FAMILY BACKGROUND AND EDUCATIONAL SUCCESS IN DENMARK.

James McIntosh[¤,y] and Martin D. Munk[y]

[¤]Economics Department
Concordia University
1455 De Maisonneuve Blvd. W.
Montreal Quebec, H3G 1M8, Canada
and
[y]Danish National Institute of Social Research
Herluf Trolles Gade 11
DK-1052 Copenhagen K, Denmark

January 14, 2004

ABSTRACT

This research examines the role of family background variables in the determination of educational attainment in Denmark. A categorical representation of the highest level of education attained 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 ability which is represented by a set of intelligence tests explain a small but signi¯cant portion of the variation in their children's' educational success. Women are shown to respond di®erently to their environments than men and including intelligence test scores does not remove the need to deal with unmeasured attributes.

E-mail Addresses and Telephone Numbers. jamesm@vax2.concordia.ca, +001 514 848 2424 Ex.3910 and mdm@s¯.dk, +45 33 69 77 10.

Keywords: Educational Attainment, Educational Mobility, Denmark.

FAMILY BACKGROUND AND EDUCATIONAL SUCCESS IN DENMARK

Educational attainment and the extent to which an individual participates in the educational system is, perhaps, the single most important factor in the determination of lifetime economic success. Although some research has been undertaken to explain the determinants of educational attainment it is far from being complete and there are many unresolved issues. 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. Attention focuses on factors involving the respondent's social and economic background and the occupational and educational characteristics of the respondent's parents.

In 1968 E.J. Hansen (1995), a researcher at The Danish National Institute of Social Research, organized a series of surveys of a sample of Danish children who were born in late 1954 or early in 1955. The data from this survey was analyzed by him and Ârum (1971) 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 paper has the following format. The next section provides a brief review of the literature on educational attainments as well as some of the statistical procedures that have been used in its analysis. In section 3 Danish educational attainment data is analyzed using both ordered and unordered probability models model 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 are more general. Econometric issues and the results of what other Scandinavian researchers in this area have found are also discussed in section 4.

1 The Educational Attainment Literature: A Brief Review

There are two ways of measuring educational attainment; 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.

Much of the early literature on educational attainment and mobility used regression methods applied to years of completed schooling. Featherman, Hauser, and Sewell (1975) is an 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) 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. Similar results for the United States have been obtained by Peters and Mullis (1997), Fischer et al (1996), and Korenman and Winship (2000, Appendix B).

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) was one of the first to make this point[1] and this position has become one of the cornerstones of sociological research. This is unfortunate because the regression model is an appropriate methodology for this type of data provided the problem of unobservable variables is treated explicitly.[2]

There is also a large volume of research devoted to explaining educational categories. The Mare model can also be applied to educational categories that are sequential. The papers in the Blossfeld and Shavit (1993) volume treat education in this fashion. A recent contribution to this literature is an American study based on the Panel Study of Income Dynamics by Conley (2001). Unfortunately, as Cameron and Heckman show, the major 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. 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. Francesconi (2002) using the National Child Develop-

[1] Bourdieu and Passeron (1977) also pointed out that it was important to take the problem of selection into account

[2] This result may be found in McIntosh and Munk (2003).

ment Survey is one recent example as is Lauer (2003) who 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. Breen and Jonsson (2000), for example, 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.

2 The Danish Data and its Analysis

The Danish National Institute of Social Research Longitudinal Youth Survey is a sample from the cohort of individuals who were born in 1954. 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 their educational attainments was collected in 1992.

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.

Summaries of the key variables are displayed in Table 1. The data for occupation and education refer to categories so the mean is just the proportion of respondents with a parent in this category. Fathers' occupations are, in order, the reference group which contains the unemployed, those not looking for work and other, unskilled, skilled, self employed without subordinates, and self employed with subordinates. Parental educational categories are eight or nine years of elementary school, some middle school, completed middle school, vocational training, and high school, with the reference group containing very low levels of schooling and missing educational attainment levels.

Test scores are the number of correct answers obtained on the individual tests. The first test had seventy questions and the last two forty. Income is 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. The variables `broken home', `number of siblings', and `urban' are what they appear to be and `class 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.

TABLE 1

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)
Family Background		
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)
School Quality	0.36 (0.48)	0.33 (0.47)
Father's Occupation		
Other Types	0.39 (0.49)	0.40 (0.49)
Occupation type 1	0.12 (0.33)	0.14 (0.35)
Occupation type 2	0.23 (0.42)	0.20 (0.40)
Occupation type 3	0.13 (0.34)	0.11 (0.32)
Occupation type 4	0.14 (0.34)	0.15 (0.35)
Father's Education		
Other Types	0.59 (0.49)	0.57 (0.49)
Educational category 1	0.09 (0.29)	0.08 (0.28)
Educational category 2	0.02 (0.15)	0.03 (0.18)
Educational category 3	0.08 (0.27)	0.08 (0.27)
Educational category 3	0.08 (0.27)	0.09 (0.29)
Educational category 5	0.05 (0.21)	0.05 (0.22)
Mother's Education		
Other Types	0.59 (0.49)	0.58 (0.49)
Educational category 1	0.10 (0.30)	0.10 (0.29)
Educational category 2	0.03 (0.18)	0.03 (0.18)
Educational category 3	0.07 (0.26)	0.07 (0.26)
Educational category 4	0.10 (0.30)	0.11 (0.31)
Educational category 5	0.03 (0.16)	0.03 (0.17)

The initial framework for analyzing the data will be a mixed ordered probability model. Later the results from this model will be compared with an unordered logit model.

Following Heckman and Singer (1984) and Cameron and Heckman (1998), unobservables will be treated by assuming that there are a small number of types of respondent and that for type ℓ educational categories are determined by a latent variable crossing a set of thresholds. Assuming that there are L different types of individual this latent variable has a probability distribution which is a mixture of normal distributions, $\sum_{\ell=1} p_\ell N(\mu_\ell;\sigma)$; where p_ℓ is the probability of type ℓ, $\sum_{\ell=1} p_\ell = 1$, and $\mu_\ell(X_i;\beta_\ell) = \beta_\ell X_i$, where X_i is a vector of covariates. for individual i. This distribution has a mean which is equal to $\sum_{\ell=1} p_\ell \beta_\ell X_i$: Another way of describing this process is to write $\mu_\ell(X_i;\beta_\ell)$ as $\mu(X_i;\beta) + \theta_\ell(X_i;\beta_\ell)$: Researchers often assume that the θ_ℓ are constants which alter the mean. Here, however, we are assuming that there are unobservable effects which alter the mean of the distribution which are correlated with the characteristics of the household. When the functions $(\mu;\theta_\ell)$ are linear we get the above representation. In practice, only a small number of distributions can be used in this procedure. Most practitioners find that two is usually enough. We do as well, although we actually estimate models involving three mixing distributions to show that two is always sufficient. Parameter estimates are shown in Table 2.

While it is clear form the data in Table 1 that the 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 they can be seen as ordered in terms of their difficulty, skill requirements, and the number of years (on average) needed to complete them. As a result an ordered probability model is a reasonable candidate for analyzing the data on educational categories whereas the Mare transition model is clearly not. Unordered models are also possible. Both alternatives are considered here and the ordered models are shown to be superior on the basis of non-nested tests. These are discussed in more detail in the next section which also summarizes the results from these models and discusses their implications for understanding the Danish educational system as well a series of issues that other researchers have raised.

3 Discussion Of The Results

Family background variables which include characteristics of the household when the respondent was going to school, and the educational and occupational characteristics of the respondent's parents together with the respondent's academic ability, as measured by a set of intelligence tests explain a small but significant amount of the variation in the probabilities of the educational categories. As Table 3 shows, including all of the explanatory variables in a mixed probability model explains about eleven percent of the

TABLE 2

Parameter Estimates and (Standard Errors)

Coe±cient of Variable	Males	Female
Test Scores		
Verbal	0.05¤ (0.01)	0.01 (0.01)
Spatial	0.00 (0.01)	0.01 (0.01)
Inductive	0.06¤ (0.01)	0.05¤ (0.01)
Family Background	-	
Income	0.02¤ (0.00)	0.01 (0.01)
Mother Home	0.33¤ (0.12)	0.54¤ (0.14)
Financial Problems	-0.00 (0.03)	0.00 (0.17)
Broken Home	-0.01 (0.18)	-0.57¤ (0.21)
Number of Siblings	-0.03 (0.04)	-0.20¤ (0.04)
Urban	0.56¤ (0.14)	0.40¤ (0.16)
School Quality	0.13 (0.12)	0.12 (0.14)
Father's Occupation		
Occupation type 1	0.06 (0.18)	0.57 (0.21)
Occupation type 2	0.47¤ (0.20)	0.52 (0.22)
Occupation type 3	0.66¤ (0.19)	0.88¤ (0.22)
Occupation type 4	1.16¤ (0.19)	1.38¤ (0.20)
Father's Education		
Educational category 1	-0.33 (0.47)	0.09 (0.26)
Educational category 2	-0.01 (0.42)	0.31 (0.41)
Educational category 3	-0.09 (0.22)	-0.49 (0.31)
Educational category 3	0.71¤ (0.23)	0.23 (0.30)
Educational category 5	0.54 (0.35)	1.13¤ (0.36)
Mother's Education		
Educational category 1	0.06 (0.21)	-0.66¤ (0.25)
Educational category 2	0.71¤ (0.31)	-0.12 (0.37)
Educational category 3	0.60¤ (0.27)	0.44 (0.30)
Educational category 4	0.71¤ (0.21)	0.29 (0.26)
Educational category 5	0.14 (0.41)	0.73 (0.46)
Probability: p_1	0.69¤ (0.04)	0.45¤ (0.03)
Probability: p_2	0.31¤ (0.04)	0.55¤ (0.03)
Ln-likelihood Value	-2005.71	-2034.27

¤ indicates signi¯cant at ® = 0.05.

TABLE 3
Relative Contributions To Explained Variation
Of Various Types of Variable

Type of Variable	Males Ln Likelihood Function (Cum. %)	Female Ln Likelihood Function (Cum. %)
None (Baseline)	-2257.79 (0.0)	-2260.92 (0.0)
Family Background Variables	-2095.01 (64.5)	-2124 (60.2)
Family Background Variable and Test Scores	-2026.05 (91.8)	-2094.08 (83.6)
Unobserved Heterogeneity	-2005.71. (100.0)	-2034.38 (100.0)

variation for men and ten percent for women.[3] Family background variables are the most important accounting for 64.5 and 60.2 percent of the explained variations in the ln-likelihood functions for the men and women, respectively. The effect of test scores is calculated by adding test scores to the model which already includes family background variables. Test scores are added to household background variables rather that the other way around because test scores depend on household background variables. Their inclusion leads to much smaller percentage increases in the two ln-likelihood functions of 27.3 and 13.4, respectively.[4] 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 here in Denmark. 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. However, the question of just how important intelligence is in explaining educational outcomes deserves more detailed consideration than that which comes from the information in Table 3.

In Table 4 we compare the effects of household income and the test score on inductive reasoning on educational attainment. These two variables were chosen because both are continuous and have highly significant coefficients for at least one of the genders. Conley

[3]Goodness of fit here is measured by McFadden's R^2 which is the percentage increase in the ln-likelihood function over its baseline value. The baseline value is calculated by constraining the set of covariates to a constant. For men this is (2257.79-2005.71)/2257.79 = 0.11

[4]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.

TABLE 4
Relative Contributions of Income and Inductive Reasoning
to Educational Attainment

Quartile	Males: Income E_1	Males: Income E_5	Males: Net Inductive Reasoning E_1	Males: Net Inductive Reasoning E_5	Females: Income E_1	Females: Income E_5	Females: Net Inductive Reasoning E_1	Females: Net Inductive Reasoning E_5
Bottom	0.353	0.036	0.461	0.022	0.368	0.097	0.395	0.046
Second	0.342	0.023	0.295	0.023	0.324	0.062	0.310	0.056
Third	0.365	0.035	0.282	0.048	0.336	0.078	0.303	0.137
Top	0.326	0.082	0.218	0.067	0.271	0.192	0.282	0.160
Elasticity	-0.234	0.437	-0.270	1.470	-0.074	0.249	-0.367	1.017

(2001) focuses on the effects of wealth of the household in which his respondents resided as children. This is much more stable or persistent over long periods of time and, therefore, could give better results. It also provides some information on the household's `tradition of achievement'. Unfortunately, there is no wealth data in our sample.

Inductive reasoning and the household income of the parents are divided into four quartiles. 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 Income are the proportions of males 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. In the bottom income quartile, for example, 35.3 percent of the male respondents had no further education beyond grade 9 and 3.6 percent had a university education. However, some care should be exercised in interpreting the results of Table 4 since 46.1 percent of the male respondents whose inductive reasoning test score was in the bottom quartile were in the bottom educational category. It seems that intelligence, as measured by the inductive reasoning test operates asymmetrically. Doing poorly on this test makes the higher educational categories much less accessible for male respondents but less so for females. On the other hand, doing well increases the probability of getting a university education but it is less advantageous than having parents in the top quartile of the household income distribution. The elasticities of the probabilities of educational categories are considerably larger for the inductive reasoning test score than for household income. By this measure alone one might be tempted to rank it above household income but this is clearly not justified for all respondents, especially those who obtained a university education.

The conclusion from all of this is that intelligence is important but it is 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. Furthermore, most of this variation is explained by variables not in the data set. Consequently, the more extreme views outlined in The Bell Curve are not supported by Danish sample survey data and there is no warrant for implementing policies, like selective reproductive programmes based on parental intelligence which are derived from them.

We included income and test score elasticities in Table 4 for another reason. Most of the research on mobility ¯nds that dependence on family background variables, sometimes referred to as ascription, declines as the level of attainment increases. Blossfeld and Shavit (1993) is a good example. Our results are quite di®erent. Both income and test score elasticities increase as the educational category increases.[5]

Turning now to more detail, father's occupation[6], and both sets of parental educational dummies are highly signi¯cant as a group. Respondents whose fathers had higher level occupations and whose parents were better educated achieved better academic results. The levels of statistical signi¯cance are higher for mother's educational levels, perhaps, because some of the e®ects of father's education are incorporated in the occupation of the father. Male educational success was associated with higher household income, having a mother at home, and living in an urban environment. On the other hand, female success depended on a di®erent set of variables. In addition to living in an urban area and having a mother at home, female respondents were adversely a®ected by being in larger families and experiencing household disruptions like the divorce of their parents. The two sexes are su±ciently di®erent to warrant separate treatment. Pooling the data and representing gender as a dummy variable is rejected in favour of separate analysis.

One of our results suggested that a child's' educational prospects were penalized when their mothers were working outside the home it should be viewed with considerable caution when it comes to contemporary social relations in Denmark. It is now commonplace for households to have both parents working. Arrangements for accommodating this practice are much better that in the period 1954-72, when these respondents were children or adolescents; there is also very little adverse social pressure against working mothers so it is now largely regarded as acceptable by all concerned including the children involved.[7]

[5] The elasticities, in ascending order by educational category, are for males: Income, -0.234 -0.040 0.102 0.282 0.437 and Inductive reasoning, -0.270 -0.542 0.023 0.822 2.470 and for females, Income -0.074 0.044 0.037 0.128 0.249 and Inductive reasoning: -0.367 -0.182 0.111 0.492 1.017.

[6] We use occupation rather than social class since our research on income mobility, McIntosh and Munk (2002), revealed this to be a superior measure.

[7] One of our colleagues, Else Christensen, suggested that women working was actually a proxy for ¯nancially distressed households since it was usually the case in the 1960's that women worked out of necessity.

Mixture models were employed to take account of unobserved heterogeneity across individuals. Only modest increases in the ln-likelihood functions, 8% for men and 16 % for women, are attributable to mixing which means that only a small part of the explained variation is due to unobservables. However, mixing is required because the mixed distribution has a signi¯cantly higher likelihood value. This is an interesting result. It means that intelligence tests may not fully account for ability. Not having them in a model will produce biased estimates but the parameter estimates will remain biased even if test scores are included and no procedure is employed to correct for unobservables.[8] On the other hand, test scores may adequately re°ect ability but, as Bowles et al (2001) suggest, there are other individual attributes that are likely to a®ect educational performance like ambition, reliability and organizational skills which are missing from the model.

Bourdieu (2000), and with Passeron (1976), as well as in a series of books and papers stretching over the last three decades, has stressed the notion of cultural capital and habitus, an inclination or disposition, in individual educational success. Recent empirical tests of these ideas may be found in Dumais (2002) using the American National Educational Longitudinal Study. Her notion of habitus is `occupational aspiration' (page 50). Our data base contains information on \class aspirations" but this variable is also an outcome variable in the sense that is as well determined by the respondent's family background variables as the respondent's educational attainment. Thus, as Farkas (2003 p. 547) suggests, the respondent' habitus may, in part, be in°uenced by parental habitus. In any case we regard this as an endogenous or outcome variable whose endogeneity is di±cult to accommodate in mixture models when they are estimated by maximum likelihood methods.

Notions of cultural capital as represented by parents reading ability and household cultural activities are explored by De Graaf et al (2000). Since both papers have some success with these variables our model's ability to explain the data would be improved if there was more information of this type.

The Danish welfare state has made access to higher education easier for the children of most social groups but there is still a considerable amount of inertia in the system and for the individuals in the cohort that was born in 1954-55 educational success has been very much dependent on how successful their parents were. Table 4 informs us that males whose parent's household income was in the top quartile were 2.28 = 0.082/0.036 times as likely to have attended university than those whose parents were in the bottom quartile. For females this ¯gure is 1.98 = 0.192/0.097.

[8] The parameter estimate associated with income for female respondents is 0.012 with a standard error of 0.002 in the unmixed model. This is highly signi¯cant in sharp contrast to the parameter estimate of 0.01 with standard error 0.01 when it is estimated in a mixed model

Before turning to some of the more complex econometric issues involved in this research we want to compare our results with what other researchers have recently found for European countries. 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 for unobservables.

It is well known in the literature on selection bias, Greene (2003 p. 781), that selecting a subsample based on a variable which is correlated with the variable of interest will lead to biased estimates of the parameters in regression or probability models which seek to explain the variable of interest. For example, consider the decision to attend university conditional on having graduated from high school. Only students with sufficient ability can graduate from high school. Ability is also a factor in the decision to attend university. Graduating from high school is, thus, a selection process which eliminates low ability individuals from the sample. Unless something is done to address this selection problem biased parameter estimates will be obtained when a probability model is applied to the sample of high school graduates to explain their attendance at university. On the other hand, no problems arise when a model involving the three categories: non-graduate, graduate-not at university, and graduate-at university is estimated.

It is important to distinguish between endogenous variables and exogenous variables. Including an endogenous variable as a regressor usually requires a procedure to deal with the correlation between it and the error term in the equation. Failure to do this will lead to inconsistent parameter estimates.

Papers by Hansen (1997) using Norwegian data and Davies et al (2002) using Danish data ignore these selection problems. 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 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 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 leads 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 ¯nal 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 ¯nd 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, turning to econometric issues, a number of statistical tests were performed which justify our preferred speci¯cation. First, as we noted in footnote 11, 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, unobserved heterogeneity was represented by two-point discrete distributions whose means were linear functions of all the regressors. Standard practice involving this technique is to allow the two mean functions to have di®erent intercept terms. This speci¯cation was rejected for a more general representation which allows the unobservables to be correlated with family background variables. Three point distributions were also considered. For both genders including an additional component in the mixture distribution did not lead to a signi¯cant increase in the likelihood function.

Although 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 p. 318) we rejected the logit formulation on both the Schwartz and Akaike criteria.[9] The Mare transition model was also not considered since Danish educational alternatives are not sequential.

4 Acknowledgment

Financial support from the Danish Research Council is gratefully acknowledged. We thank G¿sta Esping-Andersen, Claudia Buchman, Jens Bonke, Else Christensen, Anders Holm, J¿rgen S¿ndergaard for comments on an earlier version

[9] Vuong recommends a t test in a regression of the di®erences in the ln-likelihood functions on a constant term. The t statistics for men and for men and women are 1.48 and 1.24, respectively which means that the mixed ordered probability model ¯ts the data as well as the unordered logit mode. Since there are 46 more parameters in the logit model the mixed ordered probit models are preferred.

References

[1] Arrow, K.J, S. Bowles and S. Durlauf (2000). Meritocracy and Economic Inequality. Princeton University Press, Princeton.

[2] Blossfeld, H-P. and Y. Shavit (1993). Persistent Inequality: Changing Educational Attainment in Thirteen Countries, Westview Press, Boulder Co.

[3] Bourdieu, P. (2000). Pascalian Meditations. Polity Press, Cambridge.

[4] Bourdieu, P. and J-C. Passeron (1977). Reproduction in Education, Society, and Culture. Sage Publications, London.

[5] Bowles, S., H. Gintis and M. Osborne (2001). \The Determinants of Earnings: A Behavioral Approach", Journal of Economic Literature, XXXIX, 1137-1176

[6] Breen, R. and J.O. Jonsson (2000). \Analyzing Educational Careers: A Multinomial Transition Model", American Sociological Review, 65 754-772.

[7] Cameron, S V. and J.J. Heckman (1998). \Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males. Journal of Political Economy, 106, 262-333.

[8] Conley, Dalton (2001). \Capital For College: Parental Assets and Post-Secondary Schooling".

Sociology of Education, 74, 59-72.

[9] Davies, R., E. Heinesen and A. Holm (2002). \The Relative Risk Aversion Hypothesis of Educational Choice", Journal of Population Economics 15, 683-713.

[10] Dearden, L., S. Machin and H. Reed. (1997). \Intergenerational Mobility In Britain", The Economic Journal, 107: 47-66.

[11] De Graaf, N. G., P.M. De Graaf, and G. Kraaykamp (2000). \Parental Cultural Capital and Educational Attainment: A Re¯nement of the Cultural Capital Perspective" Sociology of Education, 73, 93-111.

[12] Dumais, S. A. (2002). \Cultural Capital, Gender, and School Success: The Role of Habitus" Sociology of Education, 75, 44-68.

[13] Ermisch, J. and Franco Francesconi (2001). \Family Matters: Impacts of Family Background on Educational Attainment" Economica, 68, 137-156.

[14] Farkas, G. (2003) \Cognitive Skills and Noncognitive Traits and Behaviors in Stratifaction Processes". Annual Review of Sociology. 29, 541-62.

[15] Featherman, D. L., R. M. Hauser W. H. Sewell. (1975). Schooling and Achievement in American Society, Academic Press, New York.

[16] Fischer, C., M. Hout, M.S. Jankowski, S.R. Lucas, A. Swidler, and K. Voss. (1996). Inequality by Design: Cracking the Bell Curve Myth, Princeton University Press, Princeton.

[17] Greene. W.H. (2003) Econometric Analysis 5th ed. Prentice-Hall Upper Saddle River. New Jersey.

[18] Hansen, E. J. (1995). En generation blev voksen, Copenhagen: Socialforskningsinstituttet, report 95: 8 (English summary 1996).

[19] Hansen, M. N. (1997). \Social and Economic Inequality in the Educational Career: Do the E®ects of Social Background Characteristics Decline? European Sociological Review 13, 305-320.

[20] Haveman, R. and B. Wolfe (1995).\The Determinants of Childrens' Attainments: A Review of Methods and Findings", Journal of Economic Literature, 33, 1829-1878

[21] Heckman, J.J. and Burton Singer (1984). \A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data" Econometrica 52, 271-320.

[22] Herrnstein, R. and C. Murray. (1994). The Bell Curve. Free Press, New York.

[23] Korenman, S and C. Winship. (2000). \A Re-analysis of The Bell Curve: Intelligence, Family Background, and Schooling", Ch. 7 in Meritocracy and Economic Inequality, edited by Arrow K., S. Bowles and S. Durlauf. Princeton University Press, Princeton

[24] Lauer, C. (2003). \Family Background, Cohort, and Education: A French-German Comparison Based on a Multivariate Ordered Probit Model of Educational Attainment" Labour Economics. 10, 231-251.

[25] Mare, R. D. (1980) \Social Background and School Continuation Decisions", Journal of the American Statistical Association, 75 295-305.

[26] McIntosh, J. and M. D. Munk (2002). \Mobility: A Critical Appraisal" SFI Working Paper 11.

[27] Marks, G. and J McMillan (2003). \Declining inequality? The changing impact of socio-economic background and ability on education in Australia". British Journal of Sociology 54, 453-471.

[28] Peters, H. Elizabeth and Natalie C. Mullis (1997) \The Role of Family Income and Sources of Income in Adolescent Achievement" Ch. 12 in Consequences of Growing Up Poor. Edited by G.C. Duncan and Jean Brooks-Gunn, Russel Sage Foundation, New York.

[29] Ârum, B. (1971). Social baggrund, intellektuelt niveau og placering i skolesystemet, Copenhagen: Socialforskningsinstituttet, Study 20.