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SCHOLASTIC ABILITY VS. FAMILY BACKGROUND IN EDUCATIONAL SUCCESS: EVIDENCE FROM DANISH SAMPLE SURVEY DATA*

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Abstract. This research examines the role of scholastic ability and family background variables in the determination of educational attainment in Denmark. A categorical representation of the highest level of education attained by the individual is the dependent variable. It is analyzed by procedures which take account of the presence of unobservable factors. Parent's education and occupation along with an indicator of scholastic ability which is represented by a set of aptitude tests explain a small but significant portion of the variation in their children's' educational success. Women are shown to respond differently to their environments than men and including these test scores does not remove the need to deal with unmeasured attributes. On the basis of the available data, family background variables as a group contribute more to the explained variation in the data than the test scores. Finally, credit constraints do not appear to be a factor in educational attainments.

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1 introduction

Educational attainment and the extent to which an individual participates in the educational system is, perhaps, one of the single most important factors in the determination of lifetime economic and social attainment. Although much research has been undertaken to explain the determinants of educational attainment it is far from being complete and there are many unresolved issues. Some of these, like the relative importance of scholastic ability and gender in educational success, as well as the importance of unobservable effects and how they should be treated are the focus of our attention. This study examines the determinants of educational attainment of a sample of Danish students who were fourteen in 1968 and who participated in the 1968 Danish Longitudinal Survey of Youth. We examine the role of the respondent's scholastic ability and social and economic background, especially the occupational and educational characteristics of the respondent's parents, parent's income, the number of siblings, and the respondent's attitude to school etc. in the respondent's success in the educational system.

Under the direction of E. J. Hansen, the Danish National Institute of Social Research organized a series of surveys of a sample of Danish children who were born in 1954 or 1955. The data from this survey was first analyzed by Ørum (1971) and more recently by Hansen (1995) using simple tabular statistical procedures. However, new methods have been developed for analyzing of this type data and it is our intention to apply these in a systematic way to explain Danish educational attainments. The Danish case is an interesting one to consider because at the time the survey was conducted Denmark had already developed an advanced set of welfare programmes with free and universal access to all levels of schooling. As a result it is not unreasonable to expect that by the end of the 1970's ability and not family background variables would be the prime determinants educational success. Our results show that this is not the case.

There are two ways of measuring educational attainment as an outcome; one is completed years of schooling and the other is a categorical representation indicating the most advanced level achieved. Our preference is for the latter because in Denmark there are usually a number of educational outcomes that can be achieved with the same number of years of formal schooling. For example, there are respondents in our sample with university degrees who took the same number of years to complete their schooling as some of the respondents with an apprenticeship or vocational qualification.

Our approach is to use a family based human capital model. In a seminal paper, Becker and Tomes (1979) suggested that parents, in valuing the characteristics of their children, were paternalistic and made household decisions which reflected the interests of all generations within the family.[1] Without actual data on the details of time and expenditure allocations within the household it is difficult to distinguish between the benefits which accrue to children through the actual investment process and those which depend on the quality of the parent as represented by his or her characteristics. In either case the idea is that the human capital accumulation process is affected by the characteristics of the family in which the individual grows up. Here we are following the tradition of Blau and Duncan (1967), and more recently, Dearden *et al* (1997) and Dearden (1999), and Bowles, Gintis, and Osborne (2001) in looking for the relevant environmental and family background variables as determinants of educational attainment.

In summary, our results which are based on mixed ordered probability models of five categories of educational attainment, are the following: i) household background variables are more important as a group in explaining the final level of educational attainment than are a battery of three test scores administered at age fourteen, ii) women's performance is determined by different variables than those which determine the success of men; in particular, test scores and unobservables play different roles for the two genders, iii) unobservable effects which are often attributed to ability are present even when test scores are included as covariates suggesting that there other non-cognitive dimensions to ability that matter in educational success, iv) unobservables are significant, as indicated by the superiority in terms of the likelihood of mixed distributions over unmixed distributions, and v), the significance of income as a regressor probably does not imply that there are credit constraints limiting access to higher levels of education.

The paper has the following format. The next section provides a brief review of the literature on educational attainment as well as some of the statistical procedures that have been used in its analysis. Results of what other researchers in this area have found are summarized here. A formal model of educational attainments is developed in section 3 and in section 4 Danish educational attainment data are analyzed using both ordered and unordered probability models which are estimated by procedures which take into account the presence of unobservable factors. Our procedures are in the spirit of the work of Cameron and Heckman (1998), but belong to the more general set of latent class models as exemplified by Deb and Trivedi (1997) and Wedel *et al* (1993). Our results are presented in section 5 where we also discuss the importance of household income and whether its significance can be interpreted as implying the presence of credit constraints on the feasibility of attending institutions of higher learning.

2 The educational attainment literature

Much of the early literature on educational attainment and mobility used regression methods applied to years of completed schooling. Featherman and Hauser is an early example but there are many more studies, many of which, are surveyed in Haveman and Wolfe (1995). Examples of this type of analysis after 1995 are the study of Dearden *et al*

(1997) and Dearden (1999) using the British National Child Development Survey. They find that father's years of education, mother's years of education, birth order, type of school, father's occupation, and the financial state of the household were significant in explaining completed years of school for both men and women. Like many other studies they find that mother's education is more important than that of the father even when scores from both verbal and mathematical ability tests are included as regressors.[2] Similar results for the United States have been obtained by Peters and Mullis (1997), Fisher *et al* (1996), and Korenman and Winship (2000, Appendix B).

Recent advances in computational methods have made it possible to estimate dynamic structural models of the full sequence of educational decisions. Major contributions here are Belzil and Hansen (2003) and Keane and Wolpin (2001). These two studies exploit the panel structure of the National Longitudinal Study of Youth. While their models are considerably more complicated than those underlying the research summarized above their conclusions are very much in line with what others have found. To us this suggests that the problems which are caused by unobservable effects and which are properly dealt with in these two papers may not be as serious as some researchers have claimed.

In many European countries, including Denmark, years of school does not correspond very well to categorical representations and there are often many different types of education that are acquired with the same number of years of school. In addition to the difficulties arising from the weak relationship between years of schooling and the actual qualification obtained the regression model has been criticized because of its alleged failure to capture the sequential nature of educational decisions. Mare (1980, 1981) was one of the first to make this point and his sequential model has become one of the cornerstones of sociological research in educational attainment. Most of the papers in the Shavit and Blossfeld (1993) volume treat education in this fashion.[3] Unfortunately, as Cameron and Heckman show, some of the conclusions which the researchers drew from this type of analysis are problematic and arise as an artifact of the logit specification of the stage probabilities when no account is taken of unobservables.[4] However, their procedure of treating the categorical probabilities for US males in the National Longitudinal Survey of Youth by an ordered probability model, corrected for unobserved heterogeneity, is certainly legitimate and, as they show, is superior on the basis of non-nested criteria to the Mare model.

Ordered models like those which Cameron and Heckman advocate are becoming more common in the literature. Ermisch and Francesconi (2001) using the British Household Panel Survey is one recent example as is the Lauer (2003) paper which uses a bivariate-variate version of the Cameron-Heckman model on French and German data. Unordered logit models are also popular and are used to explain individual educational outcome probabilities as functions of covariates. These represent household background variables like the educational qualifications of the parents, variables relating to the environment in which the respondents lived as children, and variables pertaining to the place of the household in the social hierarchy.

Studies of educational attainment have been carried out for several European countries, however, there complex unresolved econometric issues in much of this research. Three problems are common in the papers that relate to our work. They arise because of selection procedures, improper conditioning on endogenous variables, and a failure to account of unobservables.

Papers by Hansen (1997) using Norwegian data and Davies *et al* (2002) using Danish data do not take these selection problems into account. Both find that parental background variables are important in the determination of educational outcomes. Davies *et al* also find self-reported ability to be significant. Furthermore, there is no attempt to deal with unobservables in these two papers. Breen and Jonsson (2000) examine Swedish register data and use social class of the parents as well as information on the particular path that the respondent took to his or her terminal educational destination. They constructed probability models of educational outcomes which take account of the path that an individual takes through the system. This is, in principle, an interesting idea since it reduces the complexity of the analysis. But there is a cost; paths are represented by a set of dummy variables which are included as regressors in the outcome probabilities. This procedure treats previous decisions as being exogenous which they are not (improper conditioning on an endogenous variable), precisely, because they are decisions which individuals made at earlier stages. This is a specification error and it can lead to parameter biases which can be very large. On the other hand, the authors control for unobservable effects and there are no selection problems. (See page 767 of their paper).

Lauer (2003) examines French and German data in a model which includes two stages, each of which is ordered in Cameron-Heckman fashion by utility. Unlike Breen and Jonsson, both states (secondary schooling and final education) are explained simultaneously in a bivariate model. This procedure by construction, eliminates both the selection problem and the endogeneity problem. Her results are similar to ours except that we find no decline in the importance of family background variables as the level of education rises. There is no control for unobservables in her model but this is not surprising since the model is already very complex.

Finally, it should be pointed out that research which relies only on household and parent characteristics is unable to distinguish between what parents actually do for their children as opposed to what children get from their parents in terms genetic or sociocultural endowments. Todd and Wolpin (2003) emphasize the importance of the quantity, quality, and timing of inputs in the child rearing process. When this type of information is missing it is impossible to determine whether households with well educated parents, for example, are more likely to have children which do well in the educational system because they benefited genetically from their parents or because their parents passed on the habits which made them successful academically.

3 A Model of Optimal Educational Decisions

One way of modelling the educational decisions of individuals is to assume that they choose an educational profile which maximizes an intertemporal objective function. The type of educational decisions which are being examined here should, in our view, be conditioned to some extent by the preferences of the individual involved. Parents, of course, are also involved as mentors and as providers of some of the resources required for the particular action chosen. Consequently, we can think of education decisions in an expanded two-stage framework where parents make investments in their children who, conditional on these investments, make the educational decisions which best serve their own long term objectives.[5]

At each moment in time an individual has to decide which type of educational programme is best for them. For individual i the decision will depend, in part, on the level of education acquired as of time t as well as the histories of the relevant state variables, $X_i(t)$. Formally, the history vector $X_i(t) = \{x_i(s)|0 \leq s \leq t\}$. The vector of $X_i(t)$ variables is made up of variables specific to the individual, household variables, and other variables which affect individuals but lie outside the domain of the household like the returns to specific types of education or the number of university places that are available. There is uncertainty associated with future values of these variables.

Decisions will also depend on what the individual expects in terms of future benefits that derive from them. Education confers benefits to individuals in the form of financial remuneration but there are also substantial benefits involving job satisfaction, prestige, and job security. These vary over time and are represented in this model by a von-Neuman Morgenstern utility function which depends on the individuals educational attainment and the state at the time.

Here it is assumed that individuals are forward looking and maximize the present value of the stream of utilities that are expected over the remainder of his or her lifetime by selecting an educational profile from a set of J discrete alternatives. Expectations are continuously updated as new information arrives but no assumption is made about the rationality of this process since there is no way given the data available to test such an assumption.[6] The following value function describes the constrained optimization problem which represents this behaviour for individual i.

$$V_i(X_i(t), j_i(t)) = \underset{j \in J}{Max} \mathcal{E}_t \left[\sum_{\tau=t}^{T(t)} \delta^{(\tau-t)} u_i(j(\tau), x_i(\tau)|\Omega(t) \right] \tag{1}$$

subject to

$$x_i(t) = g_i(X_i(t-1), z(t)) \tag{2}$$

where $\Omega(t)$ is the information available at time t and $z(t)$ is stochastic shock.

Although this is a dynamic sequential decision problem the data that will be used to estimate the model is retrospective and we will be looking at the last educational decision at a time when no subsequent educational decisions could have been made. Without loss of generality, let j take the integer values $1, 2..., J$. Suppose for individual i that the final educational decision was was made at s_i. Let $v(I_i, k)$ be an approximation to $V_i(X_i(s_i), j_i(s_i))$ where $I_i = \beta X_i(s_i) + \epsilon_i$, k is a real number, and I_i is an index of individual characteristics observable at time s_i (parameterized by β, which is assumed to be the same for all individuals) together with a random disturbance term, ϵ_i, which captures effects which can not be observed by the researcher. I_i represents competence in some general sense and depends on environmental and family background variables as well as the individual's ability. Define

$$k(I_i) = \arg\max_k v(I_i, k) \tag{3}$$

which is the integer which maximizes $v(I_i, k)$.

The educational alternatives facing individual i will be ordered by the variable I_i, if $k'(I_i) \geq 0$. This means that the accessibility of the various levels of the educational system is determined by the competence of the individual as measured by the variable I_i. A condition for this is

$$k'(I_i) = -\frac{\partial^2 v/\partial k \partial I_i}{\partial^2 v/\partial k^2} \geq 0 \tag{4}$$

$\partial v/\partial k$ is the present value of stream of expected marginal utilities of education. The above condition will obtain if $\partial v/\partial k$ increases with the level of competence and declines with the level of educational attainment, assumptions which appear to be reasonable in our context. Since the educational choices are discrete, alternative j will be selected as optimal if I_i belongs to some interval $[\alpha_{j-1}, \alpha_j)$. As result an empirical test of the educational decision making process can be carried out using an ordered probability model.

4 Data and methods

The Danish National Institute of Social Research Longitudinal Youth Survey is a sample from the cohort of individuals who were born in 1954-55. A random sample of students aged fourteen were interviewed in 1968. The 3151 individuals (1562 girls and 1589 boys) in this survey were first contacted in 1968 and have been re-interviewed in 1976, 1992 and finally the most recent being 2001 (additional data was collected in 1969, 1970, 1971 and 1973). The survey was carefully designed and implemented. As a result most of the respondents answered most of the questions and the attrition rate over the thirty-three years between the first and last interviews was not large enough to prevent it from being a valuable source of information. In addition to collecting detailed information on the parents and households the initial survey concentrated on the educational activities of the respondents by administering intelligence tests. Information on educational attainments was collected in 1992, long after respondents had completed their education. Unfortunately, the data set is not a panel and there is insufficient household information available to permit the modeling of the respondent's progress through the educational system.

The educational categories are outcomes that are the possible alternatives that Danish students could have chosen after the completion of compulsory schooling (grade 9). The categories: no higher education and vocational education are self explanatory. Examples of higher education are police training for short higher education, teacher training for middle, and university for higher. The Danish educational system is basically characterized by two main tracks. The vocational track and the higher education track. The apprentice or vocational track is similar to the German educational system where taking a vocational education would imply both a period of time with an employer (meister) and a period of time in a technical school with exams. The other track was begins with three years of high school and from there it is possible to go on to colleges (only Bachelor degrees) or universities (with Master's and Ph.D. programmes).

Clearly, these educational categories are non-sequential in the sense that the lower level programmes do not have to be taken before going on to higher level programmes. However, they can be seen as ordered in terms of their difficulty, skill requirements, and the number of years (on average) needed to complete them. Reflecting the ordering in terms of difficulty our statistical approach will utilize ordered probability models.

Means and standard deviations of the variables are displayed in Table 1. The data for educational outcomes, occupation and parent education refer to categories so the means for these variables are just the proportion of respondents which are in the respective category. For father's occupations they are, in order, 1) the reference group which contains the unemployed, those not looking for work and other and 2), unskilled and skilled manual workers, 3) managerial, professional and independent or self-employed entrepreneurs. Parental school educational categories differ from those of the respondent reflecting an earlier regime. These are 1) the reference group containing no education beyond compulsory schooling, 2) vocational or apprenticeship, 3) intermediate levels of education leading to white collar qualifications and, 4) higher levels of education like university. For women, there were very few observations for categories 3 and 4 so these were grouped with the vocational category.

Test scores are the number of correct answers obtained on the individual tests. The first test had seventy questions and the last two forty. The verbal reasoning test is a test of language comprehension and the ability to deal with abstract concepts. The spatial test measures the ability to discern visual or geometrical equivalences. And the inductive reasoning test measures the ability to find rules and principles which pertain to a given set of data. These tests are traditional Thurstonian intelligence tests modified by S. Hegler and K. Härnqvist. See Ørum (1971 p. 25). However, we refer to these as scholastic ability measures for two reasons. First, some of the skills that students needed to do well on these tests were learned in the school environment. Secondly, students were given some instruction as to how to answer the questions so that some of the ability to deal with the test content was acquired in the classroom. In this respect, our view on what these test represent is similar to that of Neal and Johnson (1996).

Test scores are obtained at many different ages. Plomin *et al* (1997 p. 443) show, using adoption data, that the correlation between parent and respondent test scores rises with the age of the respondent, up to the age of sixteen. They also note a decline in the importance of environmental variables for the respondent's test score performance as they get older so that the overall relationship between family background variables and test scores is age dependent. The tests on which our results are based were carried out when the respondents were fourteen years old. Although age sixteen might have been better it is reasonable to assume that by age fourteen the correlations between the test scores and the rest of the variables which are used to explain educational attainments had stabilized.

Income is parent's pre-tax household income measured in thousands of Danish Kroner. The variable 'mother home' is a categorical variable which takes the value one if the respondent's mother was not involved in employment outside the home.[7] The variables 'broken home', 'number of siblings', and 'urban' are what they appear to be and 'school quality' is an assessment by the class teacher as to the quality of the average student in the class. It takes the value one if the teacher thought that the class was excellent or very good. Respondents were asked how they felt about going to school. Those who said very good or good were classified as liking school and those who said not very good or strongly dislike were classified as not liking school.

The presence of the class quality and school attitude variables in together with test scores makes the survey very unusual and, therefore, particularly valuable for researchers. Very few surveys include information on test scores and we know of no surveys which contain information on pupil attitudes towards school which at the same time contain information on the socioeconomic background of the respondent.

Table 1 about here

As we mentioned earlier, the model of the previous section can be estimated as an ordered probability model. However, there some specific features of our data set that need to be addressed. To accomplish this we decompose ϵ_i into $\theta_i + u_i$. These two error terms are unobservable. u_i is a pure random effect which is orthogonal to θ_i and all of the other explanatory variables. On the other hand θ_i, which represents unobserved components of ability or skill which the respondent inherits from his or her family, may be correlated with any of the explanatory variables. This may contain both genetic and socially determined components; however, there is no way to distinguish the actual source of these endowments. Following a procedure outlined in Heckman and Singer (1984) and Cameron and Heckman (1998), we assume that there are a small number of types of respondent and that for type ℓ, θ_i takes the value $\theta_{i\ell}$, which is a linear function of X_i, $\gamma_\ell X_i$. Conditional on $\theta_{i\ell}$, the educational outcome probabilities for category j and type ℓ are assumed to be generated by the latent variable, $I_{i\ell} = \beta X_i + \gamma_\ell X_i + u_i$, belonging to a class of sets, $\{[\alpha_{j-1,\ell}, \alpha_{j\ell}),\ j = 1, 2..J\}$. Assuming that there are $\mathcal{L}$ different types of individual the probability distribution for this individual's educational attainment is the mixture, $\sum_{\ell=1}^{\mathcal{L}} p_\ell F(a, \mu_\ell(X_i), \sigma)$, where p_ℓ is the probability of type ℓ, $\sum_{\ell=1}^{\mathcal{L}} p_\ell = 1$, $\mu_\ell(X_i) = \beta X_i + \gamma_\ell X_i$ and $F(a, \mu_\ell(X_i), \sigma) = \Pr\{u_i \leq a | \theta_i = \theta_{i\ell}\}$ is the distribution function associated with u_i whose variance is σ^2. The distribution of the mixture has a mean which is equal to $\sum_{\ell=1}^{\mathcal{L}} p_\ell \mu_\ell(X_i)$.

Most practitioners treat θ_i as constants independent of X_i. Consequently, our approach is somewhat more general than the Cameron-Heckman-Singer procedure and can be characterized as a correlated random effects procedure. Formally, as we mentioned earlier, it is a latent class model. It is usually the case that only a small number of distributions are used in this procedure. Most researchers using this technique find that two is usually enough. All of our models involve only two types as well. Attempts to use a larger number of types were never successful as the probability of the third type always converged to zero. We attribute this to the relatively small sample sizes involved. Our types are listed as 1 and 2; later we will refer to these as strong and weak types.

For comparative purposes unordered models were estimated but these were shown, on the basis of non-nested tests, to be inferior to ordered models. We return to this point in the next section. Parameter estimates are shown in Table 2.

Because of parameter identification problems these are of the form $\delta_k = \sum_{\ell=1}^{2} p_\ell \eta_{\ell k}$ where $\eta_{\ell k} = (\beta_k + \gamma_{\ell k})/\sigma$. The $\eta_{\ell k}$ coefficients have two components, a component which represents a general effect, characterized by β_k/σ, and a type specific effect which is added to the general effect and is represented by $\gamma_{\ell k}/\sigma$. The sum of the two effects can be identified but the individual components can not.

5 Results

We begin by discussing the results in Table 2. The parameter estimates in this table are coefficients of variables which have been normalized to have mean zero and a variance of unity. This means that the size of the parameter indicates its importance as an explanatory variable.[8] For males the variables that matter most in explaining educational attainment are the occupation of the father followed in order of importance by the verbal and inductive reasoning test scores, father's education, attitude to school, mother's education and then household income. Father's occupation is also the most important variable for females. This is followed by father's education, the inductive reasoning and verbal test scores, and then a school attitude variable. Coming from a broken home, the number of siblings, and household income form a less important but significant group of factors determining educational attainment. We also included birth order as a regressor but this variable had absolutely no impact on the results.

A conclusion that follows immediately from this table is that the determinants of educational attainment differ by gender both with respect to the variables which explain this outcome and the magnitudes of the parameter estimates associated with significant explanatory variables. Mother's education is a significant variable for males; but coming from a broken home or the number of siblings are not. On the other hand, coming from a broken home is important for females but mother's education is not. Parameter estimates, as a group, are significantly different for the two genders and pooling the two genders together with a gender dummy was always rejected by a likelihood ratio test in favour of distinct coefficients for each gender.

Table 2 about here

The importance of ability or intelligence in individual success as opposed to other variables is an issue that has generated much controversy among social scientists. It has also been a subject of a heated debate in Denmark (Hansen and Kreiner (1996), Nyborg (1990, 2003)). Herrnstein and Murray (1994) argued that 'intelligence' is the principal driver of success. The reactions to the results outlined in *The Bell Curve* were for the most part negative. To the extent that test scores represent intelligence, our results could also be seen as not supporting this rather extreme position. This result can already be seen from the relative importance of the test score coefficients of Table 2 but it is possible to offer a more detailed analysis.

In Table 3 natural logarithms of likelihood functions ($\ln(L)$) arising from various experiments are displayed. First, baseline models which contain no explanatory variables were run and these occupy the first row of the table. The next row uses the two education attitude dummies together with the school quality indicator. The third row uses the education variables together with all of the family background variables. The fourth row adds test scores to the list. Here the order is important. Test scores depend on family background variables; in fact, models which explain test score results actually perform better than those which are designed to explain educational attainment.[9] As a result, the increase in the log-likelihood function from row 3 to row 4 measures the net impact of test scores on educational attainment. The last row measures the contribution to the explained variation due to mixing. The variation explained by the model is captured by the difference between the baseline and final log-likelihood function values. The cumulative percentage increases and their differences are shown in columns 2 and 3 for males and 5 and 6 for females.

Table 3 about here

Adding all of the individual groups of variables incrementally leads to significant increases in the log-likelihood function. Excepting the last row, the double stars in columns 3 and 6 reflect the results of likelihood ratio tests which are significant at the one percent level.[10] Test scores account for 20.3% of the explained variation for men but only 9.4% for women. In both cases family background variables are more important than test score results in terms of explaining the variation in educational attainment, dramatically so for females.[11]

The effects of family background variables on educational attainment appear to be smaller for Denmark than Belzil and Hansen (2003) found for US white males in the National Longitudinal Survey of Youth. They attribute 67% of the explained cross-sectional variation in educational attainments to family background variables. Whereas, we found that this was about 50% for Danish respondents.

In Table 4 we look at this issue from the perspective of mobility by comparing the effects of household income and the test score on net inductive reasoning on educational attainment in terms of transition probabilities. As previously noted, inductive reasoning scores depend on family background variables so a net score is used. This is computed as the residual in a regression of the score on all of the household background variables. The two entries in the column under household income are the predicted proportions of males or females with no further education and the proportion with a university education. The column headings are E_1 and E_5, respectively, corresponding to the notation in Table 1.

Here the same pattern of results emerges. For both males and females the probabilities of ending up in the lowest educational category are higher if the respondent came from a household in the bottom quartile of the household income distribution as opposed to being in the bottom inductive reasoning quartile: 0.532 *vs*.0.436 for males and 0.453 *vs* 0.374 for females, respectively. More surprising, given the presumed importance of ability in success at university, is the result that a higher proportion of women were predicted to obtain a university education if they came from families in the top quartile of the household income distribution than would occur if they were in the top test score quartile.

Table 4 about here

The conclusion from all of this is that test score results play a role but they are just one of many factors which determine educational success. There are several other equally important variables which are observed and explain a small but significant proportion of the variation in attainments. Consequently, the more extreme views outlined in *The Bell Curve* are not supported by Danish sample survey data (see also Korenman and Winship 2000).

Mixture models were employed to take account of unobserved heterogeneity across individuals. The increases in the log-likelihood functions due to unobservables are 18.7 percent for men and 28.5 percent for women. While these are not as large as the proportion of the explained variation attributable to household background variables, for example; mixing is required because the mixed distribution has a significantly higher likelihood value. Parameter estimates also change when mixed models are used. For example, the parameter estimate associated with the verbal test score for female respondents is 0.174 with a standard error of 0.079 in the mixed model. It is significant at the 5% level and is nearly twice the size of the parameter estimate of 0.088 with standard error 0.108 which arises in an unmixed model. This is not significant. On average, the difference in parameter estimates are not nearly as large. While this shows that it is important to use mixed models in order to get the most reliable results, relying on models which did not correct for the effects of unobservables would not have lead to a dramatic change in the conclusions.

The fact that there are unobservables which affect educational attainments even when test scores are included as regressors is an interesting result. It means that intelligence or scholastic achievement tests may not fully account for ability. Bowles *et al*

(2001) suggest, there are other individual attributes that are likely to affect educational performance like ambition, reliability and organizational skills. There is no information on these variables available in our sample so we group them together and treat them as a random effect that is possibly correlated with some of the characteristics of the respondent's childhood household.

Our mixture distributions are generated by types. Our two types are hierarchical and can be characterized as weak and strong. The probability of obtaining a particular level of educational attainment, level k for example, conditional on being the strong type is

$$\Pr\{j = k|\ell = s\} = F_s(\alpha_{ks} - I_s) - F_s(\alpha_{k-1,s} - I_s) \tag{5}$$

For the weak type this is

$$\Pr\{j = k|\ell = w\} = F_w(\alpha_{kw} - I_w) - F_w(\alpha_{k-1,w} - I_w) \tag{6}$$

where s and w refer to the strong and weak types, respectively. Given these probabilities it is possible, using Bayes Law, to compute the conditional probabilities of a particular type given the educational outcome, so that

$$\Pr\{\ell = s|j = k\} = \frac{\Pr\{j = k|\ell = s\} * \Pr\{\ell = s\}}{[\Pr\{j = k|\ell = s\} * \Pr\{\ell = s\} + \Pr\{j = k|\ell = w\} * \Pr\{\ell = w\}]} \tag{7}$$

These are displayed in Table 5 for both genders.

Table 5 about here

In the present context, this ordering of types turns out to be a natural one. Respondents who had a large chance of being characterized as strong - say 75% or higher, for example - had parents with better than average levels of education and better occupations, higher household incomes, better test scores and fewer siblings. The opposite is the case for respondents who have high probabilities of being weak. A typology of this sort is, in fact, exactly what should arise given the significance of the variables included as regressors and the fact that mixed distributions outperform single distributions.

In addition to helping us understand the underlying mechanisms that determine educational attainments this typology provides some insight about the differences between male and female performance. At the lower end of the educational attainment distribution the conditional probabilities for being weak or strong types are just about the same for men. This is not the case for women for whom the hierarchy is much better defined. The reason why this occurs is because the component of the explained variation which is attributable to mixing or unobservables is much larger for females. As would be expected, both males and females who obtained the highest level of education had very high probabilities of having strong family backgrounds: 0.916 for males and 0.901 for females, respectively.

Earlier we mentioned some of the difficulties in relating our model to that of Becker and Tomes. The situation is not completely hopeless, however, and some of our results can be interpreted as supporting this type of model. The result that the number of siblings has a negative effect on attainments is consistent with Beckerian theory which sees households with more children producing 'lower quality' children because of parental time and resource constraints. Our view of the decision making process emphasized a role for both generations. Since there is no information on resource transfers or time devoted to children the only information which is informative about parental decisions is the number of children in the household. Count models of children ever born produce standard Beckerian results; higher levels of education, household income, and better occupations lead to smaller family sizes. Beckerian perspectives also explain the role of father's education. The coefficient for other advanced education is actually larger than that associated with higher education (university). Beckerians would explain this as being caused by better educated males having a higher value of time and, therefore, are less willing to get involved in time intensive activities with their children.

Our primary concern in this paper has been to examine the role of test scores and household background variables in educational attainments. However, a particular aspect of this issue involves the question of credit constraints and whether the availability of economic resources within the household limits the opportunities of children going on to university. There is quite a large literature on this issue[12] which finds varying degrees of support for the proposition. Our results are relevant to this debate because, unlike the situation in the United States where tuition fees and other expenses can be a factor in college decisions even for attending state universities, the respondents in our sample were almost surely not credit constrained. In the period 1972-82 when higher education could have been undertaken there were no tuition fees and students enrolled in vocational training or higher education programmes would have received a salary or stipend for participating. Furthermore, the variable which indicates the presence of household financial problems is not significant for either gender. Yet, household income is significant for both genders even if it is not the most important variable. As an alternative to using two father's occupation dummies we used the average household income of the occupation instead. While this variable is highly significant it leads to a substantial reduction in the likelihood function. This suggests to us that even when household income is a significant regressor it is serving as a proxy for the benefits that accrue to children from the skills and attributes that high income parents have rather than an indicator of resources for financing higher education choices of children when they become young adults. This is also the view of both Heckman and his associates and that of Keane and Wolpin (2001).

Before turning to some technical statistical issues we want to discuss the effects of the respondent's attitude towards school. This is one of the more significant regressors, especially for males, and plays an important role in determining educational attainments. For example, male respondents who reported liking school were 62% less likely to be in the bottom attainment category than the respondents who were either indifferent or disliked school. Unlike test scores, this variable is almost independent of household background variables. Less than 1% of the variation in school attitudes is explained by household background variables; however, one variable which does explain a significant portion of the variation in the respondent's attitude towards school is the location of the school that the respondent attended. At the time the survey was carried out rural schools were much more popular with students than schools in large urban areas or the capital region. Educational reforms in the early 1960's completely changed the character of primary education in rural areas (Nørgaard *et al.* 1978). Schooling in rural areas became more centralized and much larger yet retained its informal more relaxed atmosphere unlike schools in urban areas which had always been much more anonymous, impersonal and more prone to disciplinary problems.

Two conclusions follow from this. First, since school attitudes are almost unrelated to observable family background characteristics it is highly probable that these are largely shaped by the schools that the respondents attended.[13] Secondly, since school attitudes appear to influenced by the 'cultural environment' of the school changes in methods and curricula which emphasize a more positive approach which is more personal and gives more recognition to the individual will lead to an atmosphere which pupils will find more appealing.[14]

In our analysis, a number of statistical tests were performed which justify our preferred specification. First, as reported earlier, genders have to be treated separately. Likelihood ratio tests never supported pooled estimates in any of the models even when a gender dummy was included. Secondly, while the ordered probability formulation for the categorical data has much intuitive appeal we considered the possibility that it was too restrictive by estimating a multinomial logit model. Using non-nested tests developed by Vuong (1989) we rejected the logit formulation on both the Bayesian information and Akaike criteria. The Mare transition model was also not considered since Danish educational alternatives are not sequential.

Although we were not able to mix more than two distributions the question of whether a single distribution should be replaced by a mixture of two distributions needs to be demonstrated. Deb and Trivedi (1997 p. 321), among others, rule out a likelihood ratio test because the null hypothesis when there are two mixing distributions is $H_0 : p_2 = 0$ and involves the boundary of the parameter space and consequently, a non-standard test statistic. However, the null can also be written as $H_0 : (\delta_1, \alpha_{j1}) = (\delta_2, \alpha_{j2})$ which does not involve the the probability parameters or the boundary of the parameter space. This means that there is no difference between the two constituent distributions; mixing is not required; and there is no unobserved heterogeneity present. We employ Wald tests which overwhelmingly reject the null hypothesis for both genders. The recommended standard procedure is to use the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) to select the number of mixing distributions. Unfortunately for us, these two criteria give conflicting results with AIC supporting the mixture and BIC rejecting it.

6 Summary of the results

We found that scholastic ability matters in educational attainment but that family background in general is much more important when it comes to attaining education in Denmark. In fact, it is father's occupation that has the largest impact on attainments. Other variables like parental education, number of siblings, disrupted childhoods, attitudes to school, and household income are also significant but with different effects on the two genders. Genders are different in many ways; for example, verbal test score coefficients are twice as large for male respondents. Our procedures controlled for unobservable effects. These are important and ignoring them will lead to biased estimates. Their inclusion also adds meaning to the results in terms of identifying a family typology which characterizes household as being weak or strong. The importance of these family background variables suggests that the cumulative effect of social reforms as of the 1960's had not fully eradicated the effects of inequality on educational success. It is, therefore, important to determine whether the programmes which have been implemented since then have made Danish students less dependent on their families for their educational success. This is the next project in our research agenda.

7 Endnotes

1. On page 1155 they write "Our theory incorporates the human capital approach to inequality because parents maximize their utility by choosing optimal investments in the human and nonhuman capital of children and other members.

2. Behrman and Rosenzweig (2002) using twin data suggest that this result is due to omitted variables correlated with the mother's education level.

3. A recent contribution to this literature is an American study based on the Panel Study of Income Dynamics by Conley (2001).

4. In a novel approach to the problem, Lillard and Willis (1994) treat unobservables in the Mare model by including a random effect. The presence of random effects requires that the higher stage probabilities be represented by multivariate distributions rather than the product of univariate distributions. Their estimated variance coefficients are highly significant suggesting that unobservable effects are very important.

5. This approach is consistent with a dynamic sequential version of the Becker-Tomes model where children maximize their welfare given the parent's investments. Parents then impose sub-game perfection by maximizing family welfare taking account of their children's responses.

6. We know of no studies in this area which impose rationality on the expectation formation mechanism. It is, perhaps, unreasonable even to suggest such a procedure because of the additional complexity involved.

7. The occupational classification used for fathers is not siutable for mothers because of the small numbers of women in advances occupations.

8. In regression and simple ordered probability models the t-statstics are identical for the coefficients of a variable x and its normalized value so that there are no issues of inference involved by using normalized regressors. This is not true for the mixed models estimated here; however, there are no major differences between the two representations.

9. Simultaneous equation regression models as well as multivariate count models were used to explain the three test score variables. Like Neal and Johnson (1996) and Peters and Mullis (1997) we find that household background variables explain a significant proportion of the variation of these variables. These results are described in a companion paper "What Do Test Scores Really Measure?"

10. Later we will show that a mixture of two distributions is significantly better than a single distribution function.

11. This is not what Marks and McMillan (2003) found using an Australian cohort of students who were tested in 1995. There are several possible reasons why this could happen. The first and most important is that we are taking account of the fact that test scores depend on family background variables by adding them as regressors to a model which already contains family background variables. Marks and McMillan do the opposite! Secondly, their measure of educational attainment is "participation at university" which should be expected to be more dependent on academic ability than our more general measure of educational attainment. They also do not control for unobservables.

12. See, for example, Cameron and Heckman (1998, 2001), Heckman (2001), Keane and Wolpin (2001).

13. Of course, it should be recognized that some children dislike school because they are unhappy or disturbed by problems at home.

14. Some Danish schools have already adopted procedures to make them more attractive. In their analysis of a sample of Danish elementary schools Munk and Sloth (2005 p. 11) write "The high performance schools with low SES in general give priority to social aspects by taking care of the pupils and tackling their difficulties. The schools focus on having a positive approach to and finding the strengths of each individual as well as concentrating on the pupil's life as a whole. Their goals are to create self-confidence, joy and a unified whole for the children, and also to provide the pupils with the best qualifications possible in view of their background.

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TABLES

TABLE I
Variable Means and (Standard Deviations)

Variable		Males	Females	
Education				
E_1 None	0.31	(0.19)	0.33	(0.13)
E_2 Apprenticeship or Vocational	0.32	(0.10)	0.37	(0.14)
E_3 Short Higher	0.16	(0.07)	0.09	(0.04)
E_4 Middle Higher	0.17	(0.12)	0.12	(0.06)
E_5 Long Higher	0.04	(0.07)	0.10	(0.12)
Test Scores				
Verbal	35.73	(10.05)	35.25	(10.92)
Spatial	21.41	(7.95)	22.71	(8.76)
Inductive	21.78	(9.19)	21.85	(9.61)
School Variables				
Indifferent To School	0.39	(0.47)	0.52	(0.50)
Likes School	0.52	(0.49)	0.30	(0.48)
Dislikes School	0.09	(0.29)	0.18	(0.38)
School Quality	0.36	(0.48)	0.33	(0.47
Household Variables				
Income	30.36	(16.88)	30.75	(16.80)
Mother Home	0.37	(0.48)	0.37	(0.48)
Financial Problems	0.25	(0.43)	0.20	(0.40)
Broken Home	0.13	(0.34)	0.11	(0.31)
Number of Siblings	2.13	(1.50)	2.05	(0.03)
Urban	0.24	(0.43)	0.25	(0.43)
Father's Occupation				
Other Types	0.21	(0.49)	0.24	(0.43)
Manual Labour	0.29	(0.33)	0.29	(0.46)
Professional and Managerial and Independent Entrepreneurs	0.49	(0.42)	0.46	(0.50)
Father's Education				
Other Types	0.63	(0.49)	0.60	(0.49)
Apprenticeship or Vocational	0.04	(0.29)	0.05	(0.22)
Other Advanced Education	0.03	(0.15)	0.03	(0.18)
Higher Education	0.29	(0.27)	0.31	(0.46)
Mother's Education				
Other Types	0.79	(0.49)	0.78	(0.49)
Apprenticeship Or Above	0.21	(0.30)	0.22	(0.46)

TABLE 2
Parameter Estimates (Standard Error)

Coefficient of Variable	Males		Females	
Test Scores				
Verbal	0.408**	(0.101)	0.174*	(0.107)
Spatial	0.029	(0.081)	0.022	(0.085)
Inductive	0.413**	(0.092)	0.370**	(0.102)
School Variables				
Likes School	0.278**	(0.063)	0.076	(0.073)
Dislikes School	-0.221**	(0.080)	-0.172**	(0.059)
School Quality	0.079	(0.057)	0.022	(0.064)
Household Variables				
Household Income	0.186**	(0.062)	0.113†	(0.063)
Mother Home	-0.022	(0.058)	0.006	(0.064)
Financial Problems	-0.057	(0.057)	-0.023	(0.065)
Broken Home	-0.016	(0.094)	-0.160**	(0.106)
Number of Siblings	-0.018	(0.070)	-0.141**	(0.068)
Urban	0.067	(0.067)	0.022	(0.063)
Father's Occupation				
Manual Labour	0.881**	(0.278)	0.370**	(0.129)
Professional and Managerial and Independent Entrepreneurs	1.258**	(0.302)	1.019**	(0.207)
Father's Education				
Apprenticeship	0.102†	(0.061)	0.106†	(0.070)
Other Advanced Education	0.328*	(0.166)	0.471**	(0.151)
Higher Education	0.216**	(0.065)	0.117	(0.079)
Mother's Education				
Apprenticeship Or Above	0.254**	(0.062)	0.120	(0.069)
Mixing Probabilities				
p_1	0.543**	(0.041)	0.502**	(0.029)
p_2	0.456**	(0.041)	0.498**	(0.029)

†, *, and ** indicate significant at 10, 5, and 1 percent levels, respectively.

TABLE 3
Relative Contributions To Explained Variation of Various Types of Variables and Goodness of Fit Statistics

Type of Variable Added	Males			Females		
	$ln(L)$	Cum. %	ΔCum. %	$ln(L)$	Cum %	ΔCum. %
1. None (Baseline)	-2257.79	0.0	0.0	-2260.92	0.0	0.0
2. School Variables	-2219.17	12.3	12.3**	-2231.67	10.2	10.2**
3. Family Background Variables	-2066.70	61.0	48.7**	-2084.53	61.9	51.7**
4. Test Scores	-2003.63	81.3	20.3**	-2055.86	71.5	9.4**
5. Unobserved Heterogeneity (Mixing)	-1944.96	100.0	18.7**	-1975.90	100.0	28.5**
McFadden's R^2		0.139**			0.126**	

TABLE 4
Relative Contributions of Household Income And Net Inductive Reasoning to Educational Attainment

Category	**Males**				**Females**			
	Household Income		Net Inductive Reasoning		Household Income		Net Inductive Reasoning	
	E_1	E_5	E_1	E_5	E_1	E_5	E_1	E_5
Bottom Quartile	0.532	0.013	0.436	0.018	0.453	0.037	0.374	0.059
Top Quartile	0.318	0.097	0.198	0.074	0.398	0.209	0.222	0.156

TABLE 5
Conditional Probabilities of Having a Strong Family Background Given Educational Attainment

Variable	Males	Females
Education		
E_1 None	0.508	0.289
E_2 Apprenticeship or Vocational	0.562	0.391
E_3 Short Higher	0.663	0.606
E_4 Middle Higher	0.834	0.780
E_5 Long Higher	0.916	0.901