MODELLING INTERGENERATIONAL TRANSMISSION IN LONGITUDINAL BIRTH COHORTS USING MULTILEVEL METHODS

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Contents

0.1 INTRODUCTION

The fifth sweep of the National Child Development Study (Ferri, 1993) is the first to contain measures made on the children of NCDS members (Shepherd, 1985). The data now holds great potential for those researchers whose interests include the analysis of educational, health and economic circumstances of families. The data is suitable for intergenerational analysis. An intergenerational analysis of the NCDS involving the children of NCDS members would usually include an examination of the extent to which the characteristics and circumstances of the cohort member generation influences the characteristics of their offspring. Such intergenerational analyses could use regression analyses where the younger generation outcome is viewed as dependent on various measures from the older generation. This approach, however, ignores the hierarchal structure present in families. An assumption of independence between children is made which is false when children come from the same family. An appropriate, alternative approach to intergenerational analysis is to use multilevel modelling methods (Goldstein, 1987) [1] where children are nested within families. This permits any within family variation or clustering to be identified.the multilevel modellin

The data was derived from the fifth sweep of the NCDS and originally examined by Scott Montgomery and John Bynner (ALBSU, 1993). The analysis described here extends the exploration of intergenerational transmission using multilevel models in ML3 (Prosser et al, 1991). The focus of interest centres on the attainment of children in the context of relevant family characteristics.

1.0 THE DATA

During the fifth sweep approximately one-third of cohort members with children were targeted by the NCDS team. Female cohort members and the female partners of male cohort members in the subsample were asked further questions about their children. Only responses from natural mothers are used in this analysis. This subsample of cohort members was asked

[1] Interested readers may also wish to consult Longford (1993) or Bryk and Raudenbush (1992).

to allow their children to participate in various tests and complete questionnaires. It was decided to invite only those children aged 5 years and above to participate in the educational assessments. Overall response was good. Almost all of the eligible cohort members with children agreed to participate (see Ferri, 1993, table 1.1). Of the 2647 children identified, 2150 with complete data for the characteristics included in the analysis were included (81% of those eligible).

Characteristics are identified at the two levels of the nesting hierarchy. Cohort member at level 2 and child at level 1. Tables 1a to 1c describe explanatory cohort member variables which were measured at level 2. Tables 2a and 2b describe explanatory child variables which were measured at the level 1 and are described at level 1.

The child level data was elicited by interview from the child's natural mother for all child variables except the measure of numeracy which acts as our response variable. Child numeracy was measured using the Mathematical Assessment subtest from the Peabody Individual Achievement Test (PIAT) (Dunn and Markwardt, 1970). Transformed values of the raw PIAT scores are used in the analysis and their derivation is described in section 2.2. Concern about the quality of the social class measure led to a decision to use a simple manual, non-manual dichotomy. Cohort member data was elicited by interview and self-completion questionnaire from the cohort member.

Characteristics of the cohort member are included but those of the other parent are not directly considered. In the analysis undertaken, an assumption is made that the cohort member characteristics can act as a surrogate for those of any partner. Where this assumption is not justified then some of the unseen intergenerational effect will remain in the unexplained residual error.

2.0 <u>ANALYSIS</u>

This section considers two methodological issues which underpin the multilevel modelling presented in the final section*)*. Firstly, standardization and then the selection effect.

2.1 Standardization

Scores on the PIAT subtests generally increase with age and so it would seem advisable to standardize the results by age to ensure that age and test score are statistically independent. Achievement scores were standardized against published norms. These norms were based on extensive testing developed in the United States (Dunn and Markwardt, 1970). Despite the fact that these norms were collected twenty-two years earlier than the NCDS data, in another country and in a school rather than a home environment, they were the best available at the time. Contrasting unstandardized and standardized or "normed" scores are shown in table 3. The poorer performance of older children compared to the younger is clearly evident from column 4. What we are witnessing may well be a "selection effect" due to cohort member parent's age at birth of their offspring, i.e. older children are born to younger mothers, rather than a weakness in the selection of norms for standardization.

Centring the "normed" results by subtracting the overall mean and dividing by the sample standard deviation produces a reasonably close approximation to a Standardized Normal Distribution.. Figure 1 provides evidence of good approximation apart from the extremes of the distribution which have an excess of observations. These standardized numeracy scores are labelled as PIATMATH. Histograms and Normal Plots were examined for PIATMATH at each year of age from five through thirteen and then for ages fourteen through seventeen combined. PIATMATH was approximately Normal for each age group although with less satisfactory fits than seen for the whole sample.

2.2 Selection or age effect

Cohort studies are subject to age and period effects (Goldstein, 1979). This analysis is also affected by an extra confounding effect in that children are not randomly drawn from their age group. As children are not of the same age their cohort member parent will be at different ages at the birth of the child. These cohort member differences in age at birth may well reflect differences in economic and social circumstances. For example, children who were aged fourteen years and over in March, 1991 were born to teenage cohort members. Teenage motherhood is associated with social impoverishment (Di Salvo, 1992). It would not be surprising, therefore, if overall scores obtained in various educational assessments were worse for the children of teenage cohort members than for their peers in the general population. Similarly, the younger children in the sample will be more likely to have been planned, are born to older parents and less likely to be deprived. Again, it would not be surprising if the improved circumstances of the younger children were reflected by better overall performances on the tests than would a more representative sample of their peers. We will refer to this extra confounding as a selection or age effect which may persist despite careful standardization for other social factors.

2.3 Multilevel Modelling

All multilevel linear models consist of a fixed and a random component. In the simplest case for a 2-level hierarchy a dependent variable y_{ij} is expressed as a function of an intercept, a, the fixed part and two random terms: u_j which permits between family variation and e_{ij} which allows for within family variation for a child i. Essentially, in this "null" model each child's achievement score would be predicted by the mean across all children in all families. The random terms, u_j and e_{ij}, or residuals are assumed to be normally distributed with zero means and variances, var(u_j), the variation between families, and var(e_{ij}), the variation within families. This model is described algebraically as

$$y_{ij}=a+u_j+e_{ij} \qquad (1)$$

Here y_{ij} represents the dependent measure, PIATMATH, made on the ith child of the jth cohort member. We use the term family rather than cohort member to represent the context of influence for a child.

The estimated value of a here is 0.01917 with u_j estimated to have a variance of 0.349 and e_{ij} a variance of 0.651, thus 35% of the total variance is at level 2 (between families) and 65% is at level 1(between children within families). Considerable variation (35%) in children's achievement is due to differences between families. Conventional single level analysis where, $y_{ij}=a+e_{ij}$, would not have demonstrated this variability.

The null model provides a convenient "benchmark" for further analysis. Level-1 and level-2 characteristics can be introduced to explain the respective variation at family and child level . The relative importance of various terms in the model are assessed using a likelihood ratio test (Woodhouse, 1993) . However, the primary objective of the analysis was to explore the relationship of the standardized outcome with age of child. If selection effects were absent and standardization were successful one would proceed with generalizations about the influence of generational transmission and child characteristics. Introducing age as a fixed effect the model becomes

$$y_{ij}=a+bx_{ij}+u_j+e_{ij} \qquad (2)$$

The term b represents the regression of coefficient of age. We have used (age-10) so that the constant term 'a' represents the achievement score for a typical child aged 10 years. Here the constant a was estimated as -0.0771 and the regression coefficient for (age-10) as -0.0708.

The level two variance of u_j is estimated as 0.2985 with a standard error of 0.0356 and that for the variance of e_{ij} is estimated as 0.6514 with a standard error of 0.0332.

Multilevel modelling allows the analyst to do one or more things with the model at this stage. It is possible to allow the relationship with age to vary across families ("random slopes regression") or to model the level-1 variance as a function of age. At present the level-1 variance is assumed constant for children of all ages. However, there is convincing evidence that this assumption can be relaxed a*s* the level-1 variance decreases with age. (For a detailed example of modelling level 1 variance see Woodhouse, 1993). The formula for this model is given in (3) below.

$$y_{ij}=a+(b+v_{ij})(x_{ij})+u_j+e_{ij} \qquad (3)$$

Here x_{ij} represents child's age (centred), b is the fixed coefficient of x_{ij} and v_{ij} is the random coefficient of x_{ij} at level 1, a term whose sole purpose it to allow us to model level-1 variance..

The formula for total level 1 variance for this model is given by

$$\mathrm{var}(e_{ij} + v_{ij}*(x_{ij}))=\mathrm{var}(e_{ij})+2\mathrm{cov}(e_{ij}v_{ij})*(x_{ij})+\mathrm{var}(v_{ij})*(x_{ij})^2 \qquad (4)$$

Thus the level-1 variance is now a quadratic in x_{ij}.

The ML3 run resulted in the following estimates for this model:-

y_{ij}= -0.07739 -0.06995*(x_{ij}).

Thus the typical child aged 10 or above will be achieving below average results in PIATMATH.

The estimated values for the random part of this model are given below:-

Estimated (var(u_j)) = 0.2772.

Estimated(var(e_{ij})) = 0.6048.

Estimated(var(v_{ij})) = 0.001153.

Estimated(cov($e_{ij}v_{ij}$))= -0.0206.

Applying formula (4), the total level 1 variance is estimated as

$0.6048+2*(-0.0206)*(x_{ij})+0.001153*(x_{ij})^2$.

Values of this estimated variance at the ages of five, ten and fifteen are 0.8396, 0.6048 and 0.4276. Thus it is seen that level 1 variance decreases with age in this model the level-1 variance in PIATMATH for children aged 5 years is almost twice that for those aged 15. The level 2 variance estimate remains constant in this model and takes a value of 0.2772. Figure 2 shows the relationship between the variance estimates and age of the child.

The level 1 variance is thus about one and a half times greater than the level 2 variance for the older children and about three times greater for the youngest children. This initial conclusion stresses the importance of leaving age in the model despite standardization. The subsequent reduction in the deviance statistic of the null model is significant ($\chi^{2=}$113.23,d.f.=3). This model will now be though of as a "baseline" for all further attempt to predict y_{ij} and model the variation. If age does represent a "selection effect" it is important to explore the extent to which it persists as additional characteristic are introduced into the model.

The next stage of the modelling process tests cohort member variables entering the model given above. Each cohort member variable is introduced in turn. The aim is to establish a priority for building a main effects model. Once the effect of a candidate variable has been noted it is withdrawn from the model and the next cohort member variable is tested. Cohort member variables first enter the fixed part of the current model as described in (5) below.

$$y_{ij}= a+(b+v_{ij})(x_{ij})+c^*z_j+u_j+e_{ij} \qquad (5)$$

Here c is the fixed coefficient for the particular cohort member variable z_j being tested. So when NUMBPROB is included, z_j takes the value of NUMBPROB for the jth cohort member.

The deviance for this model, with z_j taking values for NUMBPROB, is 5875.43 with 7 d.f.. Comparing this, with the previous likelihood of 5887.93 on 6 d.f. gives a highly significant χ^2 value of 12.5 on 1 d.f.

Once a cohort member variable has been tested in the fixed part, it is tested in the random part of the model at level 2 so as to model the level-2 variance. This is attempted irrespective of whether the characteristic has made a significant contribution in the fixed part of the model. A variable that adds nothing to the fixed part of the model can add to the random part. In such an instance the variance between families may differ for different levels of the characteristics. Formula (5) now expands to include a random term for w_j, for the coefficient of z_j, at level 2. This amended formula is given in (6) below.

$$y_{ij}= a+(b+v_{ij})(x_{ij})+(c+w_j)z_j+u_j+e_{ij} \qquad (6)$$

The presence of w_j allows the analyst to model the level-2 variance. Indeed, inclusion of NUMBPROB in the random part of the model does significantly reduce the deviance (χ^2 value of 4.1, 1 d.f.). The implication is that the level 2 variance is over sixty percent greater for those families where the cohort member has reported a number problems than those without. Each cohort member characteristic was tested separately for inclusion. A summary table for this stage of the modelling is given in table 4.

Adding individual family characteristics in this manner suggests that gender (CMSEX) and presence of a partner (PARTNER) do not improve the model when introduced into the fixed part. They have no significant effect in reducing the overall level of residual variation in the model.

However, the remaining family characteristics each individually make a contribution to the fixed part of the model and NUMBPROB and NKIDS help explain between family variation.

These cohort member characteristics were then successively introduced into the model in ascending order of the magnitude of their likelihoods. Two items, problems with reading (READPROB) and family income per person (FAMNETPP) were no longer significant in the presence of other family characteristics. Numeracy problems (NUMBPROB) continued to provide an interesting differential in level-2 variance but no longer contributes to the fixed part of the model. The results of this model are summarized in Table 5. The likelihood for this model is 5747.83. The results in Table 5 suggest that parental achievement and social status enhance an offspring's numeracy score. Indeed, there is a steady increasing gradient in achievement across level of parental qualification (NVQ1-5). However if the child happens to have a parent who her/himself have problems with number or reading or is in a large family they will do less well themselves irrespective of social status. Whilst parental problems with number cease to have any strong influence in the fixed part of the model the differential in the variance at level 2 between those with and those without an expressed number problem remains. It now becomes interesting to examine whether such an interpretation holds in the presence of child level characteristics.

Measures made on cohort member's children were added to the model one at a time. Their effect on the model in both-- the fixed part and then at random level 2 was assessed by examining their impact on the likelihood. The results are presented in Table 6.

This main effects model has a likelihood of 5656.02 with 20 parameters. All the cohort member variables remain in the model and three additional child level variables were found to explain some of the level 1 variance found in the earlier cohort member model. The fixed regression coefficient for birth order in family (RANK) informs us that earlier births are associated with improved scores. Preschooling (PRESCHD) is also associated with improved scores. Difficulties in learning at school, caused by illhealth or other problems (LEARNING), was associated with diminished scores. LEARNING was also found to have a random slope reflecting possible differences in the affect across different families.

Finally, interactions between all variables remaining in the fixed part of the model were examined. An interaction term is added to equation (6) and the new model is given in (7) below

$$y_{ij}= a+(b+v_{ij})(x_{ij})+(c+w_j)z_j+d*z_j*z_j^{'}+u_j+e_{ij} \qquad (7)$$

In order to keep the equation simple, the interaction term implies that only interactions between cohort member variables were examined. In fact, interactions between all combinations of cohort member level and child level variables were examined but to express this mathematically required a tedious extension to the formula. Again, the regression coefficients and predictor variables should properly be expressed as vectors rather than in the current but simpler univariate form. Such formulation would be cumbersome and not add to an understanding of the model.

Results from the realization of this model are presented in Table 7. Four interaction terms were found to be significant. These were between AGE10 and LEARNING, AGE10 and NKIDS, LEARNING and PRESCHD and NKIDS and RANK.

A table of PIATMATH scores for the various categories of AGE10 and LEARNING seems to offer a plausible explanation for the significant interaction between these two. As mentioned earlier (2.1), older children were found to have lower scores than younger children. Additionally, those with learning difficulties were found to have lower scores than those without such difficulties. The tabulation revealed that older children with learning difficulties were found to have lower scores than would be expected. The interaction between NKIDS and AGE10 also helped to identify that there were lower than expected scores for older children with two or more siblings.

Children who had some pre-schooling had significantly higher scores than those without pre-schooling. Those whose school attendance was limited had significantly lower scores than the rest. Those who had pre-schooling and had difficulties in attending had significantly lower scores than would be expected. Perhaps such a result is expected as those who experienced problems in attending school might earlier have been detected as having problems which lead to a recommendation for pre-schooling. This may be a plausible explanation but really requires further investigation.

The interaction term for NKIDS and RANK is interesting. It implies that younger children in larger families will have lower than expected scores.

CONCLUSIONS

Multilevel modelling has provided a powerful framework to explore both methodological and substantive questions. Age standardization does not work in isolation. The main effects analysis (Table 6) would imply that "age" must be present in any modelling. Subsequent analyses which include age interaction effects suggest that any residual "selection" effect represented by age can be largely eliminated. Age taken in conjunction with family size and expressed learning difficulties are the most important interactions. This suggests that it is important to trace the life course for those older children in larger families where learning difficulties have been encountered. It may well be that the parents of such children have very similar characteristics and experiences. It would also allow us to focus on the nature of any selection effects associated with age.

From an intergenerational perspective parental social class and educational background are influential determinants of a child's attainment in numeracy. A parent's difficulty with writing appears to have a direct effect on a child's attainment. Interestingly, parental problems with number have less explanatory power when considered alongside other characteristics and interactions between them. Clearly much more needs to be known about the way in which parental difficulties translate themselves into problems of child numeracy.

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TABLES 1a and 1b - COHORT MEMBER VARIABLES - NOMINAL AND ORDINAL MEASURES

TABLE 1a

VARIABLE	ACRONYM[2]	BASE CATEGORY CODED 0 (%)	OTHER CATEGORY CODED 1 (%)
Sex	CMSEX	Female (63.7%)	Male (36.3%)
Living with a partner at the 5th. sweep	PARTNER	No (10.2%)	Yes (89.8%)
Difficulties[3] with...			
...arithmetic	NUMBPROB	No (96.6%)	Yes (3.4%)
...reading	READPROB	No (96.6%)	Yes (3.4%)
...writing or spelling	WRITPROB	No (91.3%)	Yes (8.7%)
Social Class	NONMAN	Manual/missing (50.0%)	Non-Manual (50.0%)

TABLE 1b

Highest level of qualification reached based on NVQ scales 1-6 and expressed in analysis using five dummy variables NVQ1 to NVQ5.	Percentage (%)
No qualifications	16.0%
One (any qualification)	15.4%
Two (e.g CSE grade 2-5)	34.7%
Three (e.g CSE grade 1, O'levels A-C)	15.9%
Four (e.g. GCE A'Level, ONC, OND)	12.5%
Five or Six (e.g. HNC, teaching certificates, first degree and higher)	5.5%

[2]Label used in subsequent modelling

[3]Difficulties since leaving school excluding those caused through poor eyesight

TABLE 1c - COHORT MEMBER VARIABLES

- INTERVAL MEASURES

VARIABLE	ACRONYM	VALUE	PERCENTAGES
Number of children in cohort member's family	NKIDS	One Two Three Four or more	(44.4%) (35.5%) (15.7%) (4.4%)

TABLE 1c - COHORT MEMBER VARIABLES

- CONTINUOUS MEASURES

VARIABLE	ACRONYM	PARAMETER
Weekly family net income per capita (pounds sterling)	FAMNETPP	MEAN=104.23 MEDIAN=51.91 STANDARD DEVIATION=637.13 QUARTILE DEVIATION=25.96

TABLE 2a - CHILD LEVEL VARIABLES

- CATEGORICAL MEASURES

VARIABLES	ACRONYM	BASE CATEGORY CODED 0 (%)	OTHER CATEGORY CODED 1 (%)
Sex	KIDSEX	Female (51.3%)	Male (48.7%)
Whether any preschooling was undertaken	PRESCHD	No (21.1%)	Yes (78.9%)
Whether school attendance has been affected by illhealth or other problems	ATTEND	No (93.2%)	Yes (6.8%)
Whether learning at school attendance has been affected by illhealth or other problems	LEARNING	No (96.9%)	Yes (3.1%)

TABLE 2b - CHILD LEVEL VARIABLES

- ORDINAL AND INTERVAL MEASURES

VARIABLES	ACRONYM	VALUE	PERCENTAGE
Birth order in family	RANK	1 - Firstborn	(66.9%)
		2 - Secondborn	(26.0%)
		3-5 Third or later	(7.1%)
Age of child (last birthday)	KIDSAGE	Five	(13.8%)
		Six	(14.1%)
		Seven	(11.9%)
		Eight	(11.9%)
		Nine	(11.3%)
		Ten	(9.3%)
		Eleven	(9.2%)
		Twelve	(6.6%)
		Thirteen to Seventeen	(11.9%)

Table 3

Tabulation (by age) of the mean and standard deviation for the raw, "normed" and standardized "normed" PIAT maths scores

Age of children	Raw Score Means	Raw Score S.D.	Normed Means	Normed S.D.	Standard-ized Normed Means	Standard-ized Normed S.D.	Number of children
Five	16.2	5.08	0.78	1.24	0.25	1.143	297
Six	23.6	7.57	0.79	1.201	0.27	1.108	303
Seven	32.6	8.69	0.69	0.896	0.17	0.826	256
Eight	39.6	8.97	0.52	0.906	0.01	0.835	256
Nine	45.1	9.50	0.60	1.032	0.09	0.952	244
Ten	48.5	9.33	0.29	1.085	-0.20	1.000	200
Eleven	50.9	10.99	0.25	1.181	-0.24	1.089	197
Twelve	54.0	9.65	0.21	0.893	-0.27	0.823	142
Thirteen	55.3	10.16	0.05	0.958	-0.42	0.884	110
Fourteen	58.5	8.76	0.11	0.811	-0.36	0.748	71
Fifteen	59.8	10.74	0.05	0.968	-0.42	0.892	57
Sixteen	64.9	7.72	0.33	0.628	-0.16	0.579	14
Seventeen	63.3	4.51	0.06	0.382	-0.41	0.352	3
TOTAL	38.9	16.43	0.5	1.085	0	1.000	2150

TABLE 4
Likelihoods from assessing cohort member variables with age present (Base model)

(1) Cohort member variable	(2) Likelihood with cohort member variable added to the fixed part.[1] .	(3) Likelihood with cohort member variable added to the fixed **and** random (level-2) parts. [2]
CMSEX	5887.17.	5885.57 n.s.
PARTNER	5883.98.	5883.50 n.s.
NUMBPROB	5875.43	5871.33 $p<0.05$
READPROB	5876.45	5875.37 n.s.
WRITPROB	5868.38	5866.09 n.s.
NONMAN	5840.16	5836.52 n.s.
NVQ1-NVQ5	5779.51	5770.40 n.s. (based on 5 d.f.)
NKIDS	5877.41	5872.05 $p<0.05$
FAMNETPP	5877.10	*Model not converging -*

[1] Levels of significance compared with base model

[2]Levels of significance based on comparing likelihood with column 2 likelihoods.

TABLE 5
Results from cohort member variable only model

Fixed part

Fixed part variables	Regression Coefficient	Standard Error
AGE10	-0.0493	0.0071
NVQ1	0.1932	0.0749
NVQ2	0.3519	0.0671
NVQ3	0.4645	0.0793
NVQ4	0.5420	0.0886
NVQ5	0.7433	0.1172
WRITPROB	-0.1686	0.0787
NONMAN	0.1638	0.0469
NKIDS	-0.0598	0.0227
Intercept	-0.3234	0.0731

Random part

Parameter	Estimate	Standard error
Var(u_j)	0.1936	0.0312
Cov(u_j,NUMBPROB)	0.1932	0.1004
Var(e_{ij})	0.5906	0.0387
Cov(e_{ij},AGE10$_{ij}$)	-0.0239	0.0041
Var(AGE10$_{ij}$)	0.0025	0.0027

TABLE 6
Results from cohort member and child level variable model

Fixed part

Fixed part variables	Regression Coefficient	Standard Error
AGE10	-0.0581	0.0077
NVQ1	0.1499	0.0732
NVQ2	0.2926	0.0660
NVQ3	0.3840	0.0784
NVQ4	0.4539	0.0877
NVQ5	0.6598	0.1165
WRITPROB	-0.1653	0.0763
NONMAN	0.1539	0.0461
NKIDS	-0.0177	0.0244
RANK	-0.1361	0.0354
LEARNING	-0.6146	0.1827
PRESCHD	0.1207	0.0510
Intercept	-0.2545	0.0876

Random part

Parameter	Estimate	Standard error
Var(u_j)	0.2056	0.0299
Cov(u_j,NUMBPROB)	0.0880	0.0766
Cov(u_j,LEARNING)	-0.1894	0.2117
Var(LEARNING)	1.5220	0.5431
Var(e_{ij})	0.5290	0.0356
Cov(e_{ij},AGE10$_{ij}$)	-0.0274	0.0037
Var(AGE10$_{ij}$)	0.0022	0.0024

TABLE 7
Results from cohort member and child level variable model
Fixed part

Fixed part variables	Regression Coefficient	Standard Error
AGE10	-0.0152	0.0164
NVQ1	`0.1525	0.0730
NVQ2	0.2933	0.0660
NVQ3	0.3774	0.0785
NVQ4	0.4612	0.0877
NVQ5	0.6594	0.1164
WRITPROB	-0.1484	0.0754
NONMAN	0.1483	0.0461
NKIDS	0.0796	0.0468
RANK	0.0394	0.1033
LEARNING	0.0275	0.3169
PRESCHD	0.1307	0.0514
AGE10*LEARNING	-0.1464	0.0504
AGE10*NKIDS	-0.0215	0.0076
LEARNING*PRESCHD	-0.9123	0.3752
NKIDS*RANK	-0.0756	0.0331
Intercept	-0.4693	0.1398

Random Part

Parameter	Estimate	Standard error
Var(u_j)	0.2141	0.0297
Cov(u_j,LEARNING)	-0.1022	0.1941
Var(LEARNING)	1.0900	0.4629
Var(e_{ij})	0.5283	0.0355
Cov(e_{ij},AGE10$_{ij}$)	-0.0263	0.0037
Var(AGE10$_{ij}$)	0.0017	0.0024

6 January 1995