lower second, third or below): for males, the premium is 14% while for females it is just 4%. There are also some differences according to degree subject area; for males the premium for a Social Science degree over an Arts and Humanities degree is 11%; for females it is 21%. The wage differences between Science and Arts and Humanities are

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<sup>7</sup>Indeed, there is little if any difference in the average wage rate between those with one or more and those with two or more A-levels.

<sup>8</sup>This is important in avoiding inclusion of individuals for whom family background information is completely missing.

quite modest.

The BCS70 follow-up surveys were affected by panel attrition. From an original sample size of 16,135 individuals, the sample reduced to 14,875 individuals in the 10-year follow-up, to 11,622 individuals in the 16-year follow-up, to 11,261 individuals in the 30-year follow-up and to 9,665 in the 34-year follow-up.<sup>9</sup> The high rate of item non-response in the 16-year wave is the main reason for our use of family background variables at age 10, along with the availability of an indicator of ‘innate’ or ‘early’ ability (the British Ability Scales score, see Elliot *et al.*, 1979) at this age. As to the representativeness of the different waves, the Office for National Statistics (1999, p. 11) states: ‘Analysis of differential response comparing achieved samples and target samples for any follow-up, using data gathered during the birth and earlier follow-ups, shows that the achieved samples are broadly representative of the target sample’.

## 4 OLS, endogeneity biases and the Control Function Approach

When we estimate the wage returns to different educational qualifications, we consider the effect of a multiple treatment, namely educational qualifications, denoted as  $j = 1, \dots, J$ , on individual wages,  $w_i$ . We consider four different educational qualifications: 2+ A-levels only ( $j = 1$ , the reference group), non-degree Higher Education ( $j = 2$ ), undergraduate (UG) degrees ( $j = 3$ ) and postgraduate (PG) degrees ( $j = 4$ ). If we indicate with  $w_i$  the gross hourly wage of individual  $i$ , our model can then be written as follows:

$$\ln w_i = \mathbf{X}_i' \mathbf{m} + \sum_{j=2}^J b_j Q_{ij} + u_i \quad (1)$$

where  $\mathbf{X}_i' \mathbf{m}$  is a linear function of the observed variables  $\mathbf{X}_i$ , which we will refer to as the no-treatment outcome,  $Q_{ij}$  are dichotomous variables assuming value 1 if individual  $i$  has as her/his highest educational attainment a qualification of level  $j$  and 0 otherwise,

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<sup>9</sup>The first three figures are taken from Office for National Statistics (1999, p.11) while the last three refer to the number of observations in the microdata files released by the UK Data Archive.

and the  $b_j$ 's are the effects of these educational qualifications on log-wages; i.e., they are our parameters of interest. We abstract for the moment from problems concerning the correct specification of the no-treatment outcome and assume that a linear function is an appropriate representation of the log-wage data generating process, as this is the usual assumption in most of the existing empirical literature on the returns to education. In the case  $E(u_i|\mathbf{X}_i, Q_{ij}) = 0$ , the  $b_j$  parameters can be estimated without bias using ordinary least squares (OLS, hereafter). Assuming no heterogeneity in the returns to education, the Average Treatment on the Treated (ATT), the Average Treatment on the Non-Treated (ATNT), and the Average Treatment Effect (ATE) all coincide and are recovered by the  $b_j$ 's.

However, as stressed in Blundell *et al.* (2005) there are several reasons why we may expect a non-zero correlation between educational qualifications and the error term in the log-wage equation. These include:

1. *Ability bias.* We might assume that the error term  $u_i$  in equation (1) consists of two components, i.e.  $u_i = \alpha_i + \epsilon_i$ , one reflecting unobserved earnings capacity ( $\alpha_i$ ), with  $E(\alpha_i|\mathbf{X}_i, Q_{ij}) \neq 0$  and the other some unobserved factors uncorrelated with all covariates included in the wage regression  $E(\epsilon_i|\mathbf{X}_i, Q_{ij}) = 0$ . It is the non-zero correlation between unobserved earnings capacity (also referred to in the literature as ability) and education which causes the so-called 'ability bias'. In particular, we may expect high ability individuals both to acquire more education and to earn higher wages. Earnings capacity is potentially observed by the individual but not by the analyst;
2. *Return bias.* The returns to the different educational qualifications may not be homogeneous across individuals, but may vary according to unobservable characteristics. Let the individual's return to qualification  $j$  be specified as  $b_j + b_{ij}$ , where  $b_{ij}$  is an educational qualification-specific idiosyncratic component pertaining to the individual  $i$ . In this case, we will have a distribution of  $b_{ij}$ 's.<sup>10</sup> There is a return bias when  $E(b_{ij}|\mathbf{X}_i, Q_{ij}) \neq 0$ , i.e. individuals self-select into the different

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<sup>10</sup>In this specification  $b_{ij}$  is a random coefficient.

educational qualifications according to their idiosyncratic returns, which depend in turn on characteristics that are observable to the individual but not to the researcher;

3. *Measurement error bias.* The educational variables may be measured with error. In our case, where education is a categorical variable, measurement error is non-classical and in general it is not possible to say anything on the direction and magnitude of the bias (see Kane *et al.*, 1999).

In our analysis in the current paper, we focus only on the first two sources of *endogeneity* bias. As to measurement errors, we think that this third source of bias should not be very severe in our specific application mainly for two reasons: 1) in most of the analysis we consider broad educational qualifications (A-level, Non-degree Higher Education, UG degree, PG degree) rather than the number of years of schooling or more detailed types of qualifications; 2) recall errors on the highest educational qualification should be only minor for 30 year old individuals.

A possible approach to tackle endogeneity issues when the dataset is particularly rich, as in our case, is to include in the right-hand-side of the wage equation a wide set of controls. This approach, which is followed for instance in Blundell *et al.* (2000) and Blundell *et al.* (2005), is referred to as the ‘proxying and matching’ method. The main identifying assumption is that *selection occurs only on the observables*: including among the individual characteristics,  $\mathbf{X}_i$ , factors which are likely to affect both the educational qualification achieved and wages, and by proxying the unobserved component  $\alpha_i$  with observed factors highly correlated with it, the error term in the wage equation becomes white-noise ( $u_i = \epsilon_i$ ) and OLS can be used. Equation (1) can be viewed as a form of regression-based linear matching. It follows that the estimates which we present in section 5 can be argued to have been obtained using a method which addresses the issue of endogeneity of education.

However, selection also on unobservable characteristics cannot be excluded *a priori*. For this reason we also use a control function approach (CFA, hereafter).<sup>11</sup> In our

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<sup>11</sup>See Vella and Verbeek (1999).

specific context, this method consists of estimating an ordered probit for the highest educational qualification achieved and then estimating a wage equation which includes an additional regressor, called the generalized residual (or inverse Mill's ratio), obtained from the ordered probit equation.<sup>12</sup> The estimated equation then becomes:

$$\ln w_i = \mathbf{X}_i' \mathbf{m} + \sum_{j=2}^J b_j Q_{ij} + r_a \lambda_{ij}(\mathbf{X}_i, \mathbf{Z}_i) + u_i. \quad (2)$$

where  $\lambda_{ij}(\cdot)$  are the generalized residuals computed from the ordered probit model for the highest educational qualification achieved, which depend on  $\mathbf{X}_i$ , and on other variables not included in the wage equation ( $\mathbf{Z}_i$ ) which are necessary for the model to be identified other than simply by functional form. The CFA offers a direct test for endogeneity of educational qualifications, which can also be interpreted as a specification test in the spirit of Heckman (1979). In particular, an *ability bias* is absent if the coefficient on the generalized residual (i.e.  $r_a$ ) is not statistically different from zero. Implicitly, this tests whether or not the omitted variables in the wage equation and in the education equation are correlated, and therefore whether or not the educational qualifications dummies are correlated with  $u_i$ . The presence of a *return bias* can be instead tested by augmenting equation (2) with interaction terms between the educational qualifications and the generalized residuals from the ordered probit model:

$$\ln w_i = \mathbf{X}_i' \mathbf{m} + \sum_{j=2}^J b_j Q_{ij} + r_a \lambda_{ij}(\mathbf{X}_i, \mathbf{Z}_i) + \sum_{j=2}^J r_{b_j} \lambda_{ij}(\mathbf{X}_i, \mathbf{Z}_i) Q_{ij} + u_i. \quad (3)$$

In particular a return bias is absent if the  $r_{b_j}$ 's, which capture the correlation between the idiosyncratic component of educational returns and the error term in the ordered probit model, are jointly insignificantly different from zero (see Blundell *et al.*, 2005).

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<sup>12</sup>For the analytical expressions of the generalized residuals, based on the moments of the truncated normal distribution, see Gouieroux *et al.* (1987).

## 5 Results

### 5.1 Returns to HE qualifications

The application of the *proxying and matching method* requires the availability and inclusion among the  $\mathbf{X}_i$ 's of a wide set of individual characteristics affecting education and wages.

In particular, we include among the  $\mathbf{X}_i$ 's in our wage equation:

1. Personal characteristics: region of residence at age 10, ethnicity. We conduct separate analyses by gender.
2. Family background variables: family social class (as the highest between father's and mother's social class), presence of the father, family income, number of younger siblings, number of elder siblings, parental interest in child's education; all at age 10.
3. Ability at age 10: score in the verbal and non-verbal sections of the British Ability Scales (BAS, hereafter) questionnaire, as proxies for verbal and quantitative innate (or early) ability.

We follow a specification similar to those used by Blundell *et al.* (2000) and Blundell *et al.* (2005) for the NCDS data. Like the latter, but differently from the former, we do not include the employer's characteristics for two main reasons. First, they may be endogenous in the sense of being choice variables for the individual and jointly determined with wages. Second, employers' characteristics may be affected by educational qualifications, and by excluding them we estimate the 'overall' effect of education, both on wages and on the likelihood of working for certain types of employers (see for instance Blundell *et al.*, 2005, and Pereira and Martins, 2004).<sup>13</sup> Note also that in common with

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<sup>13</sup>We have also estimated wage regressions including educational information (number and grades) collected in the 30-year follow-up on S (Supplementary), A (Advanced) and AS (Advanced Supplementary) levels, that is education at age 18, and O (Ordinary) levels, CSE (Certificate of Secondary Education) and GCSE (Certificate of Secondary Education), that is education at age 16. The effect was to reduce the return to HE qualifications. However, in the current version of the paper we present only the results of the regressions excluding these variables since they may be subject to considerable measurement error.

the rest of the literature, we are not modelling female participation decisions. Female labour supply behaviour has changed across cohorts, implying that comparisons of HE returns to women over time should model selection into employment for each cohort. We leave such considerations for further work. In the current paper we are careful to caution against the drawing of inferences from any comparison of our estimates with earlier estimates based on the 1958 cohort.

Table 2 presents both the estimates obtained using the proxying and matching (OLS) method and also those obtained from the CFA. Under both methods the comparison group comprises individuals whose highest educational qualification level is two or more A-levels. From the table we see that for the OLS estimation, the estimated coefficient on an UG degree is 0.15 for men and 0.18 for women: these convert into wage premia of 16% and 19%, respectively, using the  $e^\beta - 1$  calculation. Hereafter we will continue to report the unconverted coefficients referring to them as log-wage returns, or ‘wage returns’ for short. Male workers with non-degree HE and PG degrees do not earn significantly more than those with A-levels only. In contrast, women with a non-degree HE or PG degree do earn more than those with A-levels only (the wage returns being 0.07 and 0.10, respectively). Although we report estimates for PG degrees throughout our analysis, we emphasise that our focus is concentrated on returns to undergraduate degrees.<sup>14</sup>

The OLS regressions described in Table 2 include controls for ability, with dummy variables for cases with missing information on ability. The estimated coefficients on ability are highly significant: that is, an individual’s ability has a positive effect on wages over and above the effect of the highest educational qualification achieved. However, if we drop ability from the controls, the estimated coefficients on UG degrees do not change for either men or women and remain significant at the 1% level. If, instead, we include controls for ability but drop cases with missing ability information from the analysis,

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<sup>14</sup>There are a number of issues which we would want to address in a more detailed analysis of the returns to PG degrees. These include: modelling selection into PG study; allowing for a longer time horizon for returns to be realised; and distinguishing between different categories of PG study, which is a very heterogeneous commodity. When we examine the raw data for PG students we observe a long tail of very low earners. This is also reflected in the fact that when we use median rather than mean earnings for PGs, we obtain much higher estimates for the returns to PG degrees.

the estimated coefficient on an UG degree does not change for men but falls from 0.18 to 0.16 for women.<sup>15</sup>

As noted in section 4, the assumption of selection on the observables cannot be taken for granted, and for this reason we also use the CFA to estimate wage returns to educational qualifications. For the effect of education to be identified, other than purely on functional form, it is necessary that at least one variable that enters the ordered probit model is excluded from the wage regression. We use as identifying variables parents' education, including them only in the child's education equation.<sup>16</sup> This kind of instrument has a long tradition in labour economics (see Card, 1999), although its validity may be questioned. Indeed, in most applications a possible threat to this identification strategy would be represented by intergenerational transmission of ability between parents and children. In such a case, parents' education may be simply a proxy of parents' ability and be correlated with children's ability, which enters the error term in each of the education and the wage equations. However, one of the significant advantages of the BCS70 data is that they provide a direct measure of individual ability (the BAS score) that can be entered as a covariate and is therefore purged out from the error terms, rendering the assumption of orthogonality between parents' education and the latter more tenable. As evidence of the relevance and the validity of our instruments we report Wald tests in both the first and the second stage as suggested by Bound *et al.* (1995). All the other explanatory variables listed above are included in both the education and the wage equations. The Wald tests reported in Table 2 show that parents' educational qualifications are highly significant in the child's education equation while they are not significant in the wage regression once we control for parents' social class and income, among other factors. The null hypothesis that the educational qualifications are exogenous in the wage regressions cannot be rejected in our data. Table 2 reports the estimates obtained from the CFA alongside those for the OLS estimation. The estimated return for an UG

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<sup>15</sup>These results are not shown in the table but are available from the authors upon request.

<sup>16</sup>Previous research has shown that parents' educational qualifications are highly correlated with children's education (see for a survey Haveman and Wolfe, 1995, and Ermisch and Francesconi, 2001, for some evidence for the UK).



degree is unchanged.

## 5.2 Differences by degree class

In the previous section, we considered an undergraduate education to be a homogeneous commodity. However, students may be more or less successful in completing their UG studies. In particular, previous work has shown the positive effect of a good degree performance on graduates' earnings, see Battu *et al.* (1999) and Naylor *et al.* (2008). However, neither of these papers is able to address the issue of returns to degrees relative to non-graduate outcomes as they are based on graduate data only, with no control group of non-graduates.

BCS70 provides information on degree class for UG degrees enabling us to investigate differences in the wage return to an UG degree according to the class of degree awarded. In order to avoid small cell size problems, we consider only two broad degree classes: good degree and lower degree classes, where good denotes first or upper second class, as previously defined. This distinction is also suggested by the common practice of some employers of conditioning job offers on the attainment of a good degree result.

The estimation results for both degree class and for degree subject obtained from separate OLS regressions are presented in Table 3. We observed in Section 5.2 that the average wage return to an undergraduate degree is 0.15 for men and 0.18 for women, with two or more A-levels set as the default. We now observe the variation around this average according to degree class awarded. Relative to the comparison group, the premium for a good degree is estimated to be 0.20 for men and 0.22 for women, while that for a lower degree class is 0.11 for men and 0.14 for women. Wald tests for the equality of returns between good and lower degree classes reject the hypothesis of equality at the 5% statistical level for both genders. The difference in the wage return between good and lower degree classes is remarkably similar by gender, at 0.09 points for males and 0.08 points for females.

### 5.3 Differences by degree subject

In this section, we consider another possible source of heterogeneity in the wage return to UG degrees: that by degree subject studied. We focus on the following aggregation of subjects: Science (Medicine and Dentistry, Subjects Allied to Medicine, Biological Sciences, Agriculture, Physical Sciences, Mathematical Sciences, Computing, Engineering, Technology and Architecture), Social Science (Social Studies, Economics, Law and Politics, Business and Mass Communications) and Arts and Humanities (Classics and Literature, Modern European Languages, Other Languages, Creative Arts, Education and Other).

The results reported in Table 3 show that, relative to the comparison group of individuals with two or more A-levels and no degree, our estimated wage returns for men for the different subject groups are similar to those reported by Walker and Zhu (2001). Compared to an average wage return to a first degree of 0.15, Social Science gives the highest wage return (0.28), and Arts and Humanities the lowest wage return (0.12), which is not statistically different from zero at the 5% level. The wage return for Science is intermediate at 0.20. Wald tests for the equality of wage returns across all degree subjects cannot be rejected for men at the 10% statistical level. When we consider Social Science versus Arts and Humanities, the difference is statistically significant at the 5% level, while the differences between Arts and Humanities and Science and that between Science and Social Science are not statistically significant. For women, we observe the same ordering of subjects as for men, although the spread of the estimates around the average wage return of 0.18 is much tighter, with Social Science having the highest wage return (0.25) and Arts and Humanities the lowest wage return (0.17).

### 5.4 Differences by other characteristics

In addition to examining variations around the average return to an undergraduate degree according to factors such as degree class obtained and degree subject studied, we have considered heterogeneity of returns: by family background (i.e., parents' highest social class); by ability (i.e., quartiles of the quantitative BAS score); and by unobservable

characteristics (i.e., the generalized residuals from the ordered probit model for highest educational qualification achieved, see equation (3)). Table 4 presents OLS regression results for the three specifications for males and females separately. The comparison group remains throughout individuals with a highest educational qualification of two or more A-levels. The estimated equations include all the variables included in the estimations reported in section 5.1. Each specification considers a particular set of interactions.

As is shown in Table 4, none of the interactions with either ability or with unobservables is significant for males. The default case is that of a male from outside Social Class I, II, or III(non-manual), for whom the return to an UG degree is estimated to be a little higher at 0.17 than the average of 0.15 reported in Table 2. Relative to this default, there is a significantly lower return for an individual from a Social Class I or II background: the coefficient on this interaction term being -0.03. No other Social Class interactions with education are significant. For females, none of the estimated coefficients on the interactions between education and Social Class is significant. Similarly, the interactions with unobservables suggest no differences in the returns to an UG by unobservable characteristics. Only the interaction between an UG and BAS4 (the highest quartile of the ability distribution) has a significant estimated coefficient, at the 5% level, indicating that the return to an UG degree is substantially lower for individuals in the highest part of the ability distribution. A possible interpretation for this is that it is average graduate ability that is signalled by the possession of a degree and this undervalues the ability of the most able graduates and over-values that of the lower quartiles. In conclusion, there is rather little evidence of significant differences in returns to an UG degree by family background, ability or by unobservable characteristics.

## **6 Robustness: propensity score matching analysis**

Our previous analysis using the CFA suggests the absence of an ability bias. However, as in the case of selection exclusively on observables, OLS estimates will recover the unbiased ATT only if the no-treatment outcome has been correctly specified. This requires that the model is correctly specified in terms of the (linear) functional form chosen

and that the treatment effect is homogeneous across individuals with different observed characteristics. A semiparametric method that allows us to relax this assumption and to highlight the potential problem of the common support is the estimation of ATT based on propensity score matching (PSM): see Caliendo and Kopeinig (2008). As the results of section 5.4 show no real evidence of heterogeneity by observables, we can view this section as a further robustness check on our previous results and as yielding an indication of whether we can assume linearity in the no-treatment outcome. In this section, we estimate the wage return to (i) HE qualifications, (ii) a good as opposed to a lower degree class, and (iii) different subjects studied, using PSM.

One can define:  $\mathbf{X}_i$  as a vector of variables (the same that were used as controls in the regressions estimated in the previous sections);  $Q_i$  as the treatment variable, equal to one for the treated and zero for the non-treated (in our case it will correspond to the values of the dummy variables for having a first degree, or for degree class awarded or for degree subject studied, as appropriate); and  $w_{1i}$  and  $w_{0i}$  the log-wage for individual  $i$  in the case of treatment and no-treatment, respectively. Following Rosenbaum and Rubin (1983) the propensity score is defined as:

$$p(\mathbf{X}_i) \equiv Pr\{Q_i = 1|\mathbf{X}_i\}, \quad (4)$$

i.e., the conditional probability of receiving a treatment given pre-treatment characteristics. Rosenbaum and Rubin (1983) show that if the following two hypotheses hold:

1. *Balancing hypothesis*: If  $p(\mathbf{X}_i)$  is the propensity score, then  $Q_i \perp \mathbf{X}_i | p(\mathbf{X}_i)$ ;
2. *Unconfoundedness hypothesis*: Suppose that assignment to treatment is unconfounded,<sup>17</sup> i.e.  $w_{1i}, w_{0i} \perp Q_i | \mathbf{X}_i$ . Then assignment to treatment is unconfounded given the propensity score, i.e.  $w_{1i}, w_{0i} \perp Q_i | p(\mathbf{X}_i)$ ;

then the average treatment effect on the treated (ATT) can be estimated as follows:

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<sup>17</sup>This hypothesis is also called the Conditional Independence Assumption, i.e. selection only on observables, and cannot be tested within the propensity score-ATT framework.

$$\begin{aligned}
ATT &= E_{\mathbf{X}_i}\{w_{1i} - w_{0i}|Q_i = 1, \mathbf{X}_i\} \\
&= E_{p(\mathbf{X}_i)}\{E[w_{1i} - w_{0i}|Q_i = 1, p(\mathbf{X}_i)]\} \\
&= E_{p(\mathbf{X}_i)|Q_i=1}\{E[w_{1i}|Q_i = 1, p(\mathbf{X}_i)] - E[w_{0i}|Q_i = 0, p(\mathbf{X}_i)]\}. \tag{5}
\end{aligned}$$

In our case, PSM is implemented using kernel matching, which we prefer over other methods since it appears to be more suitable to the characteristics of our samples of treated and control individuals, which are not very large. Kernel matching uses all information available (since the counterfactual is built by using all individuals in the control group) and therefore there is a higher likelihood of obtaining significant ATT estimates even with small samples compared to methods using few control individuals to build the counterfactual. When using kernel matching the choice of the bandwidth implies a trade-off between efficiency and bias. In our case, we used a normal kernel and the bandwidth was selected optimally using cross-validation (see Härdle, 1991).

The ATT estimates, computed using as the control group individuals with two or more A-levels and imposing the common support, are reported in Table 5. PSM is successful in balancing the covariates in the samples of treated and control individuals, as both the small pseudo  $R^2$  and the small standardized bias after matching show.<sup>18</sup> From the table, the pattern of estimates obtained using PSM is generally the same as that reported in Tables 2 and 3. We observe the same ordering of returns by degree subject group studied for both men and women. There is still a substantially higher return for a good degree class than for a lower degree class. The most notable difference compared to earlier results, however, is that the estimated wage returns tend to be lower when using PSM. This might also depend on imposing the common support. The average return for an UG degree falls by about 0.02 for men and by about 0.04 for women: however, differences with respect to the OLS estimates are not statistically significant. The precision of the estimates is a little lower, compared to the OLS estimates. This is probably due to the smaller sample sizes and the fact that standard errors are bootstrapped to take

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<sup>18</sup>Moreover, although not reported in Table 5, the null hypothesis of joint exclusion of all covariates from the probit model is never rejected at conventional statistical levels.

into account the fact that propensity scores are estimated.

## 7 Concluding remarks

In this paper we have estimated the wage return to a first degree using birth cohort data from the 1970 British Cohort Survey. We estimate that there is a log wage return to an undergraduate degree of 0.15 for men and of 0.18 for women, relative to a control group of individuals with two or more A-level qualifications but without higher education.

Our analysis focuses on differences in wage returns according to both degree class awarded and degree subject studied. Our estimates show the existence of a positive wage return for a good degree class compared to a lower degree class. For both men and women, the premium for a good over a lower degree class is about 8 percentage points. Our analysis of log-wage differences by degree subjects confirms findings from related work. As far as the ranking of subjects is concerned, for instance, we have in decreasing order: Social Science, Science and Arts and Humanities, for both men and women. Moreover, Arts and Humanities degrees are associated with a positive return (relative to workers with A-levels) only in the case of women. Although our estimates suggest the presence of differences by degree subjects, the effects are not always precisely estimated and only the difference between Social Science and Arts and Humanities degrees for males appears statistically significant.

Our findings indicate that the HE wage return to women is only a little greater than that for male graduates. This is in stark contrast to the previous findings for the 1958 cohort, for whom the return for women was substantially higher than that for men. Our estimated average return to HE for men is very similar to estimates obtained previously for the 1958 birth cohort, while that for women is substantially lower than for the earlier cohort. However, meaningful comparisons of estimates across cohorts is difficult as it is not clear that the control groups are comparable over time.

Our analysis has clear policy relevance. Students in the UK - and beyond - are faced with an increasing burden of financing their higher education. In this paper, we find that the average wage return to an undergraduate degree is substantial, making the

investment decision of participating in higher education seem an attractive proposition. However, we also find that there is significant evidence of quite marked variation around this average wage return, according both to the class of degree the student is awarded and to the degree subject studied; rendering the return for investment in higher education potentially much lower at the margin.

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Table 1: Hourly wage rate by educational qualification (BCS70)

Qualification Level	<i>Males</i>				<i>Females</i>			
	Obs.	% sample (1,497 obs.)	Wage (£)		Obs.	% sample (1,422 obs.)	Wage (£)	
			Mean	S.D.			Mean	S.D.
2+ A-levels	175	11.69	10.57	6.30	163	11.46	8.28	3.23
Non-degree HE	560	37.40	10.37	10.06	550	38.68	9.09	10.59
UG degree	576	38.48	12.65	8.82	506	35.56	10.81	10.75
PG degree	186	12.42	11.25	5.30	203	13.08	9.46	2.95
UG degree class								
Good degree	274	18.30	13.53	10.74	277	19.48	11.01	4.89
Lower degree	298	19.91	11.87	6.56	228	16.03	10.60	15.09
UG degree subject								
Sciences	212	14.16	13.14	8.24	151	10.62	10.55	4.00
Social Sciences	103	6.88	14.38	9.99	113	7.95	12.78	21.12
Arts and Humanities	105	7.01	12.99	10.66	150	10.55	10.56	4.92
Other	156	10.42	10.62	7.25	96	6.75	8.84	4.59

Notes: Wage refers to gross hourly wage rate at age 30. % of sample refers to the size of the sample including 2+ A-levels control group.

Table 2: Estimates of the log-wage premia (wage ‘returns’) to HE qualifications (BCS70)

<i>Males</i>	OLS		CFA	
	Coef.	s.e.	Coef.	s.e.
Non-degree HE	0.006	0.038	0.007	0.040
UG degree	0.146 ***	0.040	0.146 ***	0.041
PG degree	0.050	0.058	0.052	0.054
$\lambda$			0.000	0.001
N.obs.	1,497		1,497	
R <sup>2</sup>	0.077		0.078	
Wald test on parents’ education (p-value)				
Education equation			0.000	
Wage equation			0.187	
<i>Females</i>	Coef.	s.e.	Coef.	s.e.
Non-degree HE	0.070 *	0.035	0.070 *	0.035
UG degree	0.178 ***	0.035	0.178 ***	0.035
PG degree	0.100 **	0.040	0.099 **	0.037
$\lambda$			0.000	0.000
N.obs.	1,422		1,422	
R <sup>2</sup>	0.110		0.111	
Wald test on parents’ education (p-value)				
Education equation			0.001	
Wage equation			0.886	

Notes. The dependent variable is the natural logarithm of gross hourly wages. Wage premia are relative to individuals with 2 or more A-levels. The wage equation also includes all the variables listed in section 5. In the OLS model the standard errors are robust to the presence of heteroskedasticity.  $\lambda$  are the generalized residuals computed from the ordered probit model for the highest educational qualification achieved. The CFA model is identified by parents’ education that is included only in the education equation and standard errors in this equation are bootstrapped with 500 replications since the model is estimated in two stages.

\*\*\*Significant at the 1% level; \*\*significant at the 5% level; \* significant at the 10% level.

Table 3: Heterogeneity in the estimates of the log-wage premia (wage ‘returns’) by degree class and degree subject (BCS70) - OLS

<i>Males</i>	Degree class		Degree subjects		
	Coef.		Coef.		s.e.
Good degree class	0.195	***	0.047		
Lower degree class	0.106	*	0.045		
Science (S)			0.202	***	0.052
Social Science (SS)			0.276	***	0.062
Arts and Humanities (AH)			0.115	*	0.069
Missing (M)			0.051		0.050
N.obs		1,493			1,497
R <sup>2</sup>		0.080			0.094
Wald test Good=Lower (p-value)		0.030			
Wald test S=SS (p-value)				0.252	
Wald test S=AH (p-value)				0.169	
Wald test SS=AH (p-value)				0.034	
Wald test all subjects = (p-value)				0.104	
<i>Females</i>	Coef.		s.e.	Coef.	s.e.
Good degree class	0.216	***	0.039		
Lower degree class	0.139	***	0.040		
Science (S)				0.197	***
Social Science (SS)				0.250	***
Arts and Humanities (AH)				0.169	***
Missing (M)				0.100	**
N.obs		1,421			1,422
R <sup>2</sup>		0.113			0.115
Wald test Good=Lower (p-value)		0.029			
Wald test S=SS (p-value)				0.301	
Wald test S=AH (p-value)				0.532	
Wald test SS=AH (p-value)				0.139	
Wald test all subjects = (p-value)				0.333	

Notes. The dependent variable is the natural logarithm of gross hourly wages. Wage premia are relative to individuals with 2 or more A-levels. The wage equation also includes all the variables listed in section 5, except parents’ education. Standard errors are robust to the presence of heteroskedasticity. The Wald test for all subjects does not include the Missing category. Estimates of degree class premia are obtained from the sample omitting individuals with missing degree class (4 males and 1 female).

\*\*\* Significant at the 1% level; \*\* significant at the 5% level; \* significant at the 10% level.

Table 4: Heterogeneity in the estimates of the log-wage premia (wage ‘returns’) by social class, ability and unobservables (BCS70) - OLS

	<i>Males</i>				<i>Females</i>												
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.									
Non-degree HE	0.072	0.059	0.062	0.047	0.009	0.047	0.126	0.058	0.073	0.045	0.085	*	0.044				
UG degree	0.168	**	0.064	0.163	***	0.050	0.143	***	0.186	**	0.061	0.220	***	0.048	0.189	***	0.045
PG degree	0.028		0.070	0.157	*	0.064	-0.080		0.179	*	0.079	0.125	*	0.054	0.008		0.067
Interactions with social class																	
Non-deg × I-II	-0.138		0.087						-0.087		0.076						
Non-deg × IINM	-0.044		0.091						-0.107		0.105						
UG × I-II	-0.027	***	0.091						-0.015		0.077						
UG × IINM	-0.074		0.108						-0.066		0.112						
PG × I-II	0.007		0.119						-0.164		0.093						
PG × IINM	0.065		0.117						0.058		0.123						
Interactions with BAS quantitative score																	
Non-deg × BAS1			-0.050	0.074							0.026				0.066		
Non-deg × BAS4			-0.073	0.061							-0.027				0.051		
UG × BAS1			-0.004	0.107							-0.081				0.096		
UG × BAS4			-0.034	0.054							-0.137	**			0.052		
PG × BAS1			-0.139	0.111							0.141				0.117		
PG × BAS4			-0.202	0.077							-0.112				0.072		
Interactions with unobservables																	
Non-deg × $\lambda$			-0.002	0.033							0.002				0.018		
UG × $\lambda$			0.001	0.011							0.007				0.009		
PG × $\lambda$			0.040	0.028							0.044	***			0.013		
$\lambda$			-0.001	0.011							-0.006				0.009		
N. obs	1,497		1,187 <sup>a</sup>	1,497					1,422		1,123 <sup>a</sup>				1,422		
R <sup>2</sup>	0.080		0.112	0.081					0.118		0.118				0.116		

The dependent variable is the natural logarithm of gross hourly wages. Wage premia are relative to individuals with 2 or more A-levels. The wage equation also includes all the variables listed in section 5, except parents’ education. I-II refers to Social Class I or II, IINM refers to social class IINM, BAS1 (BAS4) refers to the bottom (top) quartile of the BAS quantitative score.  $\lambda$  are the generalized residuals computed from the ordered probit model for the highest educational qualification achieved. Standard errors are robust to the presence of heteroskedasticity. <sup>a</sup> The estimation sample omits individuals with missing BAS score.

\*\*\*Significant at the 1% level; \*\* significant at the 5% level; \* significant at the 10% level.

Table 5: Estimates of the log-wage premia (wage 'returns') using PSM-ATT (BCS70)

Treatment	ATT <sup>a</sup>	s.e. <sup>b</sup>	No. treated	No. controls	Bandwidth <sup>c</sup>	% out of support <sup>d</sup>	Pseudo R <sup>2</sup> before <sup>e</sup>	Pseudo R <sup>2</sup> after <sup>e</sup>	Median bias before <sup>f</sup>	Median bias after <sup>f</sup>
<i>Males</i>										
Non-degree HE	0.008	0.048	560	175	0.02	8.57	0.10	0.01	8.95	2.23
UG degree	0.124	***	576	175	0.02	7.64	0.08	0.01	6.19	2.06
PG degree	0.039	0.074	186	175	0.03	9.41	0.10	0.01	8.71	2.94
Good degree class	0.171	***	274	175	0.03	9.12	0.10	0.01	9.08	1.78
Lower degree class	0.102	*	298	175	0.03	5.03	0.10	0.02	7.05	3.06
Science	0.153	**	212	174	0.04	3.30	0.16	0.02	9.76	3.39
Social Science	0.259	***	103	174	0.04	1.94	0.23	0.06	15.61	6.03
Arts and Humanities	0.084	0.098	105	174	0.04	12.38	0.21	0.02	9.31	3.12
<i>Females</i>										
Non-degree HE	0.059	0.048	550	163	0.02	10.00	0.11	0.01	7.50	1.90
UG degree	0.140	***	506	163	0.03	5.42	0.13	0.02	9.04	2.52
PG degree	0.044	0.045	203	163	0.04	1.97	0.20	0.02	9.62	3.09
Good degree class	0.171	***	277	163	0.04	5.78	0.18	0.02	9.74	2.87
Lower degree class	0.112	**	228	163	0.03	4.11	0.12	0.01	8.47	3.41
Science	0.157	***	151	161	0.04	2.65	0.18	0.01	8.40	1.78
Social Science	0.200	***	113	163	0.04	5.31	0.26	0.02	11.20	3.35
Arts and Humanities	0.110	*	150	163	0.05	4.00	0.26	0.04	10.50	3.88

Notes. The outcome variable is the natural logarithm of gross hourly wages, and the control group individuals with 2 or more A-levels. Wage premia for missing degree subject are not reported. <sup>a</sup>Average Treatment effect on the Treated (ATT) computed using PSM, namely kernel matching; <sup>b</sup>Bootstrapped standard errors, 500 replications; <sup>c</sup>Optimal Gaussian bandwidth selected using cross-validation (Härdle, 1991); <sup>d</sup>% of treated individuals out of the common support; <sup>e</sup>Pseudo R<sup>2</sup> of the probit model used to compute the propensity scores before and after matching; <sup>f</sup>Median standardized bias before and after matching (see Rosenbaum and Rubin, 1983).

\*\*\*Significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level.