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Pre-market Abilities, Education, and Employment Outcomes: An Analysis of British Females

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First draft!

Abstract

In this article, we study the connection between skills, educational choices, employment outcomes and wage levels. The study is part of a line of research that examines the role played by both cognitive and non-cognitive abilities in predicting human capital accumulation, as well as individual professional achievement. Moreover, the study integrates the issue of gender differences in labour market participation and wages into the social mobility literature. In particular, this version of the paper contributes to a deeper analysis of the issue of female labour market participation and achievement, taking into account the relationship between premarket abilities, investment in education and employment outcomes. Our aim is to understand the extent to which the factors at the origin of inequality and the skills acquired through education can determine females' occupational choices and professional achievement. In order to achieve our research goal, we propose an empirical model where education, occupational status and wage rates are estimated through a three-stage procedure, where wage rates are corrected for selection into education and employment. This allows us to provide new evidence on the relationship between educational choices, employment outcomes and earnings. The analysis is carried out based on data from the British National Child Development Study (NCDS), a longitudinal study that follows the lives of all individuals living in Great Britain that were born in one particular week of 1958. The dataset allows for the measuring of pre-market cognitive skills as well as non-cognitive skills related to family characteristics, including parents' preferences and expectations. First estimates show that both cognitive and non-cognitive skills are relevant for educational choices. However, family characteristics, such as parents' interest in children's education and parents' expectations about children's educational achievement, have a particularly prominent effect on educational outcomes. Our results show, inter alia, that 'good' employment outcomes are predetermined by high educational attainment.

Keywords: female education, employment and wages; cognitive and non-cognitive skills.

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1. Introduction

Female educational participation levels have been increasing throughout the last decade in all OECD countries (OECD, 2011). In these countries, participation in primary education has recently approached 100% for both girls and boys (data from years 2008 and 2009), with no substantial gender gaps in secondary enrolment rates (mostly within 5%, except for Turkey). However, tertiary attainment levels are higher for girls than for boys in most of the OECD economies.

The high growth in female education and females' overtaking of males in attainment rates at the highest levels of education can be interpreted as an attempt by females to offset unfavourable labour market outcomes. The research on gender wage differentials shows that, in the advanced economies, gender wage gaps are generally lower for highly educated women than for less educated women (some results from European countries can be found in Addabbo and Favaro, 2011; De la Rica *et al.*, 2008; Mussida and Picchio, 2013).[1] The information that women get from the market is that they have to invest in education in order to be paid as close as possible to what men are paid. On the other hand, the literature on education choices explains that education can play an important role in the labour market, and can act as an indicator of individual ability (Spence, 1974). Indeed, women place great confidence in education as a signalling mechanism of their individual skills (Castagnetti and Rosti, 2009).[2]

These considerations suggest that female achievement among higher levels of education could be interpreted, at the very least, as a clear signal of commitment to enter the labour market. The straight implication of this view is that an individual's investment in education may not be a decision completely detached from her expectations for future employment prospects. Women with a stronger intention to work may decide for a higher investment in their education. In turn, if a selection bias exists for employment, this could originate from selection into higher education. As a consequence, we may observe different occupational outcomes depending on levels of education, and different effects of individual, family and other productive characteristics on occupational status, depending on educational qualifications.

In this paper, we try to address this issue by proposing an empirical model where the decision of how many years to spend in education (which educational level to achieve) is determinant for subsequent employment outcomes and wage levels. The main point of the model is that the level of education is the main decision that women make, and this decision can affect (depending on the qualification achieved) their occupational status throughout their lives.

Our approach is new compared to the existing literature that studies female participation in the labour market, wages and gender wage gaps. In most of this literature, education is conceived as only an explicative variable for both occupational outcomes and wage rates, and only selection into employment is deemed to be relevant for wage levels. Only recently have contributions on the analysis of the gender wage gap started to address the issue of a possible difference in the pattern of this gap for

[1] Nevertheless, the more educated are also likely to suffer from a more pronounced glass ceiling effect.

[2] The results of this commitment are not reassuring. Several studies from various different countries show that female workers, more frequently than men, have higher qualifications than those required in their occupations.

women with different educational levels. However, these contributions do not take into account the possible selection into different educational levels (some examples from European countries include Addabbo and Favaro, 2011; Mussida and Picchio, 2012). In general, female wages and the gender pay gap are studied by focusing on the role played by selection into employment, without considering selection into education.

The present study fits into the line of research that examines the role played by both cognitive and non-cognitive abilities in predicting human capital accumulation, as well as individual professional achievement (for example, Heckman and Rubinstein, 2001; Ermisch and Francesconi, 2001; Dustmann, 2004; Cunha and Heckman, 2009; Lindley and Machin, 2012). Moreover, the study integrates the issue of gender differences in labour market participation and wages into the social mobility literature. In particular, we contribute to a deeper analysis of the issue of female labour market participation and achievement, taking into account the relationship between pre-market abilities, investment in education and employment outcomes. Our aim is to understand the extent to which the factors at the origin of inequality can determine educational achievement, and how they can interact with different education levels to determine employment and earnings outcomes.

The model we propose is a sequential model in which females first choose the level of education and then, given the achieved qualification, enter (or not) the labour market. If they enter the labour market, they work either part-time or full-time, and relative wages are observed. Occupation outcomes and wage rates are conditioned on the level of education: high, if the individual achieved an upper-secondary school diploma or more; or low, if the qualification is lower than an upper-secondary school diploma. Occupation outcomes are classified into: 'no work', 'part-time work', and 'full-time work'.

The econometric specification involves, first, the estimation of a probability equation for the educational levels. In the second stage, we employ the estimated probabilities, for high and low education levels, to derive the respective inverse Mill's ratios to be included as covariates in the occupational equations conditioned on each level of education. The inclusion of the inverse Mill's ratio in the occupation-status equations relative to each educational level aims to detect the possible joint effect of unobservable characteristics on both educational and occupational outcomes. A statistically significant inverse Mill's ratio would suggest that occupational outcomes are correlated to educational results, and that selection into education is determinant for labour market outcomes. As previously mentioned, we classify the occupational status into no work, part-time and full-time work. Wage equations are then estimated separately for the subsamples of part-timers and full-timers, and the inverse Mill's ratio relative to the considered subsample is included in each wage equation.

The analysis is carried out for the UK. The UK is of particular interest for the study of female educational outcomes and labour market participation (OECD, 2011). The UK does not rank among the best OECD economies in terms of educational rates, both for men and women. However, even for the oldest age cohorts of the population, gender differences in education are among the lowest in the developed world. In recent years, the UK has become one of the countries in which female secondary enrolment rates and tertiary attainment have surpassed male rates; the gender gap in education in the UK is thus in favour of females. In particular, if we observe the proportion of adults with tertiary education, the male to female gap is equal to 9 percentage points in favour of females. As a result, women's increased education has proven to be a key factor in narrowing British gender wage differentials over time (Lindley and Machin, 2012). In addition, the UK also has a very low gender gap in terms of employment. The British female to male gap in employment rates is as low as that of France and the Netherlands, although much of the female employment performance in these countries occurs through part-time work. The UK labour market also appears rather segmented between full-timers and part-timers and by educational levels: hours-of-work segmentation is important to understanding women's relative economic status, while less educated women and those working part-time tend to be less integrated into the labour market (Bowlus and Grogan, 2009; Manning and Robinson, 2004)

The analysis is conducted based on data from the British National Child Development Study (NCDS), a cohort study that follows all UK births occurred during the week of 3–9 March 1958.

The paper is structured as follows: in Section 2 we discuss the empirical model and methodological issues. The model is then estimated by using the NCDS, as described in Section 3. Results of the estimations are then presented in Section 4.

2. The Empirical Model: Selection into Educational Levels, Employment Outcomes and Wages

The model we propose is a sequential model in which females first choose the level of education and then, given the achieved qualification, enter (or not) the labour market. If they enter the labour market, they work either part-time or full-time, and relative wages are observed. Occupation outcomes and wage rates are conditioned on the level of education: high, if the individual achieved an upper-secondary school diploma or more; or low, if the qualification is lower than an upper-secondary school diploma. Occupation outcomes are classified into: 'no work', 'part-time work', and 'full-time work'.

The econometric specification involves, first, the estimation of a probability equation for the educational levels. Then, we employ the estimated probabilities, for high and low education levels, to derive the respective inverse Mill's ratios to be included as covariates in the occupational equations conditioned on each level of education. The inclusion of the inverse Mill's ratio in the occupation-status equations relative to each educational level (high and low) aims to detect the possible joint effect of the unobservable characteristics on both the educational and occupational outcomes. A statistically significant inverse Mill's ratio would suggest that occupational outcomes are correlated to the specific educational qualification, and that selection into that educational qualification is a determinant for the labour market outcomes.

We classify the occupational status into no work, part-time work and full-time work. Wage equations are then estimated separately for the subsamples of part-timers and full-timers, and the inverse Mill's ratio relative to the considered subsample is included in each wage equation.

The econometric analysis is carried out at two different points in time: 1991 and 2009. This means that we observe our sample of women, who weare born in 1958, when they are 33 and 51 years old. This may imply many considerations about maternity constraints, etc. (to be developed).

The first outcome we predict is the educational qualification that is achieved. The model predicts that the latent utility index of education for individual i, Q_i^*, is a linear function of individual and family characteristics:

$$Q_i^* = X_i^{'}\beta + u_i \tag{1}$$

However, since Q_i^* is not observable, the model is estimated using a discrete variable Q_i that assumes value zero if the woman has a low level of education low-educated and value 1 if she is highly-educated.

We assume that the error term is normally distributed, $u_i \approx N\left[0, \sigma_Q^2\right]$ and we estimate Equation 1 using a probit procedure, adjusting for robustness.

X_i includes the individual's and the family's characteristics we will discuss in the following section. It also includes an identification variable that will be excluded from the equation on the employment status.

After estimating Equation 1, we predict the probabilities of being highly-educated (HE) and low-educated (LE) and the inverse Mill's ratio to be included in the two employment-status equations: one for low-educated women and the other for the highly-educated. The inverse Mills' ratios are specified as follows (Heckman, 1979; Greene, 2011):

$$\lambda_{\mathrm{LE}} = \frac{-\varphi\left(\mathrm{X}^{'}\beta\right)}{\left[1-\Phi\left(\mathrm{X}^{'}\beta\right)\right]} \qquad \text{For low-educated}$$

$$\lambda_{\mathrm{HE}} = \frac{\varphi\left(-\mathrm{X}^{'}\beta\right)}{\left[1-\Phi\left(-\mathrm{X}^{'}\beta\right)\right]} \qquad \text{For highly-educated}$$

Where:
$\varphi(.)$ = normal density function;
$\Phi(.)$ = normal distribution function.

The second equation of our model is related to the occupational status observed after education. The theoretical prediction we want to test empirically is that educational attainment affects and conditions employment outcomes along the life cycle. In particular, we believe that women with a stronger intention to work self-select into higher educational levels. If this was the case, a) employment outcomes of highly-educated women would be affected by unobserved characteristics influencing their educational choices; b) productive characteristics could have distinct effects on the employment status of highly- and low-educated women. Then, we estimate separate employment equations for the two subsamples. Conditioned on each educational level, we specify an ordered probit model where the utility is defined on the following outcomes: no work, part-time work (PT), full-time work (FT). The no work outcome includes both unemployment and the out-of-work condition. The model is built around a latent regression, where the latent utility index of individual i having an educational level $e, E_{i,e}^*$, is a linear function of productive characteristics included in $Z_{i,e}$:

$$E_{i,Q}^{*} = Z_{i,Q}^{'}\gamma_{Q} + u_{i,Q} \qquad \text{for each } Q = LE, HE \quad (2)$$

with

$E_{i,Q}^{*} < 0$	if unemployed or inactive
$0 \le E_{i,Q}^{*} < \mu_{Q}$	if working part-time
$E_{i,Q}^{*} \ge \mu_{Q}$	if working full-time

As in Equation 1, the latent index is unobserved. What we observe is:

$E_{i,Q} = 0$	if $E_{i,Q}^{*} < 0$
$E_{i,Q} = 1$	if $0 \le E_{i,Q}^{*} < \mu_{Q}$
$E_{i,Q} = 2$	if $E_{i,Q}^{*} \ge \mu_{Q}$

The μ_{Q} s are defined for each *Q* level.

As before, the error term is normally distributed across observations with mean zero and variance σ_{E}^{2}. Parameters μ_{LE} and μ_{HE} are the theoretical cut points that are unknown. They are estimated together with coefficients γ_{LE} and γ_{HE}, respectively.

$Z_{i,Q}$ includes the individual and family characteristics that may affect employment outcomes as well as the inverse Mill's ratio relative to the educational-level subsample *Q* = *LE*, *HE*. For identification issues, X_{i} in Equation 1 has to include at least one variable that is not relevant for occupational outcomes. Then, this variable is excluded from $Z_{i,Q}$ in Equation 2. On the other hand, $Z_{i,Q}$ has to include at least one variable that affects occupational results, but not wages. This variable will be excluded from the set of explanatory variables in the wage rate equation. The specific variables will be discussed in the next section.

The last step of our model concerns wage rate equations. We estimate separate wage rate equations for all combinations of educational levels and employment status: highly-educated working part-time, highly-educated working full-time, low-educated part-timers, low-educated full-timers.

Our wage equation is defined as:

$$w_{i,Q,E} = W_{i,Q,E}^{'}\eta_{Q,E} + \varepsilon_{i,Q,E} \qquad \text{for } Q = LE, HE \text{ and } E = PT, FT \qquad (3)$$

The error term is normally distributed with mean zero and variance equal to σ_{w}^{2}.

$W_{i,Q,E}^{'}$ includes the inverse Mill's ratio for females belonging to each subsample, conditioned on occupational status *E* (*PT* or *FT*) and educational level *Q* (*HE* or *LE*). For each educational level *Q*, the inverse Mill's ratios that account for possible selection into part-time work and full-time work are expressed as (Greene, 2011; Main and Reilly, 1993):

$$\lambda_{Q,PT} = \frac{\varphi\left(0 - Z_Q^{'}\gamma_Q\right) - \varphi\left(\mu_Q - Z_Q^{'}\gamma_Q\right)}{\Phi\left(\mu_Q - Z_Q^{'}\gamma_Q\right) - \Phi\left(0 - Z_Q^{'}\gamma_Q\right)}$$

$$\lambda_{Q,FT} = \frac{\varphi\left(\mu_Q - Z_Q^{'}\gamma_Q\right)}{1 - \Phi\left(\mu_Q - Z_Q^{'}\gamma_Q\right)} \qquad \text{for each } Q = LE, HE \quad (4)$$

The inverse Mill's ratios described in the two components of Equation 4 are appropriate if the ordered probit model includes a constant. However, the estimation procedure we use[3] does not include a constant among the regressors. The procedure predicts two different cut points (*cut1* and *cut2*) that we use to adapt the two components of Equation 4 to the no-constant estimated model[4].

OLS estimations of Equation 3 are performed. The standard errors are corrected to account for both heteroscedasticity and the use of predicted selectivity variables, as suggested by Greene (1981) and implemented by Main and Reilly (1993).

3. The NCDS Data: Education, Employment and Wages

The data and definition of variables for the model equations

The study is carried out employing the NCDS. The NCDS is a cohort study that follows all UK births during the week of 3-9 March 1958. The main aim of the study is to improve the understanding of the factors affecting human development over the entire lifespan. The NCDS has its origin in the Perinatal Mortality Survey (PMS) that collected information on a cohort of approximately 17,000 children. Successively, the PMS became the NCDS that has gathered information on the same individuals at different times in their lives (1965, 1969, 1974, 1981, 1991, 1999-2000, 2004-2005 and 2008-2009). The available data have been reduced considerably since 1991, consisting of approximately 11,000 observations in the latest sweeps[5].

We use six sweeps of the NCDS database[6]. From the original 1958, 1965, 1969 and 1974 sweeps, we draw information about pre-market abilities (namely cognitive and non-cognitive skills), as well as the family, social and economic environments in which the children were growing up and that, possibly, affect their choice to end their

[3] The STATA procedure oprobit.

[4] The derived inverse Mill's ratios are:

$$\hat{\lambda}_{Q,PT} = \frac{\varphi\left(0 - (Z_Q^{'}\gamma_Q + cut1)\right) - \varphi\left(cut2 - (Z_Q^{'}\gamma_Q + cut1)\right)}{\Phi\left(cut2 - (Z_Q^{'}\gamma_Q + cut1)\right) - \Phi\left(0 - (Z_Q^{'}\gamma_Q + cut1)\right)} = \frac{\varphi\left(-Z_Q^{'}\gamma_Q - cut1\right) - \varphi\left(cut2 - cut1 - Z_Q^{'}\gamma_Q\right)}{\Phi\left(cut2 - cut1 - Z_Q^{'}\gamma_Q\right) - \Phi\left(-Z_Q^{'}\gamma_Q - cut1\right)};$$

$$\hat{\lambda}_{Q,FT} = \frac{\varphi\left(cut2 - (Z_Q^{'}\gamma_Q + cut1)\right)}{1 - \Phi\left(cut2 - (Z_Q^{'}\gamma_Q + cut1)\right)} = \frac{\varphi\left(cut2 - cut1 - Z_Q^{'}\gamma_Q\right)}{1 - \Phi\left(cut2 - cut1 - Z_Q^{'}\gamma_Q\right)}.$$

[5] The selection and the attrition bias problems in the NCDS data have been investigated in several papers. Among others, Dearden et al. (1997) show that attrition in the NCDS has tended to weed out individuals with lower ability and lower educational qualifications, while Hawkes and Plewis (2006) have found that the attrition and non-response issues can be associated with only a few significant predictors.

[6] The NCDS 1974-2000 work histories file has been used to determine the cumulated working experiences of cohort-members when they were aged 16-42.

educational career at the age of 16 (the compulsory school leaving age in the UK) or to stay within the education system after that limit. In our study, this discriminates between highly and low-educated, according to the categorisation based on information about the highest qualification level reached at age 23, from the 1991 NCDS sweep. Particularly, the low-educated females are those that achieved at most the O-level education (65.28% of our sample), while the highly-educated females are those that have achieved at least the A-level education (34.72% of our sample). NCDS sweeps of 1991 and 2009 are used to carry out a separate cross-sectional analysis on adult wages and employment (when cohort members are, respectively, 33 and 51 years old), accounting, in turn, for selection into employment (both full-time and part-time) and selection into high education.

The employment status is based on information about the cohort member's current economic status that allows for identifying females engaged in full-time and part-time employment, as well as females in non-employment positions (including unemployment). Self-employed people have been excluded from our analysis involving the loss of 7%-8% of observations.

The individual wage refers to the logarithm of the net hourly pay received by an employee. This value is calculated using information about the net pay, the period covered and the usual hours (including overtime) worked per week. To reduce bias from outliers, the resultant hourly wage variable has been subjected to top and bottom coding at 1%, and for the same reason, we have trimmed out from our sample individuals who worked less than 7 hours per week or more than 84 hours per week.

Because of the structure of our study and its long-term perspective, which increases the risk of losing information (both for dependent and explanatory variables), the sample includes 1751 observations in the 2009 sample. For the sake of brevity, we focus on the description of the 2009 sample, while information on the 1991 sample (including 2268 observations) remains available upon request.

One main advantage of the NCDS dataset is the availability of a wide spectrum of childhood variables, both at the personal level and the familiar level, that allow one to model the educational choices of cohort-members at age 16, and then to control the role of selection into high education in determining employment outcomes.

The specification of the education equation takes into account both the literature that focuses on the role of cognitive and non-cognitive skills on child development, and the literature that focuses on the impact that family background and parental interest in the child's education have on education and adult outcomes. In this spirit, the covariates include: birth weight (introduced in a non-linear way) to control for problems deriving from low birth weight; math and reading test results at age 7, introduced to approximate cognitive skills; the Bristol Social Adjustment Guides (BSAG) test score, measured at age 11 to diagnose the nature and the extent of behavioural disturbances in children at school[7], which was introduced with the aim of approximating (an aspect of) non-cognitive skills[8]. We also control both the role of the parents' interests in the child's education at age 11, and the role of a heterogeneous interest in the child's education at age 11 between parents. Family economic conditions have been approximated by

[7] Higher BSAG test score corresponds to higher social maladjustment, hence poorer non-cognitive skills (Engel, 1959; Stott, 1969).

[8] Cognitive and non-cognitive test scores have been introduced in a standardised form (i.e. measures have mean zero and variance one), in the econometric analysis proposed below. Further details on the standardised cognitive and non-cognitive measures are available upon request.

dummy variables, controlling for the existence of financial trouble in the family at age 15 and the family's social class at age 16. Regional dummy variables have been introduced to control for territorial heterogeneity in educational choices. Finally, we introduce a dummy variable indicating if the parents wished that their child would end her education at the minimum age (compulsory education). This dummy, which is likely to affect educational choices but not employment status, has been used for identification issues and, therefore, it is excluded from the employment-status equation in the second-stage of the econometric analysis.

The same covariates, except the latter one, have also been used to control for observable heterogeneity in the employment equation. Moreover, other standard controls have been added: a dummy variable for marriage status; a dummy variable interacting "being married" with the partner's employment status; the number of children aged 0-15 living in the household; suffering from chronic illness or disability; working experiences up to 2000 (introduced in a non-linear way) cumulated since 1974 and expressed in months.

The dummy on marital status has been used for identification issues. Then, the wage equations have been specified introducing the same controls, except marital status, and adding wage-specific dummy variables. They include: firm size (five dummy variables), public sector, union membership and temporary/atypical contracts. Finally, both in the employment and wage equations, regional dummy variables, indicating where the cohort-member lives at the age of 51, have been introduced to control for territorial heterogeneity. Descriptive statistics have been reported in Table A1.

Education, employment and wages among females NCDS cohort members

In the following section, we briefly provide preliminary evidence on the association among education, employment and wages, pointing out of the impact that cognitive and non-cognitive skills developed during childhood have on those outcomes.

Table 1. Employment and occupational status by education

Employment = 1			Full-time = 1		
	Mean	Std Err.		Mean	Std Err.
Highly- educated	0.837	0.012	Highly-educated	0.623	0.021
Low-educated	0.782	0.015	Low-educated	0.633	0.016
Z-statistics	2.747		Z-statistics	-0.385	
Significance	***		Significance		

Source: our elaboration based on the NCDS dataset. *,**,***, indicates statistically significant levels, respectively to 10%, 5% and 1%.

Looking at Table 1, what emerges is that highly educated females show a statistically significant[9] higher employment rate when compared with low-educated females (83.7% versus 78.2%), while educational attainments seem to be irrelevant in determining full-

[9] Tests of proportions are carried out using the *prtest* command, while mean comparison tests are carried out using the *ttest* both of which are available in STATA.

time or part-time occupation (62.3% versus 63.3%)[10]. The observed values reported in Table 2 show that highly educated females earn higher wages (by about 6-8%) than low-educated females, no matter their occupational status.

Table 2. Observed (log) hourly wages by occupational status and education

	Part-Time		Full-Time	
	Low-educated	Highly-educated	Low-educated	Highly-educated
Mean	1.859	2.009	2.246	2.384
Std Dev.	0.326	0.369	0.497	0.429
T-statistics	13.632		10.696	
Significance	***		***	

Source: our elaboration based on the NCDS dataset. *,**,***, indicates statistically significant levels, respectively to 10%, 5% and 1%.

Looking at the role of pre-market variables, we focus on our three indicators of cognitive and non-cognitive skills: the math and the reading test scores at age 7, and the BSAG test score at age 11.

We provide a preliminary analysis of the association between cognitive and non-cognitive skills indicators and later outcomes (Tables 3, 4 and 5). With this in mind, the test scores have been collapsed into binary variables, where median values discriminate among females with good or bad cognitive and non-cognitive skills. Table 3 shows the existence of a strong association between cognitive and non-cognitive skills and high education. As seen, 46.2% of females above the median of the math test score distribution are highly-educated versus 25.2% of the females below that median. The gap is larger for the reading test score, 47.6% and 19.7%, respectively, while 44.2% of the females above the median of the BSAG test score distribution (socially adjusted) are highly-educated versus 25.0% of the females below that median (socially maladjusted).

Table 3. Cognitive and non-cognitive skills and educational attainments

		Mean	Std Err.
Math test score at age 7	Above the median	0.462	0.018
	Below the median	0.252	0.014
	Z-statistics	9.206	
	Significance	***	
Reading test score at age 7	Above the median	0.476	0.016
	Below the median	0.197	0.014
	Z-statistics	12.206	
	Significance	***	
BSAG test score at age 11	Above the median	0.250	0.015
	Below the median	0.442	0.017
	Z-statistics	-8.431	
	Significance	***	

Source: our elaboration based on the NCDS dataset. *,**,***, indicates statistically significant levels, respectively to 10%, 5% and 1%.

[10] It follows that being low-educated, when compared with being highly-educated, is associated with a higher incidence of non-working status (21.78% versus 16.28%), and a lower incidence both of part-time work (28.7% versus 31.58%) and full-time work (49.52% versus 52.14%).

Table 4. Employment and occupational status by cognitive and non-cognitive skills

	Employment = 1			Full-time = 1		
		Mean	Std Err.		Mean	Std Err.
Math test score at age 7	Above the median	0.824	0.014	Above the median	0.633	0.019
	Below the median	0.783	0.013	Below the median	0.626	0.018
	Z-statistics	2.142		Z-statistics	0.265	
	Significance	**		Significance		
Reading test score at age 7	Above the median	0.833	0.012	Above the median	0.645	0.017
	Below the median	0.765	0.015	Below the median	0.609	0.020
	Z-statistics	3.558		Z-statistics	1.372	
	Significance	***		Significance		
BSAG test score at age 11	Above the median	0.760	0.015	Above the median	0.641	0.019
	Below the median	0.842	0.012	Below the median	0.619	0.018
	Z-statistics	-4.298		Z-statistics	0.819	
	Significance	***		Significance		

Source: our elaboration based on the NCDS dataset. *,**,***, indicates statistically significant levels, respectively to 10%, 5% and 1%.

Table 4 focuses on the association between cognitive and non-cognitive skills and employment. We provide a two-step analysis where, first, we consider the association between cognitive and non-cognitive skills and employment, and second, where we consider the occupational status (full-time/part-time). What emerges is that while employment significantly differs according to the levels of cognitive and non-cognitive skills (by 4%-8%), being employed in a full-time or in a part-time job seems to be an independent outcome with respect to the distribution of cognitive and non-cognitive skills.

Finally, Table 5 reports the average (log) hourly wages by subgroups (education and occupational status) and the levels of cognitive and non-cognitive skills. No matter what subgroup is analysed, statistically significant differences emerge with regard to the distribution of the math test score. In particular, higher scores are associated with higher wages. Similarly, higher values in the reading test score distribution are associated with higher wages, but just for the low-educated females. Finally, the low-educated females and full-timers positioned above the median of the BSAG test score distribution earn less, in a statistically significant way, than their counterparts positioned below the median.

4. Results

In this section, we discuss the main results of the econometric analysis, through which we determine the estimates of the model described in Equations 1-3. Estimates have been carried out on two different years—1991 and 2009—to try to highlight whether a) selection into high/low levels of education plays a role in explaining employment outcomes at different times of life; b) selection into full/part-time work significantly affects the wage rates; and c) cognitive and non-cognitive characteristics have different effects on employment outcomes and wages throughout women’s lives. The two considered periods allow us to evaluate the professional achievement of the females when they are still in the childbearing age (in 1991 they were 33 years old) and when they are free from maternity obligations (in 2009 they were 51 years old). Estimation results for 2009 are shown in the text (Table 6); estimation results for 1991 are shown in the Appendix[11].

Table 5. (Log) hourly-wages by education, occupational status and cognitive/non-cognitive skills

			Low-educated		Highly-educated	
			Part-Time	Full-Time	Part-Time	Full-Time
Math test score at age 7	Above the median	Mean	1.904	2.052	2.295	2.432
		Std Dev.	0.330	0.395	0.526	0.432
	Below the median	Mean	1.832	1.981	2.174	2.312
		Std Dev.	0.322	0.349	0.444	0.415
	T-statistics		1.956	2.239	1.662	2.460
	Significance		**	**	*	**
Reading test score at age 7	Above the median	Mean	1.920	2.079	2.220	2.398
		Std Dev.	0.359	0.368	0.498	0.446
	Below the median	Mean	1.810	1.948	2.305	2.336
		Std Dev.	0.290	0.359	0.495	0.365
	T-statistics		3.066	4.281	-1.085	1.094
	Significance		***	***		
BSAG test score at age 11	Above the median	Mean	1.855	1.962	2.229	2.339
		Std Dev.	0.321	0.364	0.492	0.401
	Below the median	Mean	1.865	2.064	2.254	2.409
		Std Dev.	0.333	0.367	0.501	0.443
	T-statistics		-0.284	-3.323	-0.327	-1.392
	Significance			***		

Source: our elaboration based on the NCDS dataset. *,**,***, indicates statistically significant levels, respectively to 10%, 5% and 1%.

We briefly note that there are no substantial differences in the estimation results for education between the two years (1991 and 2009). Indeed, if the composition of the two samples were exactly the same, we would not detect any dissimilarity in the effect of covariates on educational outcomes. However, due to the higher sample attrition in 2009 than in 1991, some covariates show slightly different effects on the probability of achieving higher educational levels in those two years. We note that, in general, education is significantly affected by both cognitive skills observed in the first years of school—as measured by reading and math tests at age 7—and early non-cognitive skills, such as youth behavioural problems and weight issues at birth. In more detail, higher cognitive skills sharply increase the probability of achieving higher levels of education, especially if they relate to reading skills. On the other hand, as stronger

[11] For completeness, we must say the two samples are slightly different in their compositions.

behavioural disturbances occur during early adolescence, the probability of achieving higher educational levels decreases.[12] Weight at birth has positive effects on education achievement. Non-cognitive skills related to the parents' interest and wishes for the child's education are important for educational outcomes as are the family's social class. With some distinctions between the two years (on the extent of the effect and significance), the marked difference in educational achievement seems to be determined by the outstanding attitude of the parents. A "very high interest" in the child's education indicates a probability of achieving higher educational levels that is three-times higher than the effect induced by "some interest". Moreover, belonging to a family of high social class triples the likelihood of a high education outcome.

Table 6. Probit estimates of educational outcomes. Year 2009

	Coefficient	Robust S.E.		dy/dx
Birth weight	0.054	0.018	***	0.014
Birth weight square	0.000	0.000	***	0.000
Standardised reading test at age 7	0.222	0.056	***	0.058
Standardised math test at age 7	0.129	0.041	***	0.033
Standardised BSAG score at age 11	-0.198	0.059	***	-0.051
Standardised BSAG score at age 11 square	0.052	0.021	**	0.013
Statements about interest in child education	-0.026	0.144		-0.007
Interest: some	0.101	0.143		0.026
Interest: very	0.803	0.147	***	0.208
Interest: over	1.043	0.373	***	0.271
Interest in child education (prevalence father)	0.284	0.193		0.074
Interest in child education (prevalence mother)	0.345	0.099	***	0.089
High social class	0.589	0.117	***	0.153
Medium sociale class	0.206	0.108	*	0.053
Financial trouble at age 15	-0.114	0.166		-0.030
North	0.164	0.219		0.042
North-West	0.488	0.205	**	0.127
East-West Riding	0.326	0.219		0.084
North-Midlands	0.597	0.222	***	0.155
Midlands	0.431	0.209	**	0.112
East	0.140	0.213		0.036
South-East	0.418	0.200	**	0.108
South	0.413	0.228	*	0.107
South-West	0.234	0.218		0.061
Scotland	1.014	0.204	***	0.263
Wished minimum education at age 16	-1.184	0.111	***	-0.307
Constant	-4.638	1.060	***	
Wald chi2(26)		421.310		
Prob > chi2		0.000		
Pseudo R2		0.291		
Log-pseudolikelihood	-802.124			

[12] Indeed, the effect of the BSAG score on the probability of reaching higher levels of education is non-linear, with a trend initially negative and then positive. However, around 95% of our sample takes standardised BSAG scores in the decreasing part of the probability function.

We now turn to the discussion of the estimation results for the occupational-status equations, which were estimated separately for the two educational levels, as described in Section 2. In general, cognitive and non-cognitive skills observed at age 7 and in the early teens are not strongly significant in explaining occupational outcomes, both for highly-educated and low-educated women, in particular when the women are in their early thirties. However, the employment status of the highly-educated women is affected by some cognitive skills, mathematical ones in particular (which, on the contrary, do not affect the educational choice), while the employment status of the low-educated women is influenced by non-cognitive skills (behavioural disturbances synthesised by the BSAG score at age 11). The math test score is significant in explaining the employment outcomes of the highly-educated women in both years, but its effect changes over time. Surprisingly, in the long-run (when the women are 51), the math score negatively affects the probability of being employed full-time and positively affects the probability to be either unemployed/inactive or employed part-time. For low-educated women, the effect of behavioural disturbances is significant in the long-run, with negative consequences on the probability of working full-time (and, conversely, this increases in the probability of working part-time and unemployment/inactivity).

In explaining the employment status, the most significant variables especially in the long-run, are those related to marital status, family composition, work experience and having chronic diseases. As for family characteristics, the differences between highly-educated and low-educated women mainly occur when they are younger. When the women are 33 years old, the low-educated are strongly constrained by being married, having children under the age of 16, or suffering from chronic diseases. Their family duties negatively affect their labour market participation and their likelihood of working full-time. In contrast, the highly-educated women are seriously affected only by the number of children they have. Past work experience plays a significant role at any age and educational level: in all cases, a longer work experience provides a higher probability of being employed full-time and a lower probability of working part-time or not working at all. Work experience assumes a particularly significant role for low-educated women when they are older.

We now shift our focus to a discussion of the estimated coefficient for the inverse Mill's ratio included in the employment-status equation of both highly-educated and low-educated women. A statistically significant coefficient for the inverse Mill's ratio in the employment equation (highly-educated or low-educated) implies that, for the considered educational level, the error terms in the education equation are correlated with the error terms in the employment equation. This means that there are unobservable characteristics that significantly affect both outcomes and that, if the inverse Mill's ratio is not included, the estimation results would be biased. Looking at our estimates, we do not find any significant correlation for the younger subsamples, but we do find a significant effect for highly-educated women in 2009. In this case, the inverse Mill's ratio has a positive effect on the probability of the women either "not working" or working part-time and a negative effect on the probability of the women working full-time. As previously discussed in the Introduction and in Section 2, we were expecting a significant effect of the inverse Mill's ratio in the case of highly-educated women. However, our theoretical reasoning supported the idea of a positive effect on the probability of working full-time and a negative effect on the probability of either working part-time or "not working". The reason why we obtained an opposite result could be found in our model specification. Indeed, our equations include a vast set of variables, ranging from cognitive and non-cognitive skills when young, to family social class, parents' interests and wishes about their children's education, etc. Then, not much is left to be captured by the error terms, with the exception of macroeconomic shocks (demand or supply shocks) and institutional aspects. Then, the inverse Mill's ratio in the employment-status equation of highly-educated women in 2009 might be capturing the effect of the negative shock due to the financial and economic crisis. Indeed, as recently shown by the official UK unemployment figures, older British female workers have been particularly affected by the ongoing crisis, and job losses have been especially high in the public sector where women disproportionately work. Since in our 2009 sample public sector employment covers 63% of the highly-educated workers and 43% of the low-educated workers, the economic crisis could be an explanation for a significant inverse Mill's ratio that increases the probability of "no work" and part-time work while decreasing the probability of full-time work for highly-educated women over 50.

As regards the estimation results for the wage equations, Table 8 for the year 2009 and Table A4 for the year 1991 report the coefficients, the robust standard errors and corrected standard errors and t-statistics when applying the procedure to correct the variance-covariance matrix (Greene, 1981; Main and Reilly, 1993). The tables show the results for the full-time subsample.

Our estimates generally confirm the results of the literature on the determinants of the hourly wages of full-time workers. Working experience, firm size, the sector of work, trade union membership and the type of contract, all play a significant role in determining the wage rate. However, some distinctions need to be made between highly-educated females and low-educated females. Working experience significantly and positively affects hourly wages only in the case of low-educated workers and its impact is particularly high and significant when low-educated workers grow older. No effect is detected for experience when observing highly-educated workers, at any point in time. In a way, working experience seems to compensate the low-educated workers for their lack of formal education, at least in terms of wages. With regards to firm and sector characteristics, as well as the type of contract and trade union membership, the results highlight a certain weakness of the low--educated workers. In particular, the low-educated workers are penalised in terms of wages when working in larger companies, especially when the workers are over 50. Moreover, when older, the workers receive wage benefits from being members of trade unions, something that does not happen for the highly-educated. Highly-educated females, on the other hand, suffer severe wage cuts if employed with temporary and atypical contracts. The wage penalty amounted to 25% of the wage rate in 1991 and increases to almost 31% with age. The low-educated females experience lower wage cuts, and only when they are older. The public sector provides higher wages than the private sector; the public sector wage premium is around 10% for low-educated women in both years (1991 and 2009) and 14% for highly-educated women, when they are at least 51 years old.

Table 7. Ordered probit estimates of employment-status. Year 2009*

	Highly-educated						Low-educated					
	Coef.	S.E.		dy/dx			Coef.	S.E.		dy/dx		
				NW	PT	FT				NW	PT	FT
Birth weight	0.006	0.036		-0.001	-0.001	0.002	-0.005	0.017		0.001	0.000	-0.002
Birth weight square	0.000	0.000		0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
Standardised reading test at age 7	0.147	0.116		-0.030	-0.019	0.049	0.016	0.041		-0.004	-0.002	0.005
Standardised math test at age 7	-0.144	0.065	**	0.029	0.019	-0.048	0.015	0.043		-0.004	-0.001	0.005
Standardised BSAG score at age 11	0.040	0.098		-0.008	-0.005	0.013	-0.120	0.059	**	0.029	0.012	-0.041
Standardised BSAG score at age 11 square	0.037	0.082		-0.008	-0.005	0.012	0.020	0.023		-0.005	-0.002	0.007
Statements about interest in child education at age 16	-0.484	0.282	*	0.099	0.063	-0.162	0.075	0.109		-0.018	-0.008	0.026
Interest: some	-0.035	0.266		0.007	0.004	-0.012	0.037	0.114		-0.009	-0.004	0.013
Interest: very	-0.077	0.283		0.016	0.010	-0.026	-0.013	0.152		0.003	0.001	-0.004
Interest: over	0.283	0.517		-0.058	-0.037	0.094	-0.395	0.536		0.094	0.040	-0.134
Interest in child education at age 16 (preval. father)	0.211	0.285		-0.043	-0.027	0.071	0.113	0.217		-0.027	-0.011	0.038
Interest in child education at age 16 (preval. mother)	-0.377	0.156	**	0.077	0.049	-0.126	0.060	0.093		-0.014	-0.006	0.020
Financial trouble at age 15	0.441	0.309		-0.090	-0.057	0.147	-0.207	0.129		0.050	0.021	-0.071
High social class	-0.130	0.233		0.026	0.017	-0.043	0.077	0.132		-0.018	-0.008	0.026
Medium sociale class	0.129	0.215		-0.026	-0.017	0.043	-0.013	0.087		0.003	0.001	-0.004
Married	-0.725	0.193	***	0.148	0.094	-0.242	-0.559	0.133	***	0.134	0.057	-0.190
Married*Partner employed	0.250	0.180		-0.051	-0.032	0.083	0.288	0.124	**	-0.069	-0.029	0.098
Children aged 0-15	-0.281	0.088	***	0.057	0.037	-0.094	-0.389	0.082	***	0.093	0.039	-0.133
Chronic illness/disability	-0.770	0.133	***	0.157	0.100	-0.257	-0.701	0.087	***	0.168	0.071	-0.239
Working experience up to 2000	0.006	0.004	*	-0.001	-0.001	0.002	0.010	0.002	***	-0.002	-0.001	0.003
Working experience up to 2000 square	0.000	0.000		0.000	0.000	0.000	0.000	0.000	**	0.000	0.000	0.000
Inverse Mill's Ratio	-0.592	0.244	**	0.121	0.077	-0.198	-0.051	0.163		0.012	0.005	-0.017
Cut 1	-1.059	2.302					0.159	0.974				
Cut 2	0.043	2.307					1.110	0.974				
LR chi2(31) [Prob>chi2]	156.34 [0.000]						292.290 [0.000]					
Pseudo R2	0.129						0.123					
Log-likelihood	-529.29						-1040.59					

* BHHH technique for asymptotic var-cov matrix. NW: No work; PT: tart-time work; FT: full-time work. Estimates include regional dummies.

Table 8. OLS estimates of log hourly wages. Year 2009*

	Highly-educated					Low-educated				
	Coef.	Robust S.E.	Corr. S.E.		Corr. T-stat	Coef.	Robust S.E.	Corr. S.E.		Corr. T-stat
Birth weight	0.008	0.014	0.015		0.538	0.006	0.006	0.005		1.197
Birth weight square	0.000	0.000	0.000		-0.347	0.000	0.000	0.000		-1.128
Standardised reading test at age 7	-0.013	0.059	0.062		-0.207	0.036	0.016	0.012	***	3.047
Standardised math test at age 7	0.081	0.028	0.029	***	2.762	0.033	0.018	0.013	***	2.538
Standardised BSAG score at age 11	-0.006	0.040	0.042		-0.144	-0.032	0.027	0.019	***	-1.693
Standardised BSAG score at age 11 square	-0.006	0.009	0.015		-0.416	0.010	0.010	0.007		1.494
Statements about interest in child education at age 16	-0.061	0.107	0.127		-0.480	0.008	0.044	0.033		0.254
Interest: some	0.166	0.110	0.127		1.306	0.036	0.045	0.034		1.046
Interest: very	0.152	0.105	0.127		1.198	0.033	0.053	0.040		0.833
Interest: over	0.141	0.175	0.192		0.734	0.168	0.078	0.148		1.142
Interest in child education at age 16 (preval. father)	0.103	0.096	0.116		0.887	0.010	0.085	0.065		0.153
Interest in child education at age 16 (preval. mother)	0.065	0.065	0.072		0.903	-0.005	0.036	0.028		-0.165
Financial trouble at age 15	0.015	0.133	0.124		0.123	-0.065	0.057	0.040	*	-1.651
High social class	0.149	0.089	0.091	*	1.631	0.088	0.050	0.038	***	2.332
Medium sociale class	0.147	0.085	0.090	*	1.633	-0.048	0.037	0.027		-1.780
Children aged 0-15	0.073	0.050	0.053		1.380	-0.026	0.066	0.035		-0.746
Chronic illness/disability	0.001	0.113	0.100		0.009	-0.201	0.090	0.053	***	-3.758
Working experience up to 2000	0.001	0.003	0.002		0.643	0.003	0.002	0.001	***	3.631
Working experience up to 2000 square	0.000	0.000	0.000		-0.694	0.000	0.000	0.000	**	-1.994
Firm size 11-25	0.043	0.108	0.096		0.453	0.112	0.049	0.028	***	3.936
Firm size 26-99	0.198	0.092	0.088	***	2.236	0.068	0.045	0.026	***	2.619
Firm size 100-499	0.133	0.097	0.091		1.454	0.053	0.050	0.029	*	1.852
Firm size 500+	0.218	0.093	0.090	***	2.422	0.095	0.048	0.030	***	3.175
Public sector	0.140	0.054	0.054	***	2.566	0.086	0.034	0.018	***	4.683
Union membership	0.060	0.050	0.051		1.174	0.078	0.036	0.021	***	3.712
Temporary/atypical contracts	-0.308	0.079	0.144	***	-2.140	-0.146	0.081	0.060	***	-2.434
Inverse Mill’s Ratio	-0.094	0.112	0.117		-0.810	0.201	0.172	0.103		1.958
Constant	1.174	0.970	1.097		1.070	0.771	0.409	0.479	*	1.612
Observations		317					566			
F-test [Prob > F]		3.69 [0.000]					17.90 [0.000]			
R-squared		0.207					0.206			

*Estimates include regional dummies.

Our estimations add some new results to the existing literature on wage functions. In particular, they highlight the wage effect of cognitive and non-cognitive skills at a young age. The reading and math test scores at age 7 have positive wage effects that last, in some cases, over time. On the other hand, behavioural disturbances, measured by the BSAG score at age 11, cause more significantly higher wage penalties for highly-educated workers than low-educated workers. The social class of the family of origin, finally, seems to play a lasting role in the economic realisation of women with any educational level.

We conclude this section with a few remarks relating to the estimation results for the inverse Mill's ratio that captures the eventual correlation between the error terms of employment-status and wage equations for full-time employees. The ratio is not always statistically significant in the different subsamples, which makes us think that the inclusion in the model of school cognitive measures and pre-market non-cognitive skills may have reduced the role played by the correlation between error terms. However, we find some significant selection bias for highly-educated women in 1991 and for low-educated women in 2009. In the first case the selection bias is negative. In the second case it is positive.

5. Conclusions

In this paper, we propose an empirical model of female educational choices, employment outcomes and wages. Our approach is new compared to the existing literature that studies female participation in the labour market, wages and gender wage gaps. In most of this literature, education is conceived as only an explicative variable for both occupational outcomes and wage rates, and only selection into employment is deemed to be relevant for wage levels. Moreover, the study integrates the issue of gender differences in labour market participation and wages into the social mobility literature. In particular, we contribute to a deeper analysis of the issue of female labour market participation and achievement, taking into account the relationship between pre-market abilities, investment in education and employment outcomes.

The econometric model involves, first, the estimation of a probability equation for the educational levels. In the second stage, we employ the estimated probabilities, for high and low education levels, to derive the respective inverse Mill's ratios to be included as covariates in the occupational equations conditioned on each level of education. We classify the occupational status into no work, part-time and full-time work. Wage equations are then estimated separately for the subsamples of part-timers and full-timers, and the inverse Mill's ratio relative to the considered subsample is included in each wage equation.

The analysis is conducted based on data from the British National Child Development Study (NCDS), a cohort study that follows all UK births occurred during the week of 3–9 March 1958.

Our first results show that there exists some significant selection bias into employment for highly-educated women. On the contrary, we do not find any evidence of correlation between low educational attainment and employment outcomes. As for the effect of the selection bias in the wage equation of full-time workers, we find different results for highly-educated and low-educated women. In the first case the selection bias is negative when women are younger. In the second case the selection bias is positive when women are 51.

Education is significantly affected by both cognitive skills observed in the first years of school and early non-cognitive skills, such as youth behavioural problems and weight issues at birth. On the contrary, cognitive and non-cognitive skills observed at age 7 and in the early teens are not strongly significant in explaining occupational outcomes, both for highly-educated and low-educated women, in particular when the women are in their early thirties. However, cognitive and non-cognitive skills do affect wages.

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Appendix

Table A1. Descriptive statistics

	Highly-educated				Low-educated			
	Full-time		Part-time		Full-time		Part-time	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Birth weight (in ounce)	117.139	16.128	116.281	15.857	115.201	17.994	114.527	18.265
Math test score at age 7	6.088	2.253	6.214	2.316	4.928	2.346	4.835	2.373
Reading test score at age 7	28.148	2.787	27.115	4.352	24.574	6.172	24.351	6.352
BSAG test score at age11	4.101	5.954	3.688	5.380	6.657	7.512	6.698	7.727
No say about interest in child education at age 11	0.221	0.415	0.198	0.399	0.309	0.463	0.305	0.461
Little interest in child education at age 11	0.047	0.213	0.047	0.212	0.164	0.371	0.174	0.379
Some interest in child education at age 11	0.170	0.377	0.167	0.374	0.307	0.462	0.335	0.473
Very interested in child education at age 11	0.530	0.500	0.589	0.493	0.216	0.412	0.177	0.382
Over concerned in child education at age 11	0.032	0.175	0.000	0.000	0.004	0.059	0.009	0.095
Interest in child education at age 11 (prevalence father)	0.054	0.226	0.026	0.160	0.035	0.185	0.061	0.240
Interest in child education at age 11 (father = mother)	0.697	0.460	0.724	0.448	0.640	0.481	0.652	0.477
Interest in child education at age 11 (prevalence mother)	0.249	0.433	0.250	0.434	0.325	0.469	0.287	0.453
Financial trouble at age 15	0.047	0.213	0.005	0.072	0.071	0.257	0.067	0.251
High social class at age 16	0.413	0.493	0.464	0.500	0.187	0.390	0.186	0.390
Medium social class at age 16	0.495	0.501	0.422	0.495	0.581	0.494	0.570	0.496
Low social class at age16	0.091	0.289	0.115	0.319	0.231	0.422	0.244	0.430
North at age 16	0.069	0.255	0.052	0.223	0.080	0.271	0.085	0.280
North-West at age 16	0.110	0.314	0.130	0.337	0.141	0.349	0.104	0.305
East-West Riding at age 16	0.085	0.280	0.047	0.212	0.072	0.259	0.095	0.293
North-Midlands at age 16	0.073	0.260	0.068	0.252	0.067	0.250	0.091	0.289
Midlands at age 16	0.107	0.310	0.078	0.269	0.115	0.319	0.104	0.305
East at age 16	0.073	0.260	0.089	0.285	0.090	0.287	0.122	0.328
South-East at age 16	0.158	0.365	0.182	0.387	0.136	0.343	0.128	0.335
South at age 16	0.044	0.206	0.094	0.292	0.069	0.254	0.061	0.240
South-West at age 16	0.050	0.219	0.083	0.277	0.092	0.289	0.064	0.245
Wales at age 16	0.022	0.147	0.052	0.223	0.048	0.213	0.061	0.240
Scotland at age 16	0.208	0.407	0.125	0.332	0.090	0.287	0.085	0.280
Wished minimum education at age 16	0.038	0.191	0.031	0.174	0.392	0.489	0.402	0.491
Married	0.612	0.488	0.859	0.349	0.636	0.482	0.808	0.395
Married*Partner employed	0.552	0.498	0.807	0.395	0.571	0.495	0.732	0.444
Children aged 0-15	0.218	0.522	0.484	0.655	0.090	0.338	0.265	0.553
Chronic illness/disability	0.114	0.318	0.073	0.261	0.129	0.335	0.137	0.345
Working experiences up to 2000	247.013	53.845	216.625	64.874	252.555	62.015	237.119	67.209
Firm size 1-10	0.104	0.306	0.182	0.387	0.173	0.379	0.226	0.419
Firm size 11-25	0.161	0.368	0.214	0.411	0.170	0.376	0.247	0.432
Firm size 26-99	0.262	0.440	0.240	0.428	0.265	0.442	0.229	0.421
Firm size 100-499	0.227	0.420	0.229	0.421	0.201	0.401	0.204	0.404

Firm size 500 or more	0.246	0.431	0.135	0.343	0.191	0.393	0.095	0.293
Public sector	0.653	0.477	0.599	0.491	0.468	0.499	0.369	0.483
Unione membership	0.407	0.492	0.271	0.446	0.249	0.433	0.137	0.345
Temporary/atypical contract	0.028	0.166	0.073	0.261	0.019	0.138	0.040	0.195
North	0.060	0.238	0.026	0.160	0.083	0.276	0.067	0.251
Yorkshire	0.104	0.306	0.063	0.243	0.080	0.271	0.101	0.301
East-Midlands	0.060	0.238	0.047	0.212	0.072	0.259	0.079	0.271
East-Anglia	0.019	0.136	0.047	0.212	0.042	0.202	0.043	0.202
South-East	0.243	0.430	0.344	0.476	0.247	0.432	0.259	0.439
South-West	0.088	0.284	0.130	0.337	0.106	0.308	0.104	0.305
West-Midlands	0.091	0.289	0.073	0.261	0.113	0.317	0.110	0.313
Nort-West	0.101	0.302	0.104	0.306	0.117	0.321	0.098	0.297
Wales	0.035	0.183	0.042	0.200	0.058	0.235	0.061	0.240
Scotland	0.199	0.400	0.125	0.332	0.081	0.273	0.079	0.271

Source: our elaborations based on the NCDS dataset.

Table A2. Probit estimates of educational outcomes. Year 1991

	Coefficient	Robust S.E.		dy/dx
Birth weight	0.051	0.017	***	0.013
Birth weight square	0.000	0.000	***	0.000
Standardised reading test at age 7	0.284	0.056	***	0.072
Standardised math test at age 7	0.157	0.037	***	0.040
Standardised BSAG score ate age 11	-0.208	0.052	***	-0.053
Standardised BSAG score at age 11 square	0.060	0.019	***	0.015
Statements about interest in child education	-0.024	0.126		-0.006
Interest: some	0.188	0.124		0.047
Interest: very	0.669	0.129	***	0.169
Interest: over	0.264	0.304		0.067
Interest in child education (prevalence father)	0.327	0.170	*	0.083
Interest in child education (prevalencel mother)	0.284	0.087	***	0.072
High social class	0.619	0.104	***	0.157
Medium sociale class	0.189	0.095	**	0.048
Financial trouble at age 15	-0.153	0.149		-0.039
North	-0.130	0.192		-0.033
North-West	0.217	0.176		0.055
East-West Riding	0.089	0.190		0.022
North-Midlands	0.138	0.192		0.035
Midlands	0.154	0.181		0.039
East	-0.060	0.185		-0.015
South-East	0.090	0.173		0.023
South	0.152	0.195		0.039
South-West	-0.015	0.190		-0.004
Scotland	0.767	0.178	***	0.194
Wished minimum education at age 16	-1.186	0.099	***	-0.300
Constant	-4.320	1.017	***	-
Observations		2286		
Wald chi2(26)		506.38		
Prob > chi2		0.000		
Pseudo R2		0.295		
Log-pseudolikelihood		-1019.73		

Table A3. Ordered probit estimates of employment-status. Year 1991*

	Highly-educated						Low-educated					
	Coef.	S.E.		dy/dx			Coef.	S.E.		dy/dx		
				NW	PT	FT				NW	PT	FT
Birth weight	0.026	0.031		-0.007	0.000	0.007	-0.013	0.013		0.004	-0.001	-0.003
Birth weight square	0.000	0.000		0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
Standardised reading test at age 7	-0.019	0.113		0.005	0.000	-0.005	0.041	0.038		-0.013	0.002	0.011
Standardised math test at age 7	0.125	0.064	*	-0.032	-0.001	0.033	0.023	0.039		-0.007	0.001	0.006
Standardised BSAG score ate age 11	-0.131	0.095		0.034	0.001	-0.035	-0.009	0.051		0.003	-0.001	-0.002
Standardised BSAG score at age 11 square	-0.009	0.070		0.002	0.000	-0.002	0.014	0.020		-0.004	0.000	0.004
Statements about interest in child education at age 16	0.490	0.298	*	-0.126	-0.004	0.129	0.016	0.093		-0.005	0.001	0.004
Interest: some	-0.354	0.297		0.091	0.003	-0.093	0.026	0.099		-0.008	0.001	0.007
Interest: very	-0.228	0.322		0.059	0.002	-0.060	-0.038	0.131		0.012	-0.002	-0.010
Interest: over	-0.687	0.560		0.176	0.005	-0.181	-0.402	0.361		0.124	-0.014	-0.110
Interest in child education at age 16 (preval. father)	-0.195	0.277		0.050	0.001	-0.051	-0.349	0.170	**	0.108	-0.013	-0.095
Interest in child education at age 16 (preval. mother)	-0.103	0.146		0.026	0.001	-0.027	0.038	0.074		-0.012	0.002	0.010
Financial trouble at age 15	0.280	0.275		-0.072	-0.002	0.074	0.138	0.104		-0.043	0.005	0.038
High social class	-0.059	0.202		0.015	0.000	-0.016	0.101	0.113		-0.031	0.004	0.027
Medium sociale class	-0.048	0.177		0.012	0.000	-0.013	-0.037	0.076		0.011	-0.001	-0.010
Married	-0.107	0.246		0.027	0.001	-0.028	-0.452	0.148	**	0.139	-0.016	-0.123
Married*Partner employed	-0.163	0.224		0.042	0.001	-0.043	0.572	0.134	***	-0.177	0.021	0.156
Children aged 0-15	-1.566	0.138	***	0.402	0.012	-0.413	-1.273	0.086	***	0.393	-0.046	-0.347
Chronic illness/disability	0.012	0.156		-0.003	0.000	0.003	-0.186	0.084	**	0.057	-0.007	-0.051
Working experience up to 2000	0.011	0.005	**	-0.003	0.000	0.003	0.007	0.003	**	-0.002	0.000	0.002
Working experience up to 2000 square	0.000	0.000		0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
Inverse Mill's Ratio	0.081	0.232		-0.021	-0.001	0.021	0.106	0.148		-0.033	0.004	0.029
Cut 1	1.488	2.007					-1.048	0.804				
Cut 2	2.249	2.010					-0.078	0.802				
LR chi2(31) [Prob > chi2]	374.75 [0.000]						542.05 [0.000]					
Pseudo R2	0.239						0.161					
Log-likelihood	-596.01						-1408.21					

* BHHH technique for asymptotic var-cov matrix. NW: No work; PT: tart-time work; FT: full-time work. Estimates include regional dummies as in Table 6.

Table A4. OLS estimates of log hourly wages. Year 1991*

Camione 1991	Highly-educated					Low-educated				
	Coef.	Robust S.E.	Corr. S.E.		Corr. T-stat	Coef.	Robust S.E.	Corr. S.E.		Corr. T-stat
Birth weight	-0.001	0.012	0.011		-0.132	-0.002	0.006	0.006		-0.379
Birth weight square	0.000	0.000	0.000		0.249	0.000	0.000	0.000		0.524
Standardised reading test at age 7	0.099	0.044	0.037	***	2.639	0.061	0.017	0.017	***	3.623
Standardised math test at age 7	-0.004	0.021	0.021		-0.189	0.021	0.015	0.015		1.354
Standardised BSAG score ate age 11	-0.098	0.036	0.034	***	-2.882	-0.057	0.020	0.020	***	-2.816
Standardised BSAG score at age 11 square	0.031	0.025	0.027		1.150	0.014	0.008	0.009		1.494
Statements about interest in child education at age 16	-0.042	0.100	0.103		-0.404	-0.020	0.042	0.041		-0.478
Interest: some	0.044	0.104	0.098		0.447	-0.001	0.041	0.042		-0.021
Interest: very	0.179	0.112	0.101	*	1.770	0.090	0.050	0.047	**	1.924
Interest: over	0.100	0.183	0.184		0.542	-0.025	0.154	0.141		-0.179
Interest in child education at age 16 (preval. father)	0.091	0.076	0.102		0.893	0.006	0.070	0.104		0.053
Interest in child education at age 16 (preval. mother)	0.115	0.059	0.050	***	2.291	0.031	0.030	0.031		0.995
Financial trouble at age 15	-0.030	0.074	0.096		-0.315	-0.008	0.048	0.051		-0.159
High social class	0.043	0.055	0.066		0.646	0.057	0.046	0.043		1.316
Medium sociale class	0.044	0.054	0.064		0.692	0.025	0.030	0.032		0.787
Children aged 0-14	0.016	0.084	0.058		0.273	-0.133	0.146	0.143		-0.930
Chronic illness/disability	-0.046	0.045	0.058		-0.791	-0.003	0.047	0.045		-0.068
Working experience up to 1990	0.001	0.003	0.001		0.676	0.004	0.002	0.002	*	1.733
Working experience up to 1990 square	0.000	0.000	0.000		-1.458	0.000	0.000	0.000		-0.936
Firm size 11-25	0.227	0.089	0.052	***	4.353	0.164	0.047	0.046	***	3.537
Firm size 26-99	0.257	0.084	0.052	***	4.967	0.165	0.045	0.043	***	3.869
Firm size 100-499	0.273	0.089	0.057	***	4.797	0.147	0.045	0.043	***	3.437
Firm size 500+	0.314	0.086	0.052	***	6.087	0.176	0.050	0.046	***	3.851
Public sector	-0.008	0.041	0.033		-0.251	0.097	0.031	0.028	***	3.436
Union membership	0.019	0.034	0.031		0.616	0.016	0.034	0.030		0.524
Temporary/atypical contracts	-0.255	0.123	0.083	***	-3.069	0.068	0.042	0.053		1.278
IMR	-0.238	0.260	0.070	***	-3.393	0.095	0.145	0.142		0.670
Constant	1.263	0.738	1.168		1.082	0.636	0.418	0.455		1.397
Observations			352					488		
F-test [Prob > F]			2.77 [0.000]					6.63 [0.000]		
R-squared			0.238					0.297		

*Estimates include regional dummies.