Financial transfers and educational achievement

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Abstract:

Britain youth has one of the lowest staying on rate after compulsory education. It is commonly advocated that financial constraints prevent pupils from the poorer backgrounds to invest in their own education. Previous research has shown the negative impact on educational attainment of being brought up in a poorer background. However, the effect of family income on the child's educational attainment is unclear as it is related to other family characteristics, which might also affect schooling decision. We propose a methodology that separates these effects and find that the direct effect of family income on child's schooling attainment is rather limited. A policy of educational allowance may have no significant effect on post compulsory education decision, as its effects are too belated.

I. Introduction

Adolescent educational choices are usually and perhaps trivially positively related to parents' education, social class, and other characteristics describing parental achievements: in particular wealth and/or earned income (see Haveman and Wolfe (1995) for a review of the determinants of schooling). The income effect is traditionally understood as being an indication that poorer households face some financial constraints, which limit the educational attainment of any children within the household. Such financial constraints may stem from credit market imperfections. Indeed, since ability cannot be used as collateral, students from poorer backgrounds cannot borrow to invest in their own education. This issue is of interest as Britain is characterised by a low rate of post-compulsory schooling compared to other OECD countries and as a reform of the educational maintenance allowance is imminent.

The evidence of financial constraints have been the stepping stone of educational allowance policies. However, the efficiency of these policies at reducing educational inequality has been the subject of controversy, in North America and elsewhere since the publication of the Bell Curve (Herrnstein and Murray (1995)[1]. According to these authors, cognitive ability determines success at school and the previously observed income effect only reflects the correlation between ability and family wealth. As long-term improvement of cognitive ability is costly and "of limited scope", the authors conclude that public interventions to reduce inequalities are bound to fail. The argumentation of these authors is unfortunately affected by the method used. Herrnstein and Murray define a single component of ability (the "g" factor) and attribute most of the variation in ability to genetic endowment, denying any effects of family characteristics. Cameron and Heckman (1998, 1999) support the idea that the influence of family background on educational choice is not due to short-term financial constraints but has its origin in the long-term effect of family background on ability, motivation and other unobserved characteristics[2]. Hence, the efficiency of income support policies in helping pupils from less favourable backgrounds to invest in their schooling is questionable. Alternatively, the improvement of childhood conditions, in the form of better child-care for example, is a more promising policy[3].

Studies on the determinants of educational choice have mostly relied on logit estimates and have concluded that the effect of family income peaks at the end of compulsory education and is reduced at each following transition (Mare (1980)). For the UK, previous studies have focused on post-compulsory schooling decisions. Controlling for ability, Micklewright (1989) finds that parental education and social class are major determinants of the decision to stay in education. On the other hand, family income is insignificant in explaining the schooling decisions for boys but not for girls (Rice (1987)). However, the declining influence of family background on the transition probability can be shown to be mostly spurious (Cameron and Heckman (1998)). Omitted components correlated with family characteristics, such as ability or motivation, increase the schooling transition probability and therefore bias the estimates of the effect of family income towards zero when excluded. As the schooling decision is a dynamic process, the bias due to the unexplained components increases with the number of transitions; the decreasing influence of family characteristics on schooling decisions is thus an artefact.

In this paper, we use the methodology developed by Cameron and Heckman (1998) to avoid this caveat and distinguish between long-term (ability) and short-term (financial constraint) effects of the family background on schooling decisions. We examine the determinants of the schooling decision in the UK, more specifically we investigate whether financial support policies are effective at increasing the staying-on rate in post compulsory schooling.

To summarise our findings, pupils from poorer families are less likely to invest in their education than others. The effect of the family characteristics on educational attainment stems from two sources. First, being brought up in a poorer family may have a negative effect on the child's ability, motivation, information set and also affects her rate of discount. Second, as credit markets are imperfect, a direct effect of the family's financial situation on the child's educational attainment might exist. For Britain and Wales, we find some evidence that liquidity constraints are likely to be binding and force poorer pupils to exit the educational system at an earlier stage than their ability would have predicted. An educational allowance should reduce this financial constraint and lead to an increase in the proportion of pupils from poorer backgrounds staying on in education after compulsory schooling. However, such a policy will not reduce the long-term constraints that being brought up in a poorer family imposes on pupils, hence the positive expected effect of an educational allowance policy could be drastically reduced.

II. Methodology

In this section, we review the basic model derived by Cameron and Heckman (1998). The optimal level of schooling is defined in terms of costs and returns, where the cost, $C(s \mid x)$, are defined to be convex in years of schooling and depend solely on time invariant family or individual characteristics, x, and years of schooling, s. The discounted returns to schooling, $R(s)$, are defined as a concave function of years of schooling independent of the individual characteristics. To insure the existence of a unique optimal duration of schooling, the returns to zero years of schooling are assumed to be positive, whereas the costs are null. Formally, the above model can be written as:

$$\begin{cases} \dfrac{\partial C(s \mid x)}{\partial s} > 0, \dfrac{\partial^2 C(s \mid x)}{\partial s^2} > 0, \text{and } C(0 \mid x) = 0 \\ \dfrac{\partial R(s)}{\partial s} > 0, \dfrac{\partial^2 R(s)}{\partial s^2} < 0, \text{and } R(0) > 0 \end{cases} \tag{1}$$

The optimal amount of schooling s* is then the unique solution to the maximisation function:

$$\max_{s \in \{0,\ldots,S\}} R(s) - C(s \mid x)$$

We allow for the presence of unobserved heterogeneity, and assume that the cost function has the following functional form :

$$C(s \mid x) = C(s) j(x) e, \tag{2}$$

where $j(x)$ is a function of the observed ability and e is a random variable accounting for the heterogeneity of each pupil. The heterogeneity may reflect differences in individual ability or any other unobserved characteristics which accounts for unobserved variations of the cost of reaching a certain level of schooling. Without loss of generality, we further assume that:

$$\mathrm{E}[e] = 1, \; e > 0 \text{ and } j(x) > 0.$$

The following system of inequalities guarantees that s* is the optimal level of schooling.

$$\begin{cases} R(s^*) - C(s^*)\varphi(x)\varepsilon \geq 0 \\ R(s^*) - C(s^*)\varphi(x)\varepsilon \geq R(s^*-1) - C(s^*-1)\varphi(x)\varepsilon \\ R(s^*) - C(s^*)\varphi(x)\varepsilon \geq R(s^*+1) - C(s^*+1)\varphi(x)\varepsilon \end{cases} \quad (3)$$

Thus, for each individual, at the optimal educational level, s^*, the unobserved component of the cost function, ε, is bounded.

$$\frac{R(s^*) - R(s^*-1)}{[C(s^*) - C(s^*-1)]\varphi(x)} \geq \varepsilon \geq \frac{R(s^*+1) - R(s^*)}{[C(s^*+1) - C(s^*)]\varphi(x)}\ ^4 \quad (4)$$

Assuming that ε is continuously distributed, the probability choosing s^* years of schooling when growing up in a family with characteristics x is:

$$\text{Prob}(s \mid x) = \Pr\left[\frac{R(s^*+1) - R(s^*)}{[C(s^*+1) - C(s^*)]^* \varphi(x)} \leq \varepsilon \leq \frac{R(s^*) - R(s^*-1)}{[C(s^*) - C(s^*-1)]^* \varphi(x)}\right] \quad (5)$$

This model will take the familiar form of an ordered probit model[5] when φ(x)=exp(-Xβ) and $l(s) = \ln\left(\frac{R(s^*+1) - R(s^*-1)}{[C(s^*+1) - C(s^*-1)]}\right)$, and assuming that $\ln(\varepsilon)$ is normally distributed.:

III. Data

The data used for this study comes from the National Child Development Study (NCDS) and the British Cohort Study (BCS). These two surveys were designed to observe the characteristics of children at different points in time, and therefore appears to be particularly appropriate for our analysis. Due to large attrition in the age 16 wave of the BCS, we focus on the child characteristics when in early teens.

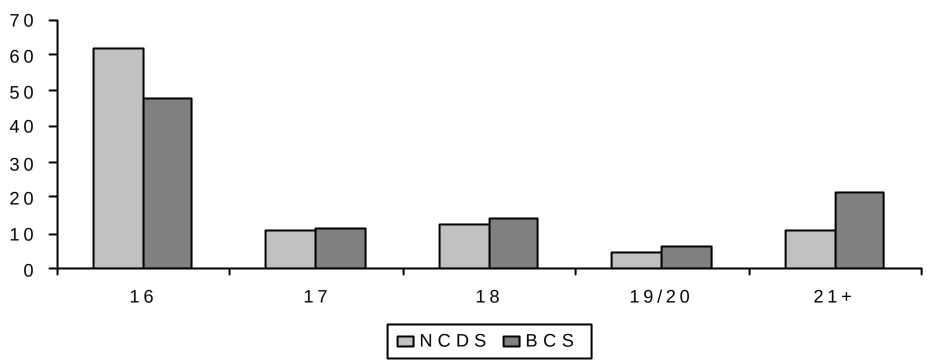
The NCDS is a continuous longitudinal survey of persons living in Great Britain who were born in the first week of March 1958. We use information collected when the respondents were aged 7, 11, and 33. From the last wave, we keep respondents who are no longer in education. The family background characteristics are collected when the child was 11. They include parental education, father's socio-economic group[6], number of siblings, and dummies for the presence of natural parents and race[7]. Neighbourhood and family wealth are approximated by a dichotomous variable equalling one when the child was brought up in a council estate. Father's earnings (in grouped category) were reported in 1974 when the child was 16; this measure is used as a proxy for family income.

At age 7, all children's abilities in reading and mathematics were measured in a series of tests. As these tests were conducted at a young age, they are not affected by schooling already attained and can be considered a good measure of natural ability[8]. These measures reflect the long-term effect of family characteristics on the child's development.

The design of the BCS is similar to the NCDS; all children born in Great Britain in the first week of April 1970 were surveyed. Children and parents were then interviewed at regular interval, when the child was 5, 10, 16 and 26. We focus on respondents who had completed their education at age 26. Hence, pupils who went on higher degree or who had a break in their study are not all observed. This selection bias is likely to be slightly more important than the one affecting the NCDS, when this information was collected at age 33. The family background variables are similar to those define for the NCDS but they were collected when the child was 10. The main difference in the definition of the variables concerns the measure of ability and family wealth. For the children observed in the BCS, family income and ability are measured at age 10. In particular the measurement of ability may be correlated with early schooling achievement and thus be a biased estimator of the child natural ability.

The data are summarised in Table 1, by cohort and gender. As Scotland has a different educational system than Britain and Wales, children living in Scotland are dropped from this analysis. The number of years in education has increased by nearly one year for the younger cohort with the average school leaving age being nearly 18 years[9]. As Figure 1 shows, among the younger cohort a smaller proportion left school at the earliest opportunity, 47% against 60% for the older cohort, and larger proportion completed some form of higher education, 21% against 10% respectively. The exit rates in between are left virtually unchanged.

Figure 1: Distribution of age when leaving education by cohort



In both cohorts, women receive more schooling than men, but the difference is never significant. Parental schooling also differs between the two cohorts; the difference being the largest for parents with more than 4 years of post-compulsory schooling (University level)[10]. In the NCDS, 4 % of father's respondent achieved this level; the corresponding figure in the BCS is 17%, a similar observation can be made about the mothers. Finally, we observe the well-documented decrease in the average family size from an average of 3 child per family for the older cohort to 2.5 in the BCS.

IV. Empirical results

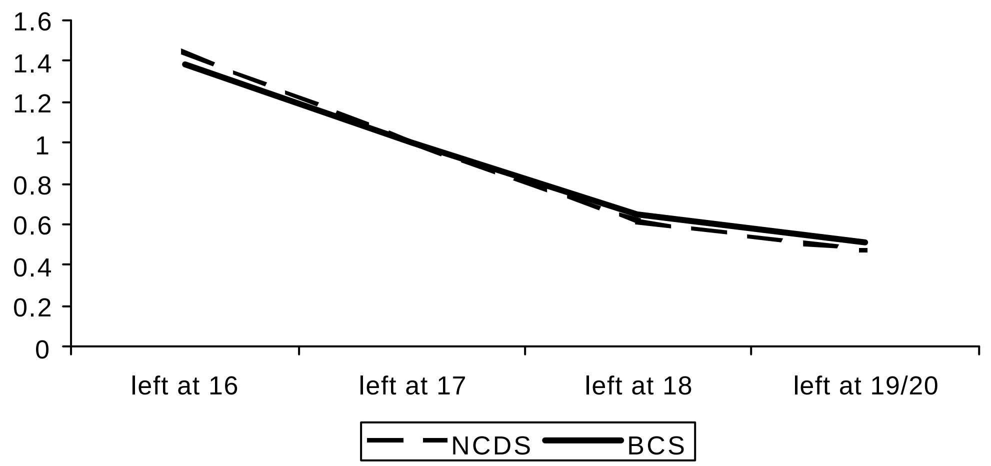
We wish to measure the economic determinant described in the model in section 2 for the five education/leaving age groups we observe: left school at minimum age, left school at 17, 18, 19 or 20, and older than 20. The categories are then numbered from 1 for pupils who left education after their 20th birthday to 5 for those who left school at 16. The reasons for the reverse ordering are purely technical and are explained below. The cut-off values obtained from the ordered probit measure the critical ratio of marginal revenue to marginal cost and define the threshold for being a constituent of a given category. Since, we define five education groups, we generate four thresholds; these values are used to calculate the marginal revenue over marginal cost for the four educational groups. As most of the pupils leave school at 16, we decided to compute the ratio of revenue over cost for school leavers rather than for university graduates. Furthermore, this ratio is decreasing in years of education and converges towards zero (Cameron and Heckman (1998)), hence the ratio of revenue over cost can be approximated as being null for graduates. Estimates of the determinants of school leaving age are presented in Table 2a for women and 2b for men.

Results are reported in columns 1 and 3 for NCDS and BCS, respectively, with a specification that does not include ability measures. Due to the ordering of the dependent variable, a negative coefficient indicates a greater likelihood of transition. The results are consistent with previous literature. Parental education, father's social class and belonging to a racial minority are positively correlated with more education whereas lower family income, number of siblings, and living in a council estate reduce the likelihood of transition. These results are similar for both genders and cohorts. The income effect appears to be more important for the 1970 cohort than for the 1958 cohort. For the older cohort, the income effect is significant for pupils whose father's earnings are in the bottom of the distribution. For example, those whose father earns between £80 and £125 net per month in 1974 are 11% less likely to invest in post compulsory education than pupils whose father earns more than £256. For the younger cohort, pupils whose father is in the top earnings category are significantly more likely to stay longer in education compared to those whose father earn between £150-200 a week in 1980. At the other end of the distribution, a poorer father is associated with an earlier exit from education.

The effect of family income on the child's educational decision has been largely documented. This evidence has been used to justify income support policies to encourage poorer pupils to remain in education. However, it is important to discriminate between the long term and short-term effects of the family background characteristics. Being brought up in a poorer family is associated with binding financial constraints. Additionally, adverse financial conditions during childhood might have some long-term effects on the development of the child and reduce her level of ability, career information, motivation and affect her discount rate (Card, 1999). Then, income support policies would be inefficient at encouraging poorer pupils to invest in their schooling. Following Cameron and Heckman (1998), we assume that, as natural ability is a function of the unobserved long-term characteristics of the family background its inclusion, in the schooling determinants model, allows us to discriminate between the long-term and short-term effects of family background on schooling attainment. In columns 2 and 4 of Table 2, we present the estimated schooling determinants when accounting for ability by including dummies for test results in mathematics and English at an early stage in childhood. Pupils in the lowest quartile define the omitted category. We expect the effect of the financial variable to be reduced by the inclusion of the ability measures.

Pupils with better scores in reading and math at an early age get substantially more schooling than other children. The reading test appears to have a slightly stronger effect than the math test on the probability of investing more in education. No substantial differences between boys and girls are observed. The inclusion of the test scores variables does not change our conclusions, most of the remaining explanatory variables are unaffected. Family characteristics affecting the development of the child (as measured by ability) have a significant effect on schooling attainment, however the family income variables remain statistically significant. Financial constraints appear to limit the schooling attainment of poorer pupils, and thus there may be scope for income support policies. Also, as ability measured at an early schooling stage, is an important determinant of educational success, policies aiming at providing support during childhood; e.g. child care, access to library, are promising ways to reduce inequalities between children[11].

Figure 2: Marginal revenue-marginal cost ratios for women



We compare the educational determinants for the two cohorts. Coefficients of an ordered probit estimation cannot be compared across equations as they are defined up to a scale parameter. First, we calculate the marginal revenue-marginal cost[12] ratio by gender and by cohort. For comparison purpose, we normalise the ratios, the marginal revenue-marginal cost ratio for pupils who left school at 17 is used as a base and is equal to unity. Figure 2 illustrates the evolution of the marginal revenue-marginal cost ratio over time for females[13]. The ratios are similar between cohorts; they are almost linearly decreasingly in years of education. Pupils with the highest costs quit school at the first opportunity, whereas those with lower costs can invest more in there own education.

The stability of the determinants of education between the two cohorts is also tested more formally. To make the parameters comparable between equations, we divide all of them by a chosen estimate (here the number of sibling) so that the estimates are independent of the scale parameter. The null hypothesis is that the coefficients are similar between cohorts. This hypothesis is rejected when the value of the test is greater than a critical value, defined by: $\chi^2((j-1)\ (k-1))$, where j is the number of equations and k is the number of parameters. In table 3, for both genders and specifications, we cannot reject that the coefficients are identical between the two cohorts. Despite the observed changes in the educational attainment between the two cohorts previously observed, the determinants of the school choice have remained stable over time.

<u>Table 3 : Test of stability of the educational determinants</u>

	Female	Male	χ^2 Critical value , p=0.025
Without ability measure	12.32	13.9	$\chi^2(30)=16.80$
With ability measure	7.87	4.08	$\chi^2(36)=20.91$

Family income during childhood appear to have a major effect on schooling decision, however this income effect is not independent of other characteristics of the family, that may explain the poor financial situation and the educational decision. Therefore we modelled the effect of an educational maintenance allowance on schooling decision. This technique allows us to release the financial constraints but maintains the family characteristics and therefore captures the pure effect of family income on schooling decision.

V. Educational allowance

So far we have found that being brought up in a poorer family has a significant negative effect on educational attainment. As education is an efficient device to reduce adult poverty, traditional policies to reduce intergenerational transmission of poverty have been concern with helping pupils from poorer backgrounds to invest in post-compulsory education. Moreover, a more educated workforce is associated with higher economic growth. The British government has been considering the implementation of an Educational Maintenance Allowance (EMA). This scheme would provide 16-18 year old from the poorer family (annual income lower than £13000) with a financial allowance of £30 a week. The scheme is means tested and the amount received declines linearly down to zero for children from a family with an annual income greater than £30000. According to the governmental projections about 70% of 16-18 year olds would receive some support. We estimate the effect that a simpler and more generous scheme (+ £30 a week for all pupils) would have had on the pupils from the 1970 cohort. The difficulty encountered is that the available data on income for the cohort of interest (BCS, measured in 1980) are grouped in 6 categories only. Hence, the only income policy that we could model using this data would be to replace each income dummy by the subsequent one, which corresponds to an increase in earnings of £50 in 1980 (~£122 in 1999 price).

To overcome these difficulties we attempt to map the information from the BCS with data obtained from the Family Expenditure Survey (FES). The FES is an annual survey of 10,000 household in the UK, which provides extensive information on earnings, but none on children and their education. We use the 1980 wave of the FES to map earnings variable on the BCS. The next few paragraphs outline the method we follow.

The model we present and estimate in the previous sections can be understood as a model where the endogenous latent variable, y^*, is the part of the cost which is individual specific, i.e. $y^* = \ln(j\,(x)) + \ln(e)$. We will assume that the correct specification is:

$$y^* = x\boldsymbol{b} + f(z) + \ln(\boldsymbol{e}) \tag{7}$$

where x is a vector of observable individual characteristics, z is a continuous variable in earnings, $f(z)$ is some non-linear function of z that can be represented exactly by a polynomial of order q, we have $f(z) = \mathbf{z}\boldsymbol{a}$. The row vector $\mathbf{z}$ is such that the pth column in $\mathbf{z}$ is z^{p-1}, for $p \in \{1,2,...q\}$, and where $\boldsymbol{a}$ is the vector of parameters which define the polynomial. The assumptions we made before ensure that $\ln(e)$ is distributed independently of x and $\mathbf{z}$. Clearly, the observed schooling levels s are transformations of latent dependent variable y^*, see equation (4).

We consider two samples . The first sample (sample **A**) contains information about x and z, but possibly no information about s. The second sample (sample **B**) is such that we observe s but we do not observe z. Instead we observe whether a particular observation belongs to a given interval among a set of m disjoint intervals which cover the range of z, that is the information about z is summarised by a vector of m dummy variables.

Sample **A** 's information, $N_{\mathbf{A}}$ observations, is collected in the matrices $\mathbf{X_A}$, $\mathbf{Z_A}$ and $\mathbf{Ä_A}$. $\mathbf{Z_A}$ is such that column p, for $p \in \{1,2,...q\}$, contains the values of z^{p-1} for each individual observation. $\mathbf{Ä_A}$ collects the individual vectors of dummy variables. Sample **B** 's information, $N_{\mathbf{B}}$ observations, is collected in the matrices $\mathbf{y_B}$, $\mathbf{X_B}$, and $\mathbf{Ä_B}$. $\mathbf{Ä_B}$ collects the individual vectors of dummy variables for this sample.

Equation (7) can be estimated by the following misspecified model using the information available in sample B:

$$y^* = x\hat{\tilde{b}} + \Delta\hat{q} + \ln(\tilde{e}) \tag{8}$$

where $\ln(\tilde{e}) = \ln(e) + f(z) - \Delta\hat{q}$, and $\hat{\tilde{b}}$ and $\hat{q}$ are consistent estimates of the pseudo-true value of $\tilde{b}$ and q, obtained for example from the maximisation of the ordered probit likelihood. Asymptotically these estimate of the pseudo-true value are such that :

$$\mathrm{E}\left[\left(y^* - x\hat{\tilde{b}}_\infty - \Delta\hat{q}_{\infty+1}\right)\left(x \quad \Delta\right)\right] = 0 \ ,$$

that is the ordered probit likelihood applied to the misspecified model (because of the imperfect observation of parental income) imposes orthogonality between the pseudo-errors and the explanatory variables (this an assumption of the misspecified model). Hence, asymptotically and provided all the relevant quantities below exist, the estimates $\hat{\tilde{b}}_\infty$ and $\hat{q}_\infty$ verify the following relationships :

$$\hat{\tilde{b}}_\infty = \left\{\mathrm{E}\left[x'x\right] - \mathrm{E}\left[x'\Delta\right]\mathrm{E}\left[\Delta'\Delta\right]^{-1}\mathrm{E}\left[\Delta'x\right]\right\}^{-1}\left\{\mathrm{E}\left[x'y^*\right] - \mathrm{E}\left[x'\Delta\right]\mathrm{E}\left[\Delta'\Delta\right]^{-1}\mathrm{E}\left[\Delta'y^*\right]\right\},$$

$$\hat{q}_\infty = \left\{\mathrm{E}\left[\Delta'\Delta\right] - \mathrm{E}\left[\Delta'x\right]\mathrm{E}\left[x'x\right]^{-1}\mathrm{E}\left[x'\Delta\right]\right\}^{-1}\left\{\mathrm{E}\left[\Delta'y^*\right] - \mathrm{E}\left[\Delta'x\right]\mathrm{E}\left[x'x\right]^{-1}\mathrm{E}\left[x'y^*\right]\right\}.$$

From these expressions, some tedious calculus gives us some relationships between the pseudo-true values and the true parameters of the correctly specified model as follows:

$$\hat{\tilde{b}}_\infty = b + \left\{\mathrm{E}\left[x'x\right] - \mathrm{E}\left[x'\Delta\right]\mathrm{E}\left[\Delta'\Delta\right]^{-1}\mathrm{E}\left[\Delta'x\right]\right\}^{-1}\left\{\mathrm{E}\left[x'\mathbf{z}\right] - \mathrm{E}\left[x'\Delta\right]\mathrm{E}\left[\Delta'\Delta\right]^{-1}\mathrm{E}\left[\Delta'\mathbf{z}\right]\right\}a,$$

$$\hat{q}_\infty = \left\{\mathrm{E}\left[\Delta'\Delta\right] - \mathrm{E}\left[\Delta'x\right]\mathrm{E}\left[x'x\right]^{-1}\mathrm{E}\left[x'\Delta\right]\right\}^{-1}\left\{\mathrm{E}\left[\Delta'\mathbf{z}\right] - \mathrm{E}\left[\Delta'x\right]\mathrm{E}\left[x'x\right]^{-1}\mathrm{E}\left[x'\mathbf{z}\right]\right\}a,$$

where we have eliminated the terms with zero expectation. The previous expressions can be rearranged as follows :

$$\boldsymbol{a} = \left\{ \mathrm{E}\left[\Delta '\mathbf{z}\right] - \mathrm{E}\left[\Delta ' x\right]\mathrm{E}\left[x ' x\right]^{-1}\mathrm{E}\left[x '\mathbf{z}\right]\right\}^{-1}\left\{\mathrm{E}\left[\Delta '\Delta\right] - \mathrm{E}\left[\Delta ' x\right]\mathrm{E}\left[x ' x\right]^{-1}\mathrm{E}\left[x '\Delta\right]\right\}\hat{\boldsymbol{q}}_{\infty},$$

$$\begin{aligned}\boldsymbol{b} = {} & \hat{\tilde{\boldsymbol{b}}}_{\infty} - \\ & \left\{\mathrm{E}\left[x ' x\right] - \mathrm{E}\left[x '\Delta\right]\mathrm{E}\left[\Delta '\Delta\right]^{-1}\mathrm{E}\left[\Delta ' x\right]\right\}^{-1}\left\{\mathrm{E}\left[x '\mathbf{z}\right] - \mathrm{E}\left[x '\Delta\right]\mathrm{E}\left[\Delta '\Delta\right]^{-1}\mathrm{E}\left[\Delta '\mathbf{z}\right]\right\} \\ & \left\{\mathrm{E}\left[\Delta '\mathbf{z}\right] - \mathrm{E}\left[\Delta ' x\right]\mathrm{E}\left[x ' x\right]^{-1}\mathrm{E}\left[x '\mathbf{z}\right]\right\}^{-1}\left\{\mathrm{E}\left[\Delta '\Delta\right] - \mathrm{E}\left[\Delta ' x\right]\mathrm{E}\left[x ' x\right]^{-1}\mathrm{E}\left[x '\Delta\right]\right\}\hat{\boldsymbol{q}}_{\infty},\end{aligned}$$

These expressions suggest some feasible asymptotic bias corrections using appropriate empirical moments from the two samples. We have [14]:

$$\hat{\boldsymbol{a}} = \left(\frac{\Delta '_A \mathbf{M}_{\mathbf{X}_A}\mathbf{Z}_A}{N_A}\right)^{-1}\frac{\Delta '_B \mathbf{M}_{\mathbf{X}_B}\Delta_B}{N_B}\hat{\boldsymbol{q}},$$

$$\hat{\boldsymbol{b}} = \hat{\tilde{\boldsymbol{b}}} - \left(\frac{\Delta '_B \mathbf{M}_{\Delta_B}\mathbf{Z}_B}{N_B}\right)^{-1}\left(\frac{\Delta '_A \mathbf{M}_{\Delta_A}\mathbf{Z}_A}{N_A}\right)\left(\frac{\Delta '_A \mathbf{M}_{\mathbf{X}_A}\mathbf{Z}_A}{N_A}\right)^{-1}\left(\frac{\Delta '_B \mathbf{M}_{\mathbf{X}_B}\Delta_B}{N_B}\right)\hat{\boldsymbol{q}},$$

where $\mathbf{M}_{\mathbf{X_B}} = \mathbf{I}_{N_\mathbf{B}} - \mathbf{X_B}\left(\mathbf{X_B'X_B}\right)^{-1}\mathbf{X_B'}$ and similarly for $\mathbf{M}_{\mathbf{X}_A}$, and $\mathbf{M}_{\mathbf{Ä_B}} = \mathbf{I}_{N_\mathbf{B}} - \mathbf{Ä_B}\left(\mathbf{Ä_B'Ä_B}\right)^{-1}\mathbf{Ä_B'}$, and similarly for $\mathbf{M}_{\mathbf{Ä}_A}$.

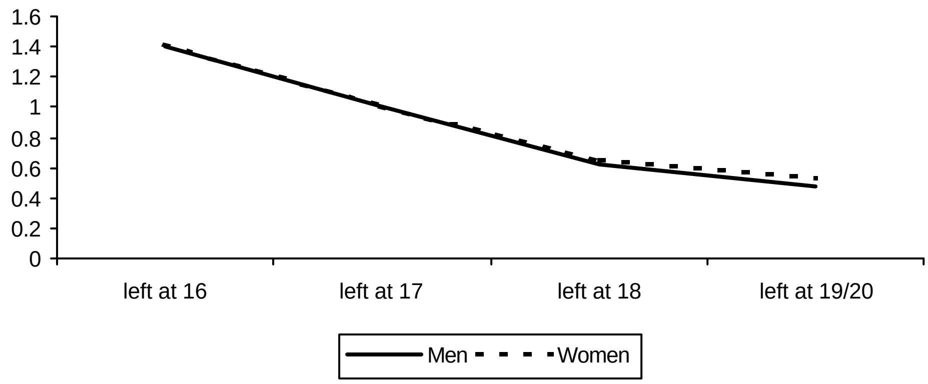
The vector *x* of continuous variables has to be identical between the two samples, thus we simplify our previous specification and keep only variables on mother's and father's education, number of siblings, family structure as well as the regional dummies. Since we introduce five dummies to describe the father's income distribution in the BCS, we fit a quartic polynomial in earnings. The estimated polynomial function is decreasing in income (see figure 3); children from richer families leave school at an older age.

These estimated values of the schooling determinants are used to calculate the cost function faced by each individual. Using the distribution of the costs, the cut-off values of the ordered probit are corrected so that at the mean cost, the probabilities obtained are identical to the probabilities observed in the original sample (BCS). Table 3 reports the probabilities of leaving school at a given age for men[15]. In the upper panel of Table 3, the school leaving age probabilities are reported by cost decile. Pupils with the highest educational cost (decile 1) have a probability of exiting education at the first opportunity of 87%. This probability of quitting school at compulsory schooling age is only 4% for children with the most favourable background.

Figure 3: Corrected estimates of the earnings effect on educational choice

Using the corrected threshold values and the earnings polynomial we defined corrected values of the ratio marginal revenue-marginal cost for men and women. The ratio for pupil leaving school at 17 is fixed at the unity for comparison purposes. These ratios of the marginal revenue-marginal cost are represented in figure 4. The pattern is similar to the one observed without correction.

Figure 4: Corrected marginal revenue-marginal cost ratio



We calculate the effect on the school leaving age distribution of an educational allowance that would affect all children irrespectively of their paternal income but accounting for their family characteristics. We add the equivalent of £30 in 1980 to all fathers' income. The results of such a reform are reported in the right hand side of Table 3. At all level of the cost distribution, the effect of such an educational allowance on the school leaving age probability is marginal.

We replicate the calculations when dividing the population by income decile; these results are presented in the lower panel of Table 3. The variation in the school leaving age distribution by income decile is not as severe as with the cost-deciles; the poorest have a probability of 62% of leaving school at 16, whereas for the richest this probability is 30%. However, the effect of the education allowance are again insignificant, changing the probability of exiting after compulsory schooling by a few tenths of a percent.

The cost function defined by this method is dominated by the effect of parental education and family situation. A change in earnings shifts the cost function only marginally. We finally test that these results are not due to the procedure that we use to define the polynomial function in earnings. We use the BCS data where the paternal earnings variable is not continuous. Each earning dummy represents a range of £50 equivalent to £122 in 1999. We shift each individual to the above category (with the exception of the top group). This fictitious EMA is four times more important than the proposed one, but it will decrease the probability of leaving school at 16 for the average individual by 6% (from 52% to 46%) for males and 11% (from 44% to 33%) for females. This latest projection confirms the limited impact that financial incentives have on the probability of staying on past compulsory education.

VI. Conclusion

Governments have been looking at incentives to increase the educational attainment of the youths for two main reasons: to reduce the intergenerational transmission of inequality and to increase the future economic growth. It is commonly advocated that financial constraints prevent pupils from the poorer backgrounds to invest in their own education. Previous research has shown the negative impact on educational attainment of being brought up in a poorer background. However, the effect of family income on the child’s educational attainment is unclear as it is related to other family characteristics, which might also affect schooling decision. We propose a methodology that separates these effects and find that the direct effect of family income on child’s schooling attainment is rather limited. A policy of educational allowance may have no significant effect on post compulsory education decision, as its effects are too belated. Adolescents may take their schooling decision at an earlier stage of their development and by the age of 16 cannot revise their investment strategies. Any policy aiming at improving the educational attainment of the youth should aim at increasing children's ability at an earlier age and enriching the information set of adolescents and therefore improving their taste for schooling.

References:

Ashenfelter O. and Rouse C. (1999), "Schooling, intelligence and income in America: Cracks in the Bell curve", NBER Working Paper, No W6902

Cameron S. and Heckman J. (1998), "Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males", Journal of Political Economics, No 106, pp262-332

Cameron S. and Heckman J. (1999), "The dynamic of educational attainment for Blacks, Hispanics and Whites", NBER Working Paper, No W7249

Card D. (1999)," The causal effect of education on earnings", Forthcoming in O. Ashenfelter and D. Card, "Handbook of Labor Economics". Elsevier, Amsterdam

Cawley J, Heckman J. and Vytlacil E. (1998), "Cognitive ability and the rising return to education", NBER Working Paper, No W6388

Currie J. and Thomas D. (1995), "Race, children's cognitive achievement and the Bell curve", NBER Working Paper, No W 5240

Currie J. and Thomas D. (1998), "School quality and the longer term effects of Head Start", NBER Working Paper, No W 6362

Feinstein L. (1999), "The relative economic importance of academic, psychological and behavioural attributes developed in childhood", LSE, mimeo

Feinstein L. and Symons J. (1999), Attainment in secondary school", Oxford Economic Paper, 51, p300-21

Hanushek E, (1992) "The trade-off between child quality and quantity", Journal of Political Economy, 100, pp 84-117

Haveman R. and Wolfe B. (1995), "The determinants of children's attainments: A review of methods and findings ", Journal of Economic Literature, Vol 33, pp 1829-78

Herrnstein R. and Murray C. (1995), "The Bell curve", Free Press, NY

Korenman S. and Winship C. (1995), "A reanalysis of the Bell curve", NBER Working Paper, No W4230

Leslie D. and Drinkwater S. (1999), "Staying on in full-time education: Reasons for higher participation rates among ethnic minority males and females", Economica, 67, p63-77

Levine D. and Painter G. (1998), "The NELS curve: Replicating the Bell Curve analyses with the National Education Longitudinal Survey", Berkeley University, Woking Paper No 66

Mare R. (1980), "Social background and school continuation decisions", Journal of the American Statistical Association, Vol 75, pp295-305

Micklewright J. (1989), "Choice at sixteen", Economica, Vol 56, pp 25-39

Rice P. (1987), "The demand for post-compulsory education", Economica, Vol 54, pp 465-74

Table 1: Summary statistics

	NCDS: Cohort 1958		BCS: Cohort 1970	
Variable	**Women**	**Men**	**Women**	**Men**
Age left school	17.1567 (1.7991)	17.0702 (1.8810)	17.9483 (2.5196)	17.8886 (2.6386)
Mother school: +1	0.1154 (0.3195)	0.1121 (0.3156)	0.1526 (0.3597)	0.1438 (0.3509)
Mother school: +2	0.0834 (0.2765)	0.0793 (0.2703)	0.0727 (0.2596)	0.0812 (0.2732)
Mother school: +3/4	0.0482 (0.2142)	0.0441 (0.2053)	0.0506 (0.2193)	0.0617 (0.2407)
Mother school: more	0.0367 (0.1880)	0.0328 (0.1781)	0.1519 (0.3590)	0.1507 (0.3578)
Father school: +1	0.0949 (0.2931)	0.0822 (0.2747)	0.1209 (0.3260)	0.1079 (0.3104)
Father school: +2	0.0787 (0.2694)	0.0765 (0.2659)	0.0538 (0.2256)	0.0548 (0.2277)
Father school: +3/4	0.0633 (0.2435)	0.0561 (0.2301)	0.0541 (0.2263)	0.0613 (0.2400)
Father school: more	0.0453 (0.2080)	0.0465 (0.2107)	0.1705 (0.3761)	0.1658 (0.3720)
Father income:1	0.0327 (0.1779)	0.0398 (0.1956)	0.0492 (0.2164)	0.0531 (0.2243)
Father income:2	0.3059 (0.4609)	0.2965 (0.4568)	0.2557 (0.4363)	0.2444 (0.4298)
Father income:3	0.3598 (0.4800)	0.3688 (0.4826)	0.3371 (0.4728)	0.3519 (0.4777)
Father income:5	0.0579 (0.2335)	0.0564 (0.2308)	0.0674 (0.2508)	0.0561 (0.2302)
Father income:6	0.0737 (0.2613)	0.0716 (0.2578)	0.0604 (0.2383)	0.0592 (0.2360)
Nbr sibling	3.0288 (1.4924)	3.0176 (1.4711)	2.4537 (0.9827)	2.4845 (0.9772)
Council estate	0.4202 (0.4937)	0.4108 (0.4921)	0.2155 (0.4112)	0.2185 (0.4133)
Father present	0.9533 (0.2111)	0.9577 (0.2013)	0.8753 (0.3304)	0.8877 (0.3158)
Mother present	0.9759 (0.1533)	0.9707 (0.1686)	0.9762 (0.1523)	0.9801 (0.1396)
White	0.9687 (0.1741)	0.9556 (0.2061)	0.9728 (0.1628)	0.9741 (0.1589)
Father soc 1	0.0500 (0.2179)	0.0596 (0.2368)	0.0625 (0.2421)	0.0643 (0.2454)
Father soc 2	0.1822 (0.3861)	0.1675 (0.3735)	0.2218 (0.4155)	0.2116 (0.4085)
Father soc 3n	0.1006 (0.3009)	0.0949 (0.2931)	0.0765 (0.2658)	0.0911 (0.2878)
Father soc 3m	0.4299 (0.4952)	0.4439 (0.4969)	0.3626 (0.4808)	0.3800 (0.4855)
Father soc 4	0.1707 (0.3763)	0.1675 (0.3735)	0.0978 (0.2971)	0.0902 (0.2866)
Father soc missing	0.0155 (0.1234)	0.0190 (0.1367)	0.1554 (0.3624)	0.1382 (0.3452)
Math test: 25/50	0.2671 (0.4425)	0.2620 (0.4398)	0.2564 (0.4367)	0.2198 (0.4142)
Math test: 50/75	0.2304 (0.4212)	0.2384 (0.4262)	0.2585 (0.4379)	0.2275 (0.4193)
Math test: 75+	0.1636 (0.3699)	0.1996 (0.3998)	0.1952 (0.3965)	0.2949 (0.4561)
Read test: 25/50	0.2746 (0.4464)	0.2884 (0.4531)	0.2469 (0.4313)	0.2327 (0.4227)
Read test: 50/75	0.2480 (0.4319)	0.2109 (0.4080)	0.2812 (0.4497)	0.2522 (0.4343)
Read test: 75+	0.2243 (0.4172)	0.1569 (0.3638)	0.2295 (0.4206)	0.2310 (0.4216)
Observations	2782	2836	2863	2316

Table 2a: Age left education determinants: Ordered Probit-Women

	NCDS: cohort 1958 – Women		**BCS: Cohort 1970- Women**	
Mother school: +1	-0.2583 (0.0711)	-0.2575 (0.0708)	-0.3423 (0.0624)	-0.2547 (0.0632)
Mother school: +2	-0.5348 (0.0831)	-0.4595 (0.0866)	-0.3842 (0.0819)	-0.3089 (0.0827)
Mother school: +3/4	-0.7236 (0.1017)	-0.6514 (0.1007)	-0.5818 (0.1039)	-0.4597 (0.1049)
Mother school: more	-0.9161 (0.1316)	-0.8444 (0.1342)	-0.3018 (0.0862)	-0.2505 (0.0855)
Father school: +1	-0.2912 (0.0804)	-0.2884 (0.0803)	-0.1096 (0.0716)	-0.0326 (0.0745)
Father school: +2	-0.3494 (0.0864)	-0.3261 (0.0887)	-0.2576 (0.0999)	-0.2403 (0.1020)
Father school: +3/4	-0.4272 (0.0997)	-0.4277 (0.0988)	-0.2308 (0.1007)	-0.2148 (0.1011)
Father school: more	-0.3881 (0.1263)	-0.3513 (0.1294)	-0.3102 (0.0872)	-0.2623 (0.0874)
Family income:1	0.0800 (0.1489)	0.0381 (0.1456)	0.1378 (0.1174)	0.0232 (0.1216)
Family income:2	0.1990 (0.0734)	0.1527 (0.0741)	0.1667 (0.0670)	0.1452 (0.0679)
Family income:3	0.1597 (0.0683)	0.1413 (0.0691)	0.0778 (0.0595)	0.0636 (0.0602)
Family income:5	0.0877 (0.1023)	0.0792 (0.1033)	-0.2588 (0.0904)	-0.2121 (0.0907)
Family income:6	-0.0532 (0.0941)	-0.0874 (0.0947)	-0.4176 (0.0986)	-0.3681 (0.1003)
Math test: 25/50		-0.0376 (0.0653)		-0.1155 (0.0631)
Math test: 50/75		-0.1442 (0.0689)		-0.2406 (0.0701)
Math test: 75+		-0.3164 (0.0782)		-0.4863 (0.0834)
Read test: 25/50		-0.0109 (0.0721)		-0.1881 (0.0667)
Read test: 50/75		-0.3918 (0.0748)		-0.4191 (0.0720)
Read test: 75+		-0.5413 (0.0790)		-0.8421 (0.0859)
Observation	2782	2782	2863	2863
Pseudo R^2	0.1244	0.1471	0.0918	0.1330

Note: the regression also includes a set of dummies for paternal class, family structure, region of residence, the number of siblings in the household, race of child and type of accommodation (Council estates)

Table 2b: Age left education determinants: Ordered Probit--Men

	NCDS: cohort 1958 - Men		BCS: Cohort 1970- Men	
Mother school: +1	-0.3585 (0.0728)	-0.3057 (0.0742)	-0.2717 (0.0743)	-0.2136 (0.0754)
Mother school: +2	-0.5457 (0.0873)	-0.4989 (0.0884)	-0.5233 (0.0959)	-0.4081 (0.0971)
Mother school: +3/4	-0.4754 (0.1031)	-0.4460 (0.1054)	-0.7227 (0.1048)	-0.5974 (0.1092)
Mother school: more	-0.5064 (0.1374)	-0.4111 (0.1452)	-0.3184 (0.0973)	-0.2044 (0.0968)
Father school: +1	-0.3499 (0.0851)	-0.3100 (0.0863)	-0.1225 (0.0846)	-0.0058 (0.0863)
Father school: +2	-0.3492 (0.0916)	-0.2972 (0.0918)	-0.1158 (0.1177)	-0.0212 (0.1198)
Father school: +3/4	-0.1836 (0.0945)	-0.1759 (0.0960)	-0.2940 (0.1015)	-0.2987 (0.1034)
Father school: more	-0.4876 (0.1323)	-0.4318 (0.1354)	-0.1952 (0.0970)	-0.1398 (0.0972)
Family income:1	0.4359 (0.1505)	0.3804 (0.1481)	0.3126 (0.1350)	0.3180 (0.1446)
Family income:2	0.2403 (0.0766)	0.2297 (0.0785)	0.1852 (0.0764)	0.1602 (0.0786)
Family income:3	0.0943 (0.0698)	0.0810 (0.0718)	0.1184 (0.0668)	0.1097 (0.0680)
Family income:5	-0.1359 (0.1123)	-0.1302 (0.1130)	-0.1901 (0.1139)	-0.1844 (0.1168)
Family income:6	-0.0619 (0.0947)	-0.0368 (0.0962)	-0.3048 (0.1073)	-0.3228 (0.1115)
Math test: 25/50		-0.1254 (0.0716)		-0.0623 (0.0828)
Math test: 50/75		-0.2643 (0.0763)		-0.2231 (0.0891)
Math test: 75+		-0.4090 (0.0809)		-0.6881 (0.0949)
Read test: 25/50		-0.1993 (0.0699)		-0.1866 (0.0817)
Read test: 50/75		-0.4937 (0.0757)		-0.3131 (0.0854)
Read test: 75+		-0.6798 (0.0829)		-0.7703 (0.0967)
Obs	2836	2836	2316	2316
Pseudo R^2	0.1182	0.1503	0.1001	0.1571

Note: the regression also includes a set of dummies for paternal class, family structure, region of residence, the number of siblings in the household, race of child and type of accommodation (Council estates).

Table 3: Probability of leaving school: Men

	Before the reform					Post school maintenance reform				
Cost decile	**Age 21+**	**Age 19/20**	**Age 18**	**Age 17**	**Age16**	**Age 21+**	**Age 19/20**	**Age 18**	**Age 17**	**Age16**
1	0.0163	0.0124	0.0429	0.0518	0.8765	0.0165	0.0126	0.0434	0.0523	0.8753
2	0.0385	0.0247	0.0751	0.0797	0.7820	0.0390	0.0250	0.0757	0.0801	0.7802
3	0.0664	0.0369	0.1024	0.0986	0.6957	0.0672	0.0372	0.1030	0.0990	0.6935
4	0.0916	0.0462	0.1206	0.1091	0.6324	0.0927	0.0465	0.1212	0.1095	0.6301
5	0.1123	0.0528	0.1324	0.1148	0.5878	0.1134	0.0531	0.1330	0.1150	0.5854
6	0.1399	0.0605	0.1449	0.1196	0.5351	0.1413	0.0609	0.1454	0.1198	0.5327
7	0.1682	0.0673	0.1546	0.1221	0.4877	0.1698	0.0677	0.1551	0.1222	0.4853
8	0.2438	0.0808	0.1692	0.1213	0.3850	0.2457	0.0811	0.1694	0.1212	0.3826
9	0.4422	0.0937	0.1636	0.0962	0.2042	0.4446	0.0937	0.1633	0.0959	0.2026
10	0.7871	0.0599	0.0784	0.0334	0.0412	0.7887	0.0596	0.0779	0.0331	0.0407

	Before the reform					Post school maintenance reform				
Income decile	**Age 21+**	**Age 19/20**	**Age 18**	**Age 17**	**Age16**	**Age 21+**	**Age 19/20**	**Age 18**	**Age 17**	**Age16**
1	0.1336	0.0446	0.1080	0.0938	0.6200	0.1346	0.0449	0.1085	0.0941	0.6180
2	0.1198	0.0427	0.1043	0.0913	0.6418	0.1208	0.0430	0.1047	0.0916	0.6398
3	0.1266	0.0441	0.1071	0.0933	0.6290	0.1276	0.0443	0.1075	0.0936	0.6270
4	0.1819	0.0506	0.1149	0.0941	0.5585	0.1830	0.0508	0.1153	0.0942	0.5566
5	0.1674	0.0508	0.1189	0.0993	0.5637	0.1686	0.0510	0.1193	0.0995	0.5616
6	0.1977	0.0570	0.1286	0.1029	0.5137	0.1990	0.0573	0.1290	0.1030	0.5117
7	0.2251	0.0640	0.1382	0.1058	0.4669	0.2266	0.0642	0.1385	0.1058	0.4649
8	0.2553	0.0598	0.1266	0.0967	0.4616	0.2568	0.0600	0.1268	0.0967	0.4597
9	0.2479	0.0591	0.1252	0.0957	0.4721	0.2493	0.0593	0.1254	0.0958	0.4702
10	0.4556	0.0621	0.1111	0.0730	0.2982	0.4571	0.0621	0.1110	0.0729	0.2968

[1] This book has generated numerous replications (Cawley *et al*. (1998); Currie and Thomas (1995); Korenman and Winship (1996) and Levine and Painter (1999). These articles have criticized the method used by Herrnstein and Murray and particularly the definition of the family background index. Using broader definition of family background, the role of ability at explaining various outcomes was seriously reduced. Also, Korenman and Winship (1996) found that education had a significant impact that did not appear in the original study. Hence, to paraphrase Herrnstein and Murray, "schools are a good place to reduce inequalities". Ashenfelter and Rouse (1999) accumulate evidence that returns to schooling are not merely returns to ability.

[2] Feinstein (1999) stresses that parental education and income but also measures of the child psychological development at age 10 have a major effect on school attainment, even when controlling for ability. The psychological attributes can be seen as being the outcome of long-term family characteristics.

[3] In the UK, a parenting support program (SURE-start) has recently been introduced. This programme also encourages parents to register their children to pre-school. American evidences on the long-term benefit of the Head-Start programme have so far been mixed. The positive effects on educational attainment of attending pre-school may be only temporary depending on the school quality (Currie and Thomas, 1998).

[4] Note that the model is not observationally distinct from a model where the revenue function and the cost function have the following functional form: either $R(s|x,h,e)=R(s)y(x,h,e)$ and $C(s|x,h,e)=C(s)y(x,h,e)j(x)e$, or $R(s|x,h,e)=R(s)\frac{y(x,h,e)}{j(x)e}$ and $C(s|x,h,e)=C(s)y(x,h,e)$, where h is some unobservable and $y(x,h,e)$ is any positive function of x, h and e. Indeed the expression for the probability of observing a given level of schooling does not change.

[5] A large part of Cameron and Heckman (1998) contribution studies the condition under which the model is non-parametrically identified. The data we use, does not allow us to identify non-parametrically the distribution of the unobserved heterogeneity.

[6] Hanusheck (1992) and Feinstein and Symons (1999) stress the importance of parental interest in the child's education (time spent with child)as a significant factor explaining schooling attainment. Parents from higher socio-economic group tend to spend more time with their children either because they have fewer children or because they value education more than other parents.

[7] The data used does not allow us to differentiate between the different ethnic minorities. On average, ethnic minorities have a greater likelihood to stay in education after compulsory schooling but variations between ethnic groups should be important (See Leslie and Drinkwater (1999)).

[8] The AFQT used in the "Bell Curve" has been criticised for being dependent on schooling

achievement as it was measuring ability at age ranging from 14 to 24.

[9] The NCDS cohort was the first cohort to face the compulsory school leaving age of 16. The difference in schooling achieved is thus not due to a law change but to a real increase in the decision to stay in education for the younger cohort.

[10] We use post-compulsory schooling as opposed to years of schooling since the minimum school leaving age was increased in 1948 from 14 to 15. The observed increase in education between the two generations of parents is therefore not picking up the effect of the change in minimum school leaving age but instead a real increase in the decision to invest in post-compulsory education.

[11] The effect of this type of measures is usually difficult to measure. For example, access to a library increases the likelihood of investing in education, however, as library are usually more frequented by pupils from a middle class background, more libraries might increase the dispersion of educational achievement between poor and other children.

[12] The ratio of marginal revenue over marginal cost for each year of schooling is deducted from the ordered probit estimation of this model.

$$\frac{mR(s=j)}{mC(s=j)} = \frac{m_j}{\exp(-X\boldsymbol{b})}$$

where μ_j is such that $Pr(s=j)=\Phi(\mu_j - X\beta)-\Phi(\mu_{j-1} - X\beta)$ and $X\beta$ is measured at the average characteristics of the cohort.

[13] The marginal revenue-marginal cost ratios presented are derived from the estimates based on the equations including ability. The exclusion of the ability measures does not change the general trend. The ratios for men follow similar pattern and are available upon request.

[14] Given the relationship between the asymptotic pseudo-true value, the true value and the error term it is straighforward to obtain an expression for the asymptotic variance-covariance of $\left(\hat{\boldsymbol{b}},\hat{\boldsymbol{a}}\right)$. The feasible estimator depends clearly on the estimated variance-covariance of $\left(\hat{\hat{\boldsymbol{b}}},\hat{\boldsymbol{q}}\right)$.

[15] Results for females are similar and are not reproduced here.