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Female long-term labour market outcomes: the role of early-life abilities and education

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Abstract

We study how early-life cognitive skills, non-cognitive abilities and family characteristics influence educational choices and affect later employment outcomes and wages. The analysis was carried out on a cohort of UK females observed at different life stages and by adopting 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.

Our findings provide evidence of how early-life abilities and family characteristics affect both educational attainments and later labour market outcomes of female workers. On the other hand, we find that the educational levels interact with early-life abilities, productive characteristics in general and other characteristics, giving rise to different employment outcomes and income prospects conditioned on educational attainment. Occupational outcomes and wages of low-educated women are more sensitive to factors that are not strictly linked to productivity.

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

1. Introduction

In this article, we study how early-life cognitive and non-cognitive abilities influence educational choices and affect employment outcomes and wages both at the beginning of British females' working careers and later in their working lives.

The literature on the labour market effects of cognitive skills shows how the exclusion of some measures of cognitive skills from the wage equation implies an overestimation of the effect of education on earnings (Hanushek et al., 2015; Murnane et al., 2000, Bowles et al., 2001). The results on the US labour market show how cognitive skills have become more and more important in wage determination since the 1980s (Murnane et al., 1995). Hanushek and Woessmann (2008), using a macroeconomic approach, show the powerful relationship that exists between cognitive skills and individual earnings, income distribution and economic growth. Hanushek et al. (2015) highlight the role of early skills together with school attainment in determining wages not only for early-career workers but over a person's full lifecycle. Evidence on the UK is scarce. Vignoles et al. (2011) propose a study of the effect on wages of literacy and numeracy skills evaluated during childhood. They find that women and men with better numeracy skills earn similar wage premia in the labour market. The premium is slightly lower for women when considering numeracy skills. Unlike in the US, they do not find any evidence of an increasing effect over time. On the other hand, the literature agrees in recognizing the role of early cognitive abilities in the accumulation of human capital (Heckman and Rubinstein, 2001; Ermisch and Francesconi, 2001; Dustmann, 2004; Cunha and Heckman, 2009). These studies show how educational attainment rates are strictly related to the cognitive abilities measured during childhood.

Non-cognitive skills have been largely recognized as important in determining individual achievement. Heckman et al. (2006) show that both cognitive and non-cognitive abilities affect individuals' labour market outcomes and social behaviour and the impact is stronger for females. "Inequality among families in parenting and lack of support given to children in schools are major contributors to inequality in adult skills…Many children raised in disadvantaged environments start behind and stay behind." (Kautz et al., 2014). Cognitive tests capture only one of the many skills required for a successful life (Heckman and Rubinstein, 2001). Gregg and Machin (2000) show that economic and social disadvantages British individuals faced during childhood have a persistent association with subsequent economic success. Family characteristics associated with adverse economic and social child development play an important role in subsequent success or failure in the labour market. Gregg and Machin, using the longitudinal National Childhood Development Study (NCDS), were able to evaluate the persistence of negative effects of juvenile disadvantaged backgrounds even at age 33. Using the same database, Silles (2010) shows that childhood social maladjustment has detrimental effects on future cognitive development that are larger in magnitude relative to differences in early cognitive development. Studies on Australia confirm these results (Le et al., 2005).

Other contributions propose an interesting analysis of the link between family characteristics during childhood and educational choices/attainment. Ermisch and Francesconi (2001) show how British parents' educational attainments are very powerful predictors of their children's educational attainments. The role of parents' education and profession in educational choices is confirmed in Dustmann (2004), where secondary school track decisions of Germans are analysed. Dustmann finds that educational achievement and subsequent earnings are strongly associated, and wage careers of individuals tend to be highly related to their parents' background.

In this article, we try to contribute to the analysis of the effect of cognitive and non-cognitive skills and parental characteristics on female achievement by proposing a study of educational and working outcomes in relation to early mathematical and literature skills, early-age parental background and early social maladjustment. The literature usually analyses educational and employment outcomes separately and identify which initial endowments of skills and which family background have effects on one or the other. In this paper, we try to verify how education choices can affect subsequent employment outcomes and how early skills (cognitive and not cognitive) and family background interact with the level of education in determining career successes throughout life. That is, we first verify how the initial early family characteristics and skills affect the level of education achieved and then whether these factors affect the career and job success depending on the level of education.

In order to reach our goal, we employ a three-stage empirical model that allows us to detect different paths in school/work and to control for selection into education and into different occupational types (full-time and part-time). The model assumes that the decision of how many years to study is determinant for subsequent employment outcomes and wage levels. The model is sequential: individuals first choose the level of education and then, given the achieved qualification, they 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. We condition occupation outcomes and wage rates on the level of education: high, if the individual achieves an upper-secondary school diploma or more, or low, if the qualification is lower than an upper-secondary school diploma. Occupational outcomes and earnings are observed in two different periods of workers' life: when they are 33 and 51 years old.

Our approach is new compared to the existing literature that studies female labour market participation and earnings. 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. Our model instead considers how education can condition subsequent employment and earnings outcomes during working lives. In addition, we differentiate between types of occupations (full-time and part-time jobs) and evaluate employment outcomes and earnings conditioned on occupational type.

The analysis is carried out for the UK and is restricted to the female population. The UK is of 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[1]. As a result, women's increased education has proven to be a key factor in determining British female wages over time (Lindley and Machin, 2012). In addition, the UK has also a very high female labour market participation rate and the choice of part-time work is still frequent. Indeed, the UK labour market still appears rather segmented between full-timers and part-timers and by educational levels: hours-of-work segmentation is important in understanding women's relative economic status. 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; Vignoles et al., 2011).

The analysis is based on data from the British National Child Development Study (NCDS), a cohort study that follows all UK births that 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 database described in Section 3. Results of the estimations are 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 we observe their relative wages. 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

[1] If we observe the proportion of adults with tertiary education, the male to female gap is equal to nine percentage points in favour of females.

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 (first-stage equation). 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 (second-stage equations). 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 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.

The third stage of the sequential model consists of the estimation of wage equations for part-timers and full-timers, considered separately. In this case, we add the equations’ inverse Mill’s ratios relative to the probability of being, respectively, a part-timer or a full-timer.

The econometric analysis is carried out at two different points in time: the years 1991 and 2009. This means that we observe our sample of women, who were born in 1958, when they are 33 and 51 years old. This allows us to evaluate the effect of early cognitive and non-cognitive abilities over their working lives.

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

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

where $u_i \approx N\left[0, \sigma_Q^2\right]$ and X_i include the individual and family characteristics that we will discuss in the following section. The equation also includes an identification variable that we will exclude from the second-stage equation (the employment status equation).

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

We estimate Equation 1 using a probit procedure, adjusting for robustness. 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 (see details in the Appendix).

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 over a lifetime. 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 subsamples of the two educational levels. 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), or 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 $Z_{i,e}$:

$$E^*_{i,Q} = Z'_{i,Q}\gamma_Q + u_{i,Q} \qquad \text{for each } Q = LE, HE \qquad (2)$$

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^2_E. Parameters μ_{LE} and μ_{HE} are the theoretical unknown cut points. They are estimated together with coefficients γ_{LE} and γ_{HE}, respectively. $Z_{i,Q}$ includes 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 earnings 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, and 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^2_w.

$W^{'}_{i,Q,E}$ includes the inverse Mill's ratio for females belonging to each subsample, conditioned on occupational status E and educational level Q (see details in the Appendix).

We run OLS estimations of Equation 3. We correct standard errors 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 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 from the week of 3-9 March 1958. The main aim of the study was to improve the understanding of the factors that affect human development over an entire lifespan. The NCDS had its origin in the Perinatal Mortality Survey (PMS), which collected information on a cohort of approximately 17,000 children. Successively, the PMS became the NCDS, which 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 10,000 observations in the latest sweeps[2].

We use several sweeps of the NCDS database[3]. From the original 1958, 1965, 1969 and 1974 sweeps, we draw information about pre-market abilities, namely, cognitive and non-cognitive skills,

[2] The selection and the attrition bias problems in the NCDS data have been investigated in some papers. Hawkes and Plewis (2006) have found that the attrition and non-response issues can be associated with only a few significant predictors.

[3] 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.

as well as family background. From the same sweeps, we get information on social and economic factors evaluated during childhood that may affect individuals' choices about post-compulsory education (when 16-years-old). In our study, highly educated females are those females that hold a post-compulsory school qualification[4]. 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 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 were, respectively, 33 and 51 years old. According to the model discussed in Section 2, wage and employment outcomes are evaluated accounting, in turn, for selection into employment (both full-time and part-time) and selection into high educational levels.

The employment status is based on information about the cohort member's current economic status. We distinguish females engaged in full-time and part-time employment, as well as females in non-employment positions (including unemployment). We exclude from the analysis self-employed people; this implies a loss of 7-8% of observations.

The individual wage is measured as 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 worked per week (including overtime). To reduce bias from outliers, the obtained hourly wage has been subjected to top and bottom coding at 1%. 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.

One main advantage of the NCDS dataset is the availability of a wide spectrum of childhood variables, both at the personal level and the family 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 and earnings.

We model education choices, considering both the literature that stresses the role of cognitive and non-cognitive skills on child development and the literature that underlines the impact of family background and parental interest in a child's education. In this spirit, we include in the equation the following variables: birth weight (introduced in a non-linear way) to control for problems that derive from low birth weight; math and reading test scores at age 7 to approximate cognitive skills; and 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[5], which was introduced with the aim of approximating (an aspect of) non-cognitive skills. We also include a measure of parents' interests in the child's education at age 11 and heterogeneous interest between parents in the child's education at

[4] This information was gathered from the 1991 NCDS sweep and is recovered when individuals are 33 years old.
[5] A higher BSAG test score corresponds to higher social maladjustment, hence poorer non-cognitive skills (Stott, 1969).

age 11. Parents' interest in child education is measured by a dummy variable that assumes a value equal to one if the parents express any interest in child education. Then, we add three dummies that capture the interaction between having any interest in child education and the level of interest. The survey allows us to distinguish between some interest, very interested, and over interested, while little interest is the base-category. To capture the effect of interest divergence between parents, we add two different dummies that capture whether the highest interest in child education is expressed either by the father or the mother.

Family economic conditions have been approximated by 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 include a dummy variable that captures if parents wished their child to 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 is excluded from the employment-status equation in the second stage of the econometric analysis.

The same covariates, except the last one, have been included in the employment equations (years 1991 and 2009) to control for observable heterogeneity. 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, and working experiences up to 2000 (introduced in a non-linear way) cumulated since 1974 and expressed in months. Marital status has been used for identification issues.

Wage equations (years 1991 and 2009) have been specified, introducing the same controls from the employment equations (for years 1991 and 2009, respectively), except marital status, and adding wage-specific dummy variables for firm size (five dummy variables), public sector, union membership and temporary/atypical contracts. Both in the employment and wage equations, regional dummy variables have been introduced to control for territorial heterogeneity.

Descriptive statistics for all variables related to 2009 have been reported in Table A1[6].

4. Results

In this section, we discuss the main results of the econometric analysis modelled through Equations 1-3. The model allows us to evaluate how selection into education affects employment outcomes and wages. The first-stage equation relates to educational achievement—high versus low education. Conditioned on the educational level, we estimate the second-stage equation: an ordered probit model

[6] Descriptive statistics related to 1991 can be provided upon request.

that evaluates the probability of being employed—part-time or full-time—relative to not being employed. For women employed full-time, we proceed in estimating their earnings. The analysis is carried out at different times of women's working life: when women are 33- and 51-years-old (years 1991 and 2009, respectively). This allows us to evaluate the role of early-age cognitive and non-cognitive abilities and early family characteristics along working lives and, at the same time, to compare employment outcomes and wages between age-cohorts of the female life that are different with respect to childbearing issues. It is worth noting that the indicators of cognitive and non-cognitive abilities have been introduced in their standardized forms in the regression analysis. This would be helpful in the interpretation of their effects, as standardization allows us to evaluate them in terms of an aligned scale, even though the original variables range in different supports.

In Table 1, we list the results of the estimates of educational achievement. The dependent variable assumes a value of one when education is equal to or higher than a post-compulsory school qualification (upper-secondary school diploma). We ran the regression for both years, although educational achievement does not generally change across the working life. We did so because the two samples differ slightly due to a higher sample attrition in 2009 than in 1991. Despite this, the degree of significance of coefficients and marginal effects are very similar between the two years of observation. Among the covariates, we include dummies for the region of residence when females were 16 years old.

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 behavioural disturbances occur during early adolescence, the probability of achieving higher educational levels decreases. 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, approximately 95% of our sample takes standardized BSAG scores in the decreasing part of the probability function. Weight at birth has positive effects on educational achievement.

Parents' interest and wishes for the child's education are important for educational outcomes as well as family's social class. With some distinctions between the two years (on the extent of the effect and its significance), the marked difference in educational achievement seems to be determined by the outstanding attitude of parents. A "very high interest" in a child's education indicates a probability of achieving higher educational levels that is three times higher than the effect induced by "some interest". Estimates for year 2009 reinforce this result and show a significant effect for the highest level of parents' interest in child education. It is interesting to note that when the two parents' interest levels differ, the probability of achieving the highest educational levels increases if the highest interest in child education is expressed by the mother.

Covariates on family background show that belonging to a family of high social class triples the likelihood of a high education outcome.

[Table 1]

We now turn to the discussion of the estimation results for the occupational-status equations, which were estimated separately for the two educational levels, controlling for selection into each educational level (Table 2a-b). Cognitive and non-cognitive skills observed at age 7 and in the early teens are not strongly significant in explaining occupational outcomes of low-educated females, in particular when the women are in their early thirties. In contrast, cognitive skills, in particular mathematical ones, affect the employment status of highly educated women. The math test has a positive marginal effect on the probability of working full-time and a negative effect on the probability of part-time work or no work (unemployment/inactivity) when females are young (33 years old). However, the sign of the effect changes when females are 51 years old: at this age, the higher the math test score the lower the probability of working full-time and the higher the probability of part-time work or no work.

The employment status of low-educated women is influenced by behavioural disturbances detected at age 11. The effect of behavioural disturbances is significant in the long run, with negative consequences on the probability of working full-time and conversely, an increase in the probability of working part-time and being unemployed/inactive.

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. 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 in explaining employment status at any age and educational level: in all cases, more 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 the discussion of the estimated coefficient for the inverse Mill's ratio included in the employment-status equations of highly educated and low-educated women separately considered. 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 were 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 when 51 years old (in year 2009). In this case, the inverse Mill's ratio has a positive effect on the probability of "not working" or working part-time and a negative effect on the probability of working full-time. This result is in some way surprising since we were expecting, in the case of highly educated women, a positive effect of the inverse Mill's ratio on the probability of working full-time and a negative effect on the probability of either working part-time or "not working". However, this can be explained in relation to the period we analyse and our sample age cohort. Indeed, our model specification is rather comprehensive; 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 children's education, work experience, marital status and others. 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. As recently shown by the official UK unemployment figures, adult 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.

[Table 2a]

[Table 2b]

In Table 3, we report the results of wage regressions only for females working full-time, for both year 1991 and year 2009[7]. We applied the procedure of Greene (1981) and Main and Reilly (1993) to correct the variance-covariance matrix and to obtain correct standard errors and t-statistics (see Section 2). Wage equations have been estimated for full-timers and part-timers separately considered, and selection into the two occupational types has been considered. Then, the results include the inverse Mill's ratio.

The results suggest that wage functions are rather different across years and between educational levels. The first important difference is related to the effect of selection into full-time work. Selection is significant in the equation for highly educated women when younger. In the other cases, selection into full-time work does not affect wages. This seems to suggest that a high level of education let young women with weak productive characteristics be employed in full-time jobs.

When women are 33 years old (year 1991), the productive and job characteristics that affect wages in the two subsamples are similar, but their effects are higher in absolute terms in the case of highly educated women. Regarding early abilities, we see that the wages of the low-educated and highly educated are both significantly affected by reading abilities, social maladjustment and a very high interest of parents in their children's education. However, the effect is greater for highly educated females. Having a higher reading test score increases wages: one standard increase in the standardized reading test score increases wages by almost 10% in the case of the highly educated and by approximately 6% if women are low-educated. Wages of highly educated females are also more sensitive to problems of maladjustment raised at a young age. A higher social maladjustment score penalizes wages of the highly educated. One standard increase in the standardized BSAG score decreases wages by 9.8%. The effect is almost halved if women are low-educated. The effect of the parents' interest in child education is also higher in the case of highly educated females. In particular, the effect on wages of a very high interest of parents is double for the highly educated than for the low-educated. Moreover, we detect a significant difference with respect to parents' divergence in interest in child education. We find that a mother's overriding interest in child education positively affects wages only in the case of highly educated females.

Moving to other productive and job characteristics, always for year 1991, we find that working experience does not affect wages of highly educated females, but it has some effect on the low-educated. In a way, working experience seems to compensate the low-educated workers for their lack of formal education, at least in terms of wages. Highly educated females, on the other hand, suffer severe wage cuts if employed with temporary and atypical contracts. The wage penalty amounts to

[7] We ran regressions also for part-timers, according to the model discussed in Section 3. Results can be provided upon request.

25% of the wage rate. The public sector provides higher wages than the private sector to low-educated females (10% increase). Firm-size dummies are significant in both samples and show how wages increase as females work in bigger firms. However, the effect is more pronounced if women are more educated.

When females are 51-years-old, factors that affect wages are much more related to educational levels. Early cognitive abilities still have a significant effect on wages of both highly and low-educated women (although the effect is slightly lower than when younger). However, only in the case of low-educated workers do both the reading and the math test scores positively affect wages. This occurs even in relation to the maladjustment measure, which affects wages only if women are less educated. Earnings in adulthood are significantly affected also by the economic and social condition of the family of origin. Poorly educated women suffer a wage penalty of 6.5% if their families of origin experienced financial trouble when they were young. In contrast, they earn 8.8% more if their families belonged to the high social class. The highly educated earn higher wage advantages if their families of origin were medium or high social class.

For low-educated women when 51, chronic diseases were responsible for a wage penalty of 20%, while a one-year increase in average work experience guarantees a 3% increase in wages. Low-educated women receive wage benefits from being members of trade unions, something that does not occur for the highly educated. Highly educated females suffer severe wage cuts if employed with temporary and atypical contracts. The wage penalty—amounting to 25% of the wage rate in 1991—increases to almost 31% in 2009. The temporary/atypical contract penalty is 14.6% in the case of low-educated women. Being employed in the public sector allows women to advance economically with age, independent of their educational level. The public-sector gain is higher for the highly educated (14%) than for the low-educated (8.6%).

[Table 3]

Summing up, our results show that different levels of education are responsible for different employment outcomes and income prospects. Early-life abilities, productive characteristics in general and job characteristics give rise to different employment outcomes and income prospects conditioned on educational attainment. Early-life abilities are more relevant for the employment careers and economic prospects of low-educated women than of highly educated women. Moreover, occupational outcomes and wages of low-educated women are more sensitive to other factors, such as working experience, type of contract, chronic illness, and family constraints.

5. Conclusions

In this article, we study how early-life cognitive and non-cognitive abilities influence educational choices and affect employment outcomes and wages both at the beginning of individuals' working careers and later in their working lives. The model we propose allows us to evaluate how early-life cognitive and non-cognitive abilities affect education and, subsequently, determine different working paths and earnings outcomes conditioned on the educational level achieved. This is new compared to previous literature and allows us to evaluate the constraints that the low-educated face in the labour market compared to the highly educated. The study is carried out on a cohort of UK females observed at different life stages.

An interesting result we obtain, which supports some recent evidence on the role of early-life abilities, is that cognitive and non-cognitive abilities during childhood significantly affect not only educational attainment but also employment, type of employment (part-time versus full-time) and earnings during life. Concerning cognitive abilities, we find that reading skills are particularly important in determining educational attainment, while mathematical skills are more relevant for employment outcomes and for economic realization in the long run. Non-cognitive abilities are more relevant for employment outcomes of middle-aged females with low educational levels, and for the wage levels of women in their early thirties.

Our results predict that early-life abilities do interact with educational attainment and give rise to different employment outcomes and income prospects. In general, we find that productive and job characteristics affect employment outcomes and earnings in a different way depending on the educational level achieved. Early-life abilities are more relevant for the employment careers and economic prospects of low-educated women than of highly educated women. Moreover, occupational outcomes and wages of low-educated women are more sensitive to other factors, such as working experience, type of contract, chronic illness and family constraints. This somehow highlights the role of education as a skill signaling mechanism for women. This signaling mechanism manages to stem the influence on wages of factors not directly linked to productivity.

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Table 1. Probit estimates of educational outcomes. Highly educated versus low-educated

	1991			2009		
	Coeff.		Marginal effect	Coeff.		Marginal effect
Birth weight	0.051	***	0.013	0.054	***	0.014
Birth weight square	0.000	***	0.000	0.000	***	0.000
Standardized reading test at age 7	0.284	***	0.072	0.222	***	0.058
Standardized math test at age 7	0.157	***	0.040	0.129	***	0.033
Standardized BSAG score at age 11	-0.208	***	-0.053	-0.198	***	-0.051
Standardized BSAG score at age 11 square	0.060	***	0.015	0.052	**	0.013
Statements about interest in child education	-0.024		-0.006	-0.026		-0.007
Interest: some	0.188		0.047	0.101		0.026
Interest: very	0.669	***	0.169	0.803	***	0.208
Interest: over	0.264		0.067	1.043	***	0.271
Interest in child education at age 16 (prev. father)	0.327	*	0.083	0.284		0.074
Interest in child education at age 16 (prev. mother)	0.284	***	0.072	0.345	***	0.089
High social class	0.619	***	0.157	0.589	***	0.153
Medium social class	0.189	**	0.048	0.206	*	0.053
Financial trouble at age 15	-0.153		-0.039	-0.114		-0.030
North at age 16	-0.130		-0.033	0.164		0.042
North-West at age 16	0.217		0.055	0.488	**	0.127
East-West Riding at age 16	0.089		0.022	0.326		0.084
North-Midlands at age 16	0.138		0.035	0.597	***	0.155
Midlands at age 16	0.154		0.039	0.431	**	0.112
East at age 16	-0.060		-0.015	0.140		0.036
South-East at age 16	0.090		0.023	0.418	**	0.108
South at age 16	0.152		0.039	0.413	*	0.107
South-West at age 16	-0.015		-0.004	0.234		0.061
Scotland at age 16	0.767	***	0.194	1.014	***	0.263
Wished minimum education at age 16	-1.186	***	-0.300	-1.184	***	-0.307
Constant	-4.320	***	-	-4.638	***	-
Wald chi2(26)	506.38			421.31		
Prob > chi2	0.000			0.000		
Pseudo R2	0.295			0.291		
Log-pseudolikelihood	-1019.73			-802.12		

*, **, ***, indicates statistically significant coefficients at the 10%, 5% and 1% levels, respectively.

Table 2a. Ordered probit estimates of employment-status. Year 2009

	Highly educated				Low-educated			
	Coef.		Marginal effects		Coef.		Marginal effects	
			PT	FT			PT	FT
Birth weight	0.006		-0.001	0.002	-0.005		0.000	-0.002
Birth weight square	0.000		0.000	0.000	0.000		0.000	0.000
Standardized reading test at age 7	0.147		-0.019	0.049	0.016		-0.002	0.005
Standardized math test at age 7	-0.144	**	0.019	-0.048	0.015		-0.001	0.005
Standardized BSAG score at age 11	0.040		-0.005	0.013	-0.120	**	0.012	-0.041
Standardized BSAG score at age 11 square	0.037		-0.005	0.012	0.020		-0.002	0.007
Statements about interest in child education at age 16	-0.484	*	0.063	-0.162	0.075		-0.008	0.026
Interest: some	-0.035		0.004	-0.012	0.037		-0.004	0.013
Interest: very	-0.077		0.010	-0.026	-0.013		0.001	-0.004
Interest: over	0.283		-0.037	0.094	-0.395		0.040	-0.134
Interest in child education at age 16 (preval. father)	0.211		-0.027	0.071	0.113		-0.011	0.038
Interest in child education at age 16 (preval. mother)	-0.377	**	0.049	-0.126	0.060		-0.006	0.020
Financial trouble at age 15	0.441		-0.057	0.147	-0.207		0.021	-0.071
High social class	-0.130		0.017	-0.043	0.077		-0.008	0.026
Medium social class	0.129		-0.017	0.043	-0.013		0.001	-0.004
Married	-0.725	***	0.094	-0.242	-0.559	***	0.057	-0.190
Married*Partner employed	0.250		-0.032	0.083	0.288	**	-0.029	0.098
Children aged 0-15	-0.281	***	0.037	-0.094	-0.389	***	0.039	-0.133
Chronic illness/disability	-0.770	***	0.100	-0.257	-0.701	***	0.071	-0.239
Working experience up to 2000	0.006	*	-0.001	0.002	0.010	***	-0.001	0.003
Working experience up to 2000 squared	0.000		0.000	0.000	0.000	**	0.000	0.000
Inverse Mill's Ratio	-0.592	**	0.077	-0.198	-0.051		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	-529.290				-1040.590			

BHHH technique for asymptotic var-cov matrix. NW: not working; PT: part-time work; FT: full-time work. Estimates include regional dummies.
*, **, ***, indicates statistically significant coefficients at the 10%, 5% and 1% levels, respectively.

Table 2b. Ordered probit estimates of employment-status. Year 1991

	Highly-educated				Low-educated			
	Coef.		Marginal effects		Coef.		Marginal effects	
			PT	FT			PT	FT
Birth weight	0.026		0.000	0.007	-0.013		-0.001	-0.003
Birth weight square	0.000		0.000	0.000	0.000		0.000	0.000
Standardized reading test at age 7	-0.019		0.000	-0.005	0.041		0.002	0.011
Standardized math test at age 7	0.125	*	-0.001	0.033	0.023		0.001	0.006
Standardized BSAG score ate age 11	-0.131		0.001	-0.035	-0.009		-0.001	-0.002
Standardized BSAG score at age 11 square	-0.009		0.000	-0.002	0.014		0.000	0.004
Statements about interest in child education at age 16	0.490	*	-0.004	0.129	0.016		0.001	0.004
Interest: some	-0.354		0.003	-0.093	0.026		0.001	0.007
Interest: very	-0.228		0.002	-0.060	-0.038		-0.002	-0.010
Interest: over	-0.687		0.005	-0.181	-0.402		-0.014	-0.110
Interest in child education at age 16 (preval. father)	-0.195		0.001	-0.051	-0.349	**	-0.013	-0.095
Interest in child education at age 16 (preval. mother)	-0.103		0.001	-0.027	0.038		0.002	0.010
Financial trouble at age 15	0.280		-0.002	0.074	0.138		0.005	0.038
High social class	-0.059		0.000	-0.016	0.101		0.004	0.027
Medium social class	-0.048		0.000	-0.013	-0.037		-0.001	-0.010
Married	-0.107		0.001	-0.028	-0.452	**	-0.016	-0.123
Married*Partner employed	-0.163		0.001	-0.043	0.572	***	0.021	0.156
Children aged 0-15	-1.566	***	0.012	-0.413	-1.273	***	-0.046	-0.347
Chronic illness/disability	0.012		0.000	0.003	-0.186	**	-0.007	-0.051
Working experience up to 2000	0.011	**	0.000	0.003	0.007	**	0.000	0.002
Working experience up to 2000 squared	0.000		0.000	0.000	0.000		0.000	0.000
Inverse Mill's Ratio	0.081		-0.001	0.021	0.106		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	-596.010				-1408.210			

BHHH technique for asymptotic var-cov matrix. NW: not working; PT: part-time work; FT: full-time work. Estimates include regional dummies.
*, **, ***, indicates statistically significant coefficients at the 10%, 5% and 1% levels, respectively.

Table 3. OLS estimates of full-timers' log hourly wages

	1991				2009			
	Highly-educated		Low-educated		Highly-educated		Low-educated	
	Coef.		Coef.		Coef.		Coef.	
Birth weight	-0.001		-0.002		0.008		0.006	
Birth weight square	0.000		0.000		0.000		0.000	
Standardized reading test at age 7	0.099	***	0.061	***	-0.013		0.036	***
Standardized math test at age 7	-0.004		0.021		0.081	***	0.033	***
Standardized BSAG score at age 11	-0.098	***	-0.057	***	-0.006		-0.032	***
Standardized BSAG score at age 11 sq.	0.031		0.014		-0.006		0.010	
Interest in child education at age 16	-0.042		-0.020		-0.061		0.008	
Interest: some	0.044		-0.001		0.166		0.036	
Interest: very	0.179	*	0.090	**	0.152		0.033	
Interest: over	0.100		-0.025		0.141		0.168	
Interest in child education at age 16 (prev. father)	0.091		0.006		0.103		0.010	
Interest in child education at age 16 (prev. mother)	0.115	***	0.031		0.065		-0.005	
Financial trouble at age 15	-0.030		-0.008		0.015		-0.065	*
High social class	0.043		0.057		0.149	*	0.088	***
Medium social class	0.044		0.025		0.147	*	-0.048	
Children aged 0-15	0.016		-0.133		0.073		-0.026	
Chronic illness/disability	-0.046		-0.003		0.001		-0.201	***
Working experience up to 2000	0.001		0.004	*	0.001		0.003	***
Working experience up to 2000 squared	0.000		0.000		0.000		0.000	**
Firm size 11-25	0.227	***	0.164	***	0.043		0.112	***
Firm size 26-99	0.257	***	0.165	***	0.198	***	0.068	***
Firm size 100-499	0.273	***	0.147	***	0.133		0.053	*
Firm size 500+	0.314	***	0.176	***	0.218	***	0.095	***
Public sector	-0.008		0.097	***	0.140	***	0.086	***
Union membership	0.019		0.016		0.060		0.078	***
Temporary/atypical contracts	-0.255	***	0.068		-0.308	***	-0.146	***
Inverse Mill's Ratio	-0.238	***	0.095		-0.094		0.201	
Constant	1.263		0.636		1.174		0.771	*
Observations	352		488		317		566	
F-test [Prob > F]	2.77 [0.000]		6.63 [0.000]		3.69 [0.000]		17.90 [0.000]	
R-squared	0.238		0.297		0.207		0.206	

Estimates include regional dummies. *, **, ***, indicates statistically significant coefficients at the 10%, 5% and 1% levels, respectively

Appendix

The inverse Mill's ratios (Heckman, 1979; Greene, 2011) related to Equation 1 are as follows:

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

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

where:

$\varphi(.)$ = normal density function;

$\Phi(.)$ = normal distribution function.

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):

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

For each $Q = LE, HE$

$$\lambda_{Q,FT} = \frac{\varphi(\mu_Q - Z_Q'\gamma_Q)}{1 - \Phi(\mu_Q - Z_Q'\gamma_Q)}$$

The inverse Mill's ratios described above are appropriate if the ordered probit model includes a constant. However, the estimation procedure we use does not include a constant among the regressors. Indeed, the procedure predicts two different cut points (*cut1* and *cut2*). Thus, we employ these cut points to adapt the two components of the equation to the no-constant estimated model:

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

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

Table A1. Descriptive statistics 2009

	Total		Highly educated		Low-educated	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Birth weight (ouces)	115.51	17.38	116.87	16.06	114.79	18.01
Reading test score at age 7	25.394	5.828	27.766	3.560	24.132	6.382
Math test score at age 7	5.280	2.435	6.169	2.333	4.808	2.355
BSAG test score at age11	6.167	7.481	4.002	5.657	7.318	8.058
No say about interest in child education at age 11	0.276	0.447	0.199	0.400	0.318	0.466
Little interest in child education at age 11	0.138	0.345	0.051	0.220	0.184	0.387
Some interest in child education at age 11	0.257	0.437	0.179	0.384	0.298	0.458
Very interested in child education at age 11	0.318	0.466	0.551	0.498	0.194	0.396
Over concerned in child education at age 11	0.011	0.104	0.020	0.139	0.006	0.078
Interest in child education at age 11 (prevalence father)	0.042	0.201	0.043	0.202	0.042	0.201
Interest in child education at age 11 (father = mother)	0.665	0.472	0.702	0.458	0.645	0.479
Interest in child education at age 11 (prevalence mother)	0.293	0.455	0.255	0.436	0.313	0.464
High social class at age 16	0.067	0.251	0.033	0.179	0.086	0.280
Medium social class at age 16	0.266	0.442	0.438	0.496	0.174	0.379
Low social class at age16	0.541	0.498	0.462	0.499	0.584	0.493
Financial trouble at age 15	0.193	0.395	0.100	0.301	0.242	0.429
North at age 16	0.075	0.264	0.059	0.236	0.084	0.277
North-West at age 16	0.118	0.323	0.118	0.323	0.118	0.323
East-West Riding at age 16	0.079	0.270	0.071	0.257	0.084	0.277
North-Midlands at age 16	0.078	0.268	0.076	0.265	0.079	0.269
Midlands at age 16	0.104	0.305	0.099	0.298	0.107	0.309
East at age 16	0.093	0.290	0.081	0.272	0.099	0.299
South-East at age 16	0.145	0.352	0.171	0.377	0.131	0.338
South at age 16	0.062	0.242	0.056	0.230	0.066	0.248
South-West at age 16	0.073	0.260	0.064	0.245	0.078	0.268
Wales at age 16	0.050	0.219	0.033	0.179	0.059	0.237
Scotland at age 16	0.122	0.328	0.173	0.378	0.095	0.294
Wished minimum education at age 16	0.287	0.453	0.044	0.206	0.416	0.493
Married	0.702	0.458	0.712	0.453	0.696	0.460
Married*Partner employed	0.617	0.486	0.645	0.479	0.602	0.490
Children aged 0-15	0.226	0.546	0.329	0.632	0.171	0.487
Chronic illness/disability	0.188	0.391	0.137	0.344	0.215	0.411
Working experience up to 2000 (months)	231.62	72.32	229.26	65.44	232.88	75.73
Firm size 1-10	0.171	0.377	0.134	0.341	0.192	0.394
Firm size 11-25	0.192	0.394	0.181	0.385	0.198	0.399
Firm size 26-99	0.252	0.434	0.253	0.435	0.252	0.434
Firm size 100-499	0.212	0.409	0.228	0.420	0.202	0.402
Firm size 500 or more	0.173	0.379	0.204	0.404	0.155	0.363
Public sector	0.505	0.500	0.633	0.483	0.432	0.496
Union membership	0.216	0.412	0.303	0.460	0.170	0.376
Temporary/atypical contract	0.033	0.180	0.045	0.208	0.027	0.162
North	0.066	0.248	0.041	0.199	0.079	0.269
Yorkshire	0.089	0.285	0.087	0.282	0.090	0.286
East-Midlands	0.073	0.259	0.059	0.236	0.080	0.271
East-Anglia	0.038	0.192	0.030	0.170	0.043	0.203
South-East	0.256	0.437	0.281	0.450	0.243	0.429
South-West	0.103	0.304	0.105	0.307	0.101	0.302
West-Midlands	0.101	0.302	0.084	0.277	0.110	0.313
North-West	0.102	0.302	0.105	0.307	0.100	0.300
Wales	0.057	0.232	0.039	0.195	0.066	0.249
Scotland	0.115	0.320	0.168	0.374	0.087	0.283
Highly educated at age 23	0.347	0.476	-	-	-	-
Observations	1751		608		1143	