Longitudinal Data Analysis of Linguistic Study of the African American English (AAE) Development

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1. Introduction

Over the last century, the vernacular structures of African American English (AAE) have been studied in great detail. However there are still a number of questions regarding to the development and use of these structures during the lifespan of AAE speakers. This study is very meaningful since it tracks African American speakers from early childhood through the teenaged years and thus can evaluate hypotheses about the development of vernacularism over this period. The objective of this project is to examine the development of the African American English vernacular structure over time, while accounting for the other time-dependent and time-independent covariates, such as gender, poverty status and mother's features of speaking.

Data were collected for 34 subjects, at 6 temporal points of their first 15 years. The six temporal data points are: 48 months, Grade 1 (about age 6), Grade 4 (about age 9), Grade 6 (about age 11), Grade 8 (about age 13), and Grade 10 (about age 15). At each temporal point, the proportion of AAE features per utterances (unit of speech) is recorded during a 30 minutes discussion (basically this is the number of dialect units over the total number of units of speech). Here a ratio close to 0 is indicative of very little dialect usage, while a ratio close to 1 is indicative of a lot of dialect usage. The recorded factors also include gender (0/1, female is 1 and male is 0), poverty indicator per family (0/1), and the mother's AAE features per utterance (continuous values between 0 and 1). The data contains 114 females and 90 males. Poverty is time-dependent factor which is recorded at the time of the examination. The features per utterance of a mother (MFPU) are constant which is independent on their children's age.

Key research Questions: Is there a period in the life cycle when the vernacular structures are most likely to be observed? How much variation in vernacular usage may be demonstrated from childhood through adolescence? Do children show similar or different trajectories of vernacular dialect development and change over time? How gender and financial status of a family influence the internal trend? Does mother's feature influence these trajectories? So we will tend to find out the trajectories of development in the use of AAE in both population level and individual level and how the covariates affect the features of the language development for the children using AAE.

2. Data Pre-processing and Visualization

Consider that the Children's Feature Per Utterance (CFPC) is repeated measures, this data is a longitudinal data in nature. So we will use statistical methods for longitudinal analysis. Notice that the response CFPU is a proportional response that is constrained between zero and one, so we need to do some transformation to map the response data to real line. Logit transform is the ideal one because it can map the data to the real line and the transformed data has meaningful explanation. The transformed response is the log odds of dialect per unit speech. The smaller logit value means less dialect. We denote the transformed CFPU, MFPU as LGCFPU, LMCFPU respectively. In addition, because we also interested in the pattern of earliest age 4, so we use age_0=age-4 so that the intercept represents the LGCFPU at age 4.

To visualize the data and make reasonable assumptions on our analysis, we draw spaghetti plot of the response and the mean response.

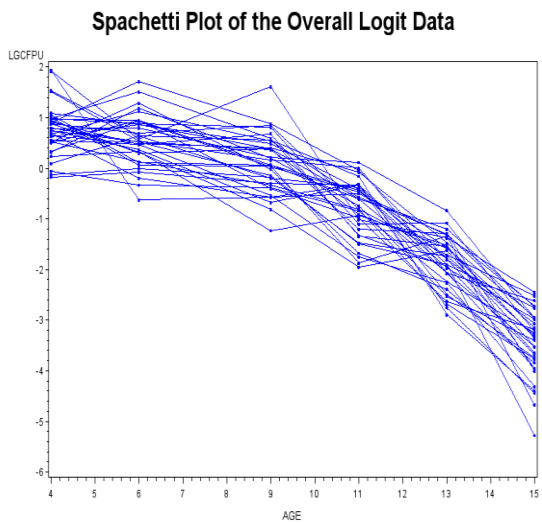

Figure 1

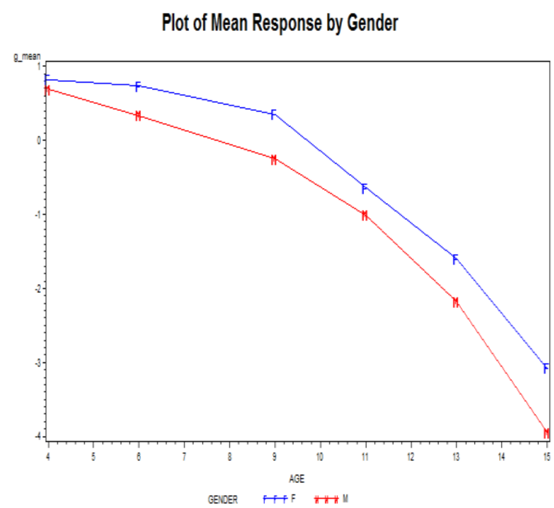

Figure 2

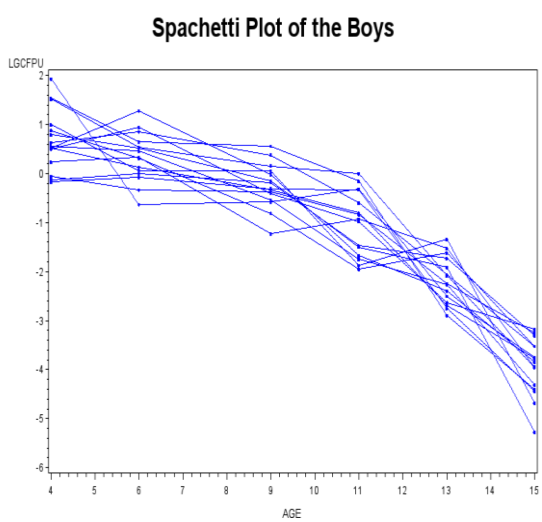

Figure 3

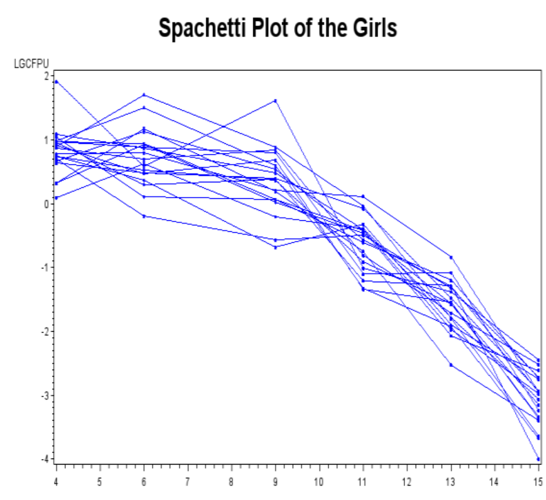

Figure 4

From the spachetti plots of figure 1, it appears that over the period of the study, LGCFPU for most children follows a downtrend curvature trajectory with few observation deviate from the overall trend. Figure 2 shows the mean trend over time by gender group. From the plot, the pattern for mean LGCFPU is different for the two gender group. While the mean for the two groups are very close at age four, they have different pattern of change for the subsequent time points. Over the time, the mean stay larger for girls than boys and the two lines are not parallel. This may indicate that in the population level, the mean log odds for boys and girls are not same, i.e, there is gender effect and this effect is different at different time point.

Compare figure 3 to figure 4, it looks that in subject level, the individual trajectories for the two gender group is not exactly the same. The girl group shows more variation than the boy group and the pattern of rate of change is also different. While the downtrend is smooth for boy group, it seems that for the girl group the plot is somewhat “plat” for the first three time points while the boy group has relatively sharper slope. After nine years, rate of change and variation become similar for the two groups.

3. Statistical Models

In the following analysis, we assume the transformed response is normally distributed.

3.1 Population Level Models and Analysis

3.1.1 Variance Structure Investigation

Since the researcher is interested in the effect of gender, age, poverty and mother’s feature, we decide to consider all of the effect in our model with the following assumption:

a) At baseline, children’s FPU is associated with gender, poverty status and mother’s feature
b) Based on the previous visualization of the data, we’d like to add a quadratic effect of age
c) How the above factors affect the CFPU over time (include the linear and quadratic of time) is different for each gender group and mothers features, and mother’s feature effect is different for different gender.
d) Poverty is a time-dependent factor, we assume that only $E(y_{ij} \mid p_{i1} ... p_{i6}) = E(y_{ij} \mid p_{ij})$, i.e, know more p_{ik} where k≠j would not give more information

Let y_{ij} denote the Logit(cfpu) for the ith child at jth time point, i=1 to 34, j=1 to 6; t_{ij} denote the time point, p_{ij} denote the poverty status for ith child at jth time point, 1 is for poverty, 0 is for not poverty; m_i is mother’s feature for the ith child; The β’s are coefficients; ε_{ij} error term that accounts in both between and with-in subject errors, it is assumed to be normally distributed.

Model 1.1: Full Model

For boy group

$$y_{ij} = (\beta_{b0} + \beta_{b0m} m_i) + \beta_{b0p} p_{ij} + (\beta_{b1} + \beta_{b1m} m_i) t_{ij} + (\beta_{b2} + \beta_{b2m} m_i) t_{ij}^2 + \varepsilon_{ij}$$

For girl group

$$y_{ij} = (\beta_{g0} + \beta_{g0m} m_i) + \beta_{g0p} p_{ij} + (\beta_{g1} + \beta_{g1m} m_i) t_{ij} + (\beta_{g2} + \beta_{g2m} m_i) t_{ij}^2 + \varepsilon_{ij}$$

We now investigate the nature of variation by trying several variance models and use AIC/BIC criteria to choose the optimal variance structure that can best describe the variance and the correlation between the observations for different time point. We here assume that the variance is same for each time point. When using SAS, we choose the variance model that gives smallest AIC.

Table 1

Models	AIC	BIC
Unstructured, same for gender	308.0	359.9
Unstructured, different for gender	304.4	389.9
Markov, same for gender	***298.7***	323.1
Markov, different for gender	299.3	326.8

From the output, we find that same Markov variance structure for the two gender groups gives the smallest AIC and BIC, so we adopt this model and will use this covariance model for our following inference. By choosing this model, we assume that the variance structure is the same for the two gender groups and correlation decays gradually as time interval gets further.

3.1.2 Model Comparison and Inference

From the output of type III test of fixed effects, we see that at the baseline(age 4), the effect of gender, mother's feature(LGMFPU) and the interaction of gender and poverty are all not significant (with p-value of 0.1363, 0.586 and 0.4141 respectively). So we conduct a likelihood ratio test to test H0: $\beta_{b0} = \beta_{g0}$ & $\beta_{b0m} = \beta_{g0m} = 0$. We fit the reduced model

Model 1.2: Reduced Model without Gender, LGMFPU and Gender*LGMFPU

For boy group

$$y_{ij} = \beta_0 + \beta_{b0p} p_{ij} + (\beta_{b1} + \beta_{b1m} m_i) t_{ij} + (\beta_{b2} + \beta_{b2m} m_i) t_{ij}^2 + \varepsilon_{ij}$$

For girl group

$$y_{ij} = \beta_0 + \beta_{g0p} p_{ij} + (\beta_{g1} + \beta_{g1m} m_i) t_{ij} + (\beta_{g2} + \beta_{g2m} m_i) t_{ij}^2 + \varepsilon_{ij}$$

The Likelihood test statistic is 269.5-266.7=2.8, which is less than the critical value 7.815 ($\chi^2_{0.05}$ with df=3). So we fail to reject H_0 and conclude that at the baseline (age 4), there is no significant gender, mother's feature effects. From wald tests, except for gender*age0 effect(with p-value 0.09), all other effects are significant (with p-value<0.05). We get our model:

$y_{ij} = 0.77 - 0.18 p_{ij} + (0.37 - 0.23 g_i + 0.26 m_i - 0.25 g_i * m_i) t_{ij} + (-.077 + .033 g_i - .029 m_i + .028 g_i m_i) t_{ij}^2$ Where g_i is 1 for girls and 0 for boys; m_i, p_{ij}, y_{ij} and t_{ij} are define as above.

For boys:

$$y_{ij} = 0.77 - 0.18 p_{ij} + (0.37 + 0.26 m_i) t_{ij} - (0.077 + 0.029 m_i) t_{ij}^2$$

For girls:

$$y_{ij} = 0.77 - 0.18 p_{ij} + (0.14 + 0.01 m_i) t_{ij} - (0.044 + 0.001 m_i) t_{ij}^2$$

3.2 Random coefficient models and analysis

3.2.1 Variance structure investigation

We now start to model each child's trajectory in part by accounting for its particular features. We will explicitly model the two sources variation, namely, among-unit variation and with-in unit variation. Since the pattern between LGCFPU and LGMFPU shows a downtrend curvature, we assume there is quadratic effect of time. And we make the following assumption:

- Assumption on effect

  a) Mean LGCFPU at 48 months are the same for all boys and girls, and mother's feature does not affect mean LGCFPU.
  b) Same assumption of P_{ij} as above, and Effect of poverty condition is the same for boy and girl throughout all the time.
  c) After 48 months, how gender and mother's feature affects LGCFPU over time are the same as above.
  d) The effect on baseline, linear effect of age, quadratic effect of age and effect of poverty are all random.

- Assumption on variation structure

  e) Variation in "inherent", true LGCFPU, is similar for both boys and girls, as is variation for both linear and quadratic effect of time and effect of poverty, also the way they co-vary. Also, we assume it is unstructured covariance. i.e. D_i is unstructured matrix and same for both boys and girls.
  f) Within-unit variation is due to two sources: measurement error e_{2ij} which is independent over i, j and biological variation e_{1ij}.
  g) The assay used to measure CFPU which then converted to LGCFPU for both boys and girls exhibits constant variation regardless of the true value of LGCFPU being ascertained.
  h) Within-subject local "fluctuations" in LGCFPU are negligible for both genders across time for all subjects, and the magnitude of such fluctuations is constant over time for

all treatments. The magnitudes of such fluctuations are independent of magnitude of the LGMFPU.

i) Magnitude of within fluctuations in LGMFPU is similar for both gender.

Our interest is to see the following:

a) Do linear and quadratic time effect different significantly among all children? In other
b) Does gender plays an important role in linear time effect and quadratic time effect?
c) Does mother's feature plays an important role in linear and quadratic time effect?
d) Will mother's feature's effect be different for boys and girls for both linear time and quadratic effect? In other words, do they have random effect?
e) Does poverty affect child's FPU?

Let Y_{ij} denote the Logit(cfpu) for the i^{th} child at j^{th} time point, i=1 to 34, j=1 to 6; T_{ij} denote the time point, P_{ij} denote the poverty status for i^{th} child at j^{th} time point, 1 is for poverty, 0 is for not poverty; m_i denote the logit(mfpu) for i^{th} child. b_{0i} is the random effect among intercept; b_{1i} is the random effect among slope; b_{2i} is the random effect among quadratic form; R_i is the covariance matrix for e_{ij}; D_i is the covariance matrix for b_i, where $bi=(b_{0i}, b_{1i}, b_{2i})'$. We then construct the model as following:

Model 2.1:

Stage 1:

For each boy, gender=0

$$y_{ij} = \beta_{0i} + \beta_{b1i} t_{ij} + \beta_{b2i} t_{ij}^2 + \beta_{pi} p_{ij} + e_{ij}$$

For each girl, gender=1

$$y_{ij} = \beta_{0i} + \beta_{g1i} t_{ij} + \beta_{g2i} t_{ij}^2 + \beta_{pi} p_{ij} + e_{ij}$$

$$e_{ij} \sim N(0, \sigma^2 I)$$

Stage 2:

$\beta_{0i} = \beta_0 + b_{0i}$ for both gender

$\beta_{1i} = \beta_{b1} + \beta_{b1m} m_i + b_{1i}$ if gender=0

$\beta_{1i} = \beta_{g1} + \beta_{g1m} m_i + b_{1i}$ if gender=1

$\beta_{2i} = \beta_{b2} + \beta_{b2m} m_i + b_{2i}$ if gender=0

$\beta_{2i} = \beta_{g2} + \beta_{g2m} m_i + b_{2i}$ if gender=1

$\beta_{pi} = \beta_p + b_{pi}$ for both gender

$$b_i = (b_{0i}, b_{1i}, b_{2i})^T \sim N(0, D_i)$$

First, we want to know whether linear and quadratic time effect different significantly among all children.

This is equivalent to test: H_0: $Var(b_{1i}) = 0 \quad Var(b_{2i}) = 0$

H_1: $Var(b_{1i}) \neq 0 \quad Var(b_{2i}) \neq 0$

Notice that $Var(b_{1i}) \geq 0 \quad Var(b_{2i}) \geq 0$ is always true.

Comparing to H_1, we got the Likelihood ratio test statistic T_{LRT} is 267.3-256.4=10.9. Due to the nature of H_0, which is at the boundary of parameter space, the classical null distribution of T_{LRT} is no longer valid. Here df for H_1 is 11, df for H_0 is 4. We use distribution that T_{LRT} $\sim 0.5\chi_4^2 + 0.5\chi_7^2$. Since 10.9 is smaller than the criteria value of the mixed distribution $0.5\chi_{4,0.05}^2 + 0.5\chi_{7,0.05}^2 = 11.78$, we fail to reject H_0 and we conclude that there is no enough evidence to show that there are random linear time effect and random quadratic time effect, i.e, for each boy, the linear and quadratic time effect is a constant without variation between subject; for each girl, the linear and quadratic time effect is a also a constant without variation between subject.

So now we assume there is no random linear and quadratic time effect. We fit the models in SAS and have the following:

For each boy, gender=0,

$$y_{ij} = (0.5990 + b_{0i}) + (0.3385 + 0.2427m_i)t_{ij} + (-0.07396 - 0.02689m_i)t_{ij}^2 + (-0.1873 + b_{pi})p_{ij} + e_{ij}$$

For each girl, gender=1,

$$y_{ij} = (0.5990 + b_{0i}) + (0.1323 + 0.0104m_i)t_{ij} + (-0.04322 - 0.00114m_i)t_{ij}^2 + (-0.1873 + b_{pi})p_{ij} + e_{ij}$$

Second, we want to know whether the effect of mother's feature is different for boys and girls for linear time effect. This is equivalent to test, H_0: $\beta_{b1m} - \beta_{g1m} = 0$. The Wald statistic T_L is 6.08 with associated p-value of 0.0148. So we reject H_0 and conclude that mother's feature's effect is different for boys and girls on linear time effect. We can notice that mother's feature coefficient is 0.2427 for boys and 0.0104 for girls, which shows a different pattern.

Also we want to know whether LGMFPU plays a role in quadratic time effect. This is equivalent to test, H_0: $\beta_{b2m} - \beta_{g2m} = 0$. The Wald statistic T_L is 6.38with associated p-value of 0.0126, which is significant. So we reject H_0 and conclude that mother's feature's effect is different for boys and girls on quadratic time effect. In the fitted model, mother's feature coefficient for quadratic time effect is -0.02689 for boys and -0.00114 for girls, which shows a different pattern.

Finally, we are interested in whether poverty affect LGCFPU. This is equivalent to test, H_0: $\beta_{pi} = 0$ .The Wald statistic T_L is 5.37 with associated p-value of 0.0350. So we reject H_0 and conclude that poverty condition will affect LGCFPU significantly.

3.3 Linear Mixed Model

Now we fit a linear mixed model which is still based on thinking about individual first.

All assumptions are the same as 3.2 part.

Let Y_i a (n_i x1) vector of LGCFPU for the i[th] children, i=1, 2,…34, n_i =1,2,…6. The model is as follows,

Model 3.1:

$y_{ij} = X_{ij}\beta + Z_{ij}b_i + e_{ij}$ where

X_{ij} is vector of p dimension covariates.

$X_{ij} = (1 \;\; t_{ij} \;\; m_i \cdot t_{ij} \;\; t_{ij}^2 \;\; m_i \cdot t_{ij}^2 \;\; p_{ij})$

$Z_{ij} = (1 \;\; p_{ij})$

$\beta = (\beta_0 \;\; \beta_{b1} \;\; \beta_{b1m} \;\; \beta_{b2} \;\; \beta_{b2m} \;\; \beta_p)^T$ gender=0, boys

$\beta = (\beta_0 \;\; \beta_{g1} \;\; \beta_{g1m} \;\; \beta_{g2} \;\; \beta_{g2m} \;\; \beta_p)^T$ gender=1, girls

$b_i = (b_{0i} \;\; b_{pi})^T$

Assume $b_i \sim N_6(0, D)$, $\varepsilon_i \sim N_6(0, R_i)$ and b_i is independent of ε_i

We then fit the models in SAS and have the following:

For each boy, gender=0,

$$y_{ij} = (0.5990 + b_{0i}) + (0.3385 + 0.2427 m_i) t_{ij} + (-0.07396 - 0.02689 m_i) t_{ij}^2 + (-0.1873 + b_{pi}) p_{ij} + e_{ij}$$

For each girl, gender=1,

$$y_{ij} = (0.5990 + b_{0i}) + (0.1323 + 0.0104 m_i) t_{ij} + (-0.04322 - 0.00114 m_i) t_{ij}^2 + (-0.1873 + b_{pi}) p_{ij} + e_{ij}$$

We can use Best Linear Unbiased Predictor (BLUP) to estimate b_i and then get each individual trajectory. The result is attached in the appendix.

4 Conclusions

In 3.1 population-averaged models, we see the model from a population level. We first modeled the mean response of the LGMFPU by some function of age, gender, mother's feature and poverty. Then we express each individual trajectory as a random deviation from the main trajectory. Here we treat among-unit variation and within-unit variation as a whole.

In 3.2 random coefficient models, we started with modeling each individual trajectory and then take the mean to obtain the mean trajectory. It will explicitly model the two sources of variation, say, among-unit and within-unit variation.

In 3.3 linear mixed models, we also view the model from a subject level. However, compared to random coefficient models, it is much more general. We can both estimate fixed effect of the mean trend and random effect of individual effect by using BLUP.

From all the three approaches we used above, we reached almost the same conclusion. Gender, mother's feature and poverty condition all have significant effect on LGCFPU, except for some slightly difference in estimated coefficients.

In all models 1.2, 2.1, 3.1, the intercept is not associated with gender and mother's feature; this makes sense because our intercept represents the log-odds at age 4. This result is consistent with our plot 2 in which we see that the two curves of mean LGCFPU for boys and girls are very close at start point age 4. Based on our assumption on poverty factor, the poverty effect is significant with negative coefficient (in model poverty=1 is baseline) of about -0.18. This suggests that given the other factors fixed, the mean log odds of CFPU for the children from rich family is 0.18 lower than for the children from poor family.

Also from our model, the curvature downtrend is significant. This matches what we see from the plots. In addition, the effect of age, both linear and quadratic, is not identical for the boy and girl group, and the mother's feature also affects the rate of change over time. Statistically, this can be seen from the significant interaction terms of the SAS output. The p-values for testing the interactions of LGMFPU*gender*age0, LGMFPU*gender*age0*age0, are less than 0.05. Notice that for girls, mother's feature has less effect on the rate of change. The coefficients of is about 0.01 and -0.001for $m_i * t_{ij}$ and $m_i * age_0 * age_0$ respectively, which is negligible. However for boys, mother's feature significantly affects the rate of change. Overall from the model, we can see that the downtrend for boys is faster than girls, and the rate of change depends on age. This again coincides with the plot 2 showing that at age 4 the mean for girls is slightly higher than boys, but then in the consequent time, the difference becomes larger.

5 Discussion

Based on the above results, overall all children's dialect decreases as they grow up. But boys tend to have less dialect than girls after 4 years old given the other condition same. The children from richer families are likely to decrease their dialect more quickly than those from poor families. This is probably due to different education, living status between the poor and rich families. Mother's dialect feature applies more influence on boys than for girls. It is not clear why this difference happens based on the limited information we have.

Since we found that the transformed response is still not very normal, next time we may use generalized linear mixed model or some non-linear models to have a further insight of the problem.

Appendix:

SAS Code:

```
**********************************************************************
**********************Read the Data**********************************;
option ps=500;
libname project "f:\Courses\2012 spring\ST 732\project\aae\";
filename lingu "f:\Courses\2012 spring\ST 732\project\aae\Linguistic.txt";
data aae;
   infile lingu dlm="," dsd firstobs=2 MISSOVER;
   input ID $ CHILD AGE CFPU GENDER $ BGENDER MFPU POVERTY;
   LGCFPU=log(cfpu/(1-cfpu));
   LGMFPU=log(mfpu/(1-mfpu));
   time=age;
   age0=age-4;
run;
****************************Explore the Data***************************
**********************************************************************;
/*Analysis of the response variable*/
title "Q-Q Plot of the Response CFPU";
proc capability data=aae noprint;
qqplot cfpu /normal(mu=est sigma=est color=red l=2) square nospeclegend;
run;

title 'Q-Q Plot of the Response CFPU';
proc univariate data=aae normal;
   histogram CFPU;
   qqplot CFPU/normal (mu=est sigma=est color=red l=1);
run;
/*The transformed data*/
title 'Q-Q Plot of the Response LGCFPU';
proc univariate data=aae normal;
   histogram LGCFPU;
   qqplot LGCFPU/normal (mu=est sigma=est color=red l=1);
run;

title 'Histogram of the Response CFPU';
proc univariate data=aae normal plot;
   histogram cfpu;
run;
proc print data=pfreq;run;*/
title "Q-Q Plot of the Response CFPU";
proc capability data=aae2 noprint;
qqplot nlgcfpu /normal(mu=est sigma=est color=red l=2)
     square nospeclegend;
run;
ods graphics off;
title 'Q-Q Plot of the Response LGCFPU';
proc univariate data=aae2 normal plot;
   histogram nLGCFPU;
   qqplot nLGCFPU/normal (mu=est sigma=est color=red l=1);
run;

************************Plot the Transformed Data*******************
*******************************************************************;
```

```
proc sort data=aae;
 by child;
run;

title"Scatter Plot of LGMFPG Vs LGCFPG for Each Child";
proc sgplot data=aae;
scatter y=LGCFPU x=LGMFPU/group=child;
by gender;
run;
proc sort datga=aae;
by age;
run;
proc print data=aae;
run;
proc sgplot data=aae;
scatter y=LGCFPU x=LGMFPU;
by age;
run;

/*below code is for checking if there is
missing value in regard to the time point
i.e, if  there are children who missed some exams*/
proc sort data=aae;
  by child;
run;
proc means data=aae;
  class child;
  var LGCFPU;
run;
/*after check, we found that there is no missing value*/

/************************************************************;
***         Generate the Spachetti Plot          ***********
************************************************************/
goptions reset=all device=png gsfname=over_spa;
symbol i=join color=blue v=dot h=.4 repeat=34;

proc gplot data=aae;
title "Spachetti Plot of the Overall Logit Data";
  plot LGCFPU*age=child/ nolegend;
run;

proc gplot data=aae(where=(gender="F"));
title "Spachetti Plot of the Girls";
  plot LGCFPU*age=child;
run;
proc gplot data=aae(where=(gender="M"));
title "Spachetti Plot of the Boys";
  plot LGCFPU*age=child;
run;


/*********** end of spachatti plot code******************************/
/***********begining of Plot of means*******************************/
proc sort data=aae;
   by gender age;
```

```
run;
proc means data=aae;
   by gender age;
   var lgcfpu;
   output out=gmean mean=g_mean;
run;
proc print data=gmean;
run;
goptions reset=all device=png gsfname=over_spa;
symbol i=join color=blue v=f h=1.2;
symbol2 i=join color=red v=m h=1.2;
ods graphics off;
title "Plot of Mean Response by Gender";
proc gplot data=gmean;
   plot g_mean*age=gender;
run;

goptions reset=all device=png gsfname=over_spa;
goptions reset=all device=png gsfname=over_spa;
symbol i=join v=1 color=red;
symbol2 i=join v=2 color=blue;
symbol3 i=join v=3 color=green;
symbol4 i=join v=4 color=black;
proc sort data=aae;
  by group age;
run;
proc means data=aae;
  by group age;
  output out=grpmean mean=Grp_mean;
run;
proc gplot data=grpmean;
   plot Grp_mean*age=group;
run;
/*-----------    end of plot means----------------*/


**************/*full model for population averaged*******************/
***************  correlation structure selection************************/;
proc sort data=aae;
by child;
run;
data lagaae(keep=child age4 age6 age9 age11 age13 age15);
array t{6} age4 age6 age9 age11 age13 age15;
do i=1 to 6;
set aae;
by child;
   t{i}=lgcfpu;
   if last.child then return;

end;
run;

symbol1 i=r v=dot h=0.6 c=black;
title "Scatterplot Matrix for LGCFPU Data";
proc sgscatter data=lagaae;
  matrix AGE4 AGE6 AGE9 AGE11 AGE13 AGE15;
run;
```

```
***********************Choose covariance Structur***********************
**********************************************************************;

title "Full Model,unstructured, same for each gender";
proc mixed data=aae method=ml;
class id child poverty gender;
model LGCFPU= poverty bgender bgender*poverty lgmfpu lgmfpu age0 bgender*age0
      lgmfpu*age0 age0*age0 bgender*lgmfpu*age0  bgender*age0*age0
      lgmfpu*age0*age0 lgmfpu*bgender*age0*age0/ solution;
repeated /type=un subject=child r rcorr;repeated /type=un subject=child r
rcorr;
run;

title "Full Model,unstructured, different for each gender";
proc mixed data=aae method=ml;
    class id child poverty gender;
    model LGCFPU= poverty bgender bgender*poverty lgmfpu lgmfpu*bgender age0
          bgender*age0 lgmfpu*age0 bgender*lgmfpu*age0 age0*age0
          bgender*age0*age0 lgmfpu*age0*age0 lgmfpu*bgender*age0*age0/
solution;
    repeated /type=un group=gender subject=child r rcorr;

run;
title "Full Model,markov, different for each gender";
proc mixed data=aae method=ml;
    class id child poverty gender;
    model LGCFPU= poverty bgender bgender*poverty lgmfpu lgmfpu*bgender age0
          bgender*age0 lgmfpu*age0 bgender*lgmfpu*age0 age0*age0
          bgender*age0*age0 lgmfpu*age0*age0 lgmfpu*bgender*age0*age0/
solution;
    repeated /type=sp(pow)(age) group=gender subject=child r rcorr;

run;
************************Population Averaged Model ***********************;
*************************************************************************;
title "Full Model,markov, same for each gender";
proc mixed data=aae method=ml;
    class id child poverty gender;
    model LGCFPU= poverty bgender bgender*poverty lgmfpu lgmfpu*bgender age0
          bgender*age0 lgmfpu*age0 bgender*lgmfpu*age0 age0*age0
          bgender*age0*age0 lgmfpu*age0*age0 lgmfpu*bgender*age0*age0/
solution;
    repeated /type=sp(pow)(age) subject=child r rcorr;
*estimate 'difference in gender' bgender 1 -1;
*estimate 'difference in poverty' bgender 0 0 poverty 1 -1;
run;

title "Model2: reduced--without gender gender*l lgmcfpu at baseline";
proc mixed data=aae method=ml;
    class id child poverty;
    model LGCFPU= poverty age0 bgender*age0 lgmfpu*age0
          bgender*lgmfpu*age0 age0*age0 bgender*age0*age0
          lgmfpu*age0*age0 lgmfpu*bgender*age0*age0/ solution;
repeated /type=sp(pow)(age) subject=child r rcorr;
*estimate 'difference in gender' bgender 1 -1;
*estimate 'difference in poverty' bgender 0 0 poverty 1 -1;
```

```
run;

**************************-Fit random coeficient Model*********************
****** Assume that the D matrix is unstructured **************************
*************and Ri is diagonal********************************************;

title"full model";
Proc mixed data=aae method=ml;
   class id child bgender gender;
   model LGCFPU= poverty age0 bgender*age0 lgmfpu*age0
         bgender*lgmfpu*age0 age0*age0 bgender*age0*age0  lgmfpu*age0*age0
         bgender*lgmfpu*age0*age0/noint solution;
   random intercept age0 age0*age0 poverty/type=un subject=child g gcorr v
vcorr;
   repeated /subject=child ;
run;

title"final reduced model not random age age*age";
Proc mixed data=aae method=ml;
   class id child bgender poverty gender;
   model LGCFPU=poverty age0 bgender*age0 lgmfpu*age0
         bgender*lgmfpu*age0 age0*age0 bgender*age0*age0
         lgmfpu*age0*age0  bgender*lgmfpu*age0*age0 / solution;
   random intercept poverty/type=un subject=child g gcorr v vcorr;
   repeated /subject=child ;
   contrast""  age0*bgender 1 -1  /chisq;
run;
***************************Code for Linear Mixed
Model*************************;
title"final reduced model not random age age*age";
Proc mixed data=aae method=ml;
   class id child bgender poverty gender;
   model LGCFPU=poverty age0 bgender*age0 lgmfpu*age0
         bgender*lgmfpu*age0 age0*age0 bgender*age0*age0
         lgmfpu*age0*age0  bgender*lgmfpu*age0*age0 / solution;
   random intercept poverty/type=un subject=child g gcorr v vcorr;
   repeated /subject=child ;
   contrast""  age0*bgender 1 -1  /chisq;
run;



********************* END*****************************************************
```

Output:

Fit Statistics	
-2 Log Likelihood	240.0
AIC (smaller is better)	308.0
AICC (smaller is better)	322.0
BIC (smaller is better)	359.9

-2 Log Likelihood	192.4
AIC (smaller is better)	304.4
AICC (smaller is better)	347.8
BIC (smaller is better)	389.9

-2 Log Likelihood	263.3
AIC (smaller is better)	299.3
AICC (smaller is better)	303.0
BIC (smaller is better)	326.8

-2 Log Likelihood	266.7
AIC (smaller is better)	298.7
AICC (smaller is better)	301.6
BIC (smaller is better)	323.1

Population averaged model

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
SP(POW)	CHILD	-0.00001
Residual		0.2164

Fit Statistics

-2 Log Likelihood	266.7
AIC (smaller is better)	298.7
AICC (smaller is better)	301.6
BIC (smaller is better)	323.1

Solution for Fixed Effects

Effect	POVERTY	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		0.7788	0.3874	30	2.01	0.0534
POVERTY	0	-0.2332	0.1065	15	-2.19	0.0447
POVERTY	1	0	.	.	.	.
BGENDER		0.1728	0.4599	30	0.38	0.7098
BGENDER*POVERTY	0	0.1216	0.1487	160	0.82	0.4145
BGENDER*POVERTY	1	0	.	.	.	.
LGMFPU		0.06868	0.2798	30	0.25	0.8078
BGENDER*LGMFPU		0.01868	0.3307	30	0.06	0.9553
age0		0.3708	0.1681	160	2.21	0.0288
BGENDER*age0		-0.2900	0.1994	160	-1.45	0.1479
LGMFPU*age0		0.2381	0.1208	160	1.97	0.0504
BGENDER*LGMFPU*age0		-0.2455	0.1418	160	-1.73	0.0853
age0*age0		-0.07690	0.01484	160	-5.18	<.0001
BGENDER*age0*age0		0.03724	0.01761	160	2.11	0.0360
LGMFPU*age0*age0		-0.02715	0.01067	160	-2.55	0.0119
BGEN*LGMFP*age0*age0		0.02739	0.01253	160	2.19	0.0303

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
POVERTY	1	15	4.80	0.0447
BGENDER	1	30	0.25	0.6196
BGENDER*POVERTY	1	160	0.67	0.4145
LGMFPU	1	30	0.06	0.8078
BGENDER*LGMFPU	1	30	0.00	0.9553
age0	1	160	4.87	0.0288
BGENDER*age0	1	160	2.11	0.1479
LGMFPU*age0	1	160	3.89	0.0504
BGENDER*LGMFPU*age0	1	160	3.00	0.0853
age0*age0	1	160	26.87	<.0001
BGENDER*age0*age0	1	160	4.47	0.0360
LGMFPU*age0*age0	1	160	6.48	0.0119
BGEN*LGMFP*age0*age0	1	160	4.78	0.0303

Population Averaged reduced Model

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
SP(POW)	CHILD	-0.00002
Residual		0.2194

Fit Statistics

-2 Log Likelihood	269.5
AIC (smaller is better)	293.5
AICC (smaller is better)	295.2
BIC (smaller is better)	311.8

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
1	0.00	1.0000

Solution for Fixed Effects

Effect	POVERTY	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		0.7743	0.07860	33	9.85	<.0001
POVERTY	0	-0.1821	0.07349	15	-2.48	0.0256
POVERTY	1	0	.	.	.	.
age0		0.3655	0.1163	161	3.14	0.0020
age0*BGENDER		-0.2315	0.1360	161	-1.70	0.0906
age0*LGMFPU		0.2616	0.08198	161	3.19	0.0017
age0*BGENDER*LGMFPU		-0.2505	0.09656	161	-2.59	0.0103
age0*age0		-0.07669	0.01235	161	-6.21	<.0001
age0*age0*BGENDER		0.03337	0.01456	161	2.29	0.0232

age0*age0*LGMFPU	-0.02878	0.008809	161	-3.27	0.0013
age0*age0*BGEN*LGMFP	0.02767	0.01035	161	2.67	0.0083

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
POVERTY	1	15	6.14	0.0256
age0	1	161	9.88	0.0020
age0*BGENDER	1	161	2.90	0.0906
age0*LGMFPU	1	161	10.18	0.0017
age0*BGENDER*LGMFPU	1	161	6.73	0.0103
age0*age0	1	161	38.54	<.0001
age0*age0*BGENDER	1	161	5.26	0.0232
age0*age0*LGMFPU	1	161	10.67	0.0013
age0*age0*BGEN*LGMFP	1	161	7.14	0.0083

Random Coefficient Model:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	CHILD	0.3850
UN(2,1)	CHILD	-0.07141
UN(2,2)	CHILD	0.003849
UN(3,1)	CHILD	0.004625
UN(3,2)	CHILD	-0.00010
UN(3,3)	CHILD	0
UN(4,1)	CHILD	-0.2189
UN(4,2)	CHILD	0.05636
UN(4,3)	CHILD	-0.00450
UN(4,4)	CHILD	0.1487
Residual	CHILD	0.2222

Fit Statistics

-2 Log Likelihood	288.0
AIC (smaller is better)	326.0
AICC (smaller is better)	330.1
BIC (smaller is better)	355.0

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
9	27.45	0.0012

Solution for Fixed Effects

Effect	BGENDER	Estimate	Standard Error	DF	t Value	Pr > |t|
POVERTY		0.4643	0.06673	15	6.96	<.0001
age0		0.2453	0.07061	30	3.47	0.0016
age0*BGENDER	0	0.2215	0.1110	85	2.00	0.0492
age0*BGENDER	1	0	.	.	.	.
age0*LGMFPU		0.002929	0.04576	85	0.06	0.9491
age0*LGMFPU*BGENDER	0	0.2416	0.07652	85	3.16	0.0022
age0*LGMFPU*BGENDER	1	0	.	.	.	.
age0*age0		-0.05063	0.007665	30	-6.61	<.0001
age0*age0*BGENDER	0	-0.03284	0.01326	85	-2.48	0.0152
age0*age0*BGENDER	1	0	.	.	.	.
age0*age0*LGMFPU		-0.00070	0.005169	85	-0.14	0.8922
age0*age0*LGMF*BGEND	0	-0.02728	0.009316	85	-2.93	0.0044
age0*age0*LGMF*BGEND	1	0	.	.	.	.

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
POVERTY	1	15	48.42	<.0001
age0	1	30	41.16	<.0001
age0*BGENDER	1	85	3.98	0.0492
age0*LGMFPU	1	85	10.49	0.0017
age0*LGMFPU*BGENDER	1	85	9.97	0.0022
age0*age0	1	30	102.73	<.0001
age0*age0*BGENDER	1	85	6.14	0.0152
age0*age0*LGMFPU	1	85	9.50	0.0028

age0*age0*LGMF*BGEND	1	85	8.57	0.0044

Reduce random Coefficient Model

Estimated G Matrix

Row	Effect	CHILD	POVERTY	Col1	Col2	Col3
1	Intercept	1		0.02565	-0.02899	-0.02851
2	POVERTY	1	0	-0.02899	0.02694	0.01051
3	POVERTY	1	1	-0.02851	0.01051	0.04493

Estimated G Correlation Matrix

Row	Effect	CHILD	POVERTY	Col1	Col2	Col3
1	Intercept	1		1.0000	-1.0000	-0.8397
2	POVERTY	1	0	-1.0000	1.0000	0.3022
3	POVERTY	1	1	-0.8397	0.3022	1.0000

Estimated V Matrix for CHILD 1

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	0.2294	0.01356	0.01356	-0.02133	-0.02133	-0.02133
2	0.01356	0.2294	0.01356	-0.02133	-0.02133	-0.02133
3	0.01356	0.01356	0.2294	-0.02133	-0.02133	-0.02133
4	-0.02133	-0.02133	-0.02133	0.2104	-0.00537	-0.00537
5	-0.02133	-0.02133	-0.02133	-0.00537	0.2104	-0.00537
6	-0.02133	-0.02133	-0.02133	-0.00537	-0.00537	0.2104

Estimated V Correlation Matrix for CHILD 1

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	1.0000	0.05914	0.05914	-0.09708	-0.09708	-0.09708
2	0.05914	1.0000	0.05914	-0.09708	-0.09708	-0.09708
3	0.05914	0.05914	1.0000	-0.09708	-0.09708	-0.09708
4	-0.09708	-0.09708	-0.09708	1.0000	-0.02554	-0.02554
5	-0.09708	-0.09708	-0.09708	-0.02554	1.0000	-0.02554
6	-0.09708	-0.09708	-0.09708	-0.02554	-0.02554	1.0000

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	CHILD	0.02565
UN(2,1)	CHILD	-0.02899
UN(2,2)	CHILD	0.02694
UN(3,1)	CHILD	-0.02851
UN(3,2)	CHILD	0.01051
UN(3,3)	CHILD	0.04493
Residual	CHILD	0.2158

Fit Statistics

-2 Log Likelihood	267.1
AIC (smaller is better)	301.1
AICC (smaller is better)	304.4

BIC (smaller is better)	327.1

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	2.37	0.8828

Solution for Fixed Effects

Effect	BGENDER	POVERTY	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept			0.7844	0.08242	15	9.52	<.0001
POVERTY		0	-0.1866	0.07885	15	-2.37	0.0319
POVERTY		1	0	.	.	.	.
age0			0.1348	0.07834	146	1.72	0.0875
age0*BGENDER	0		0.2052	0.1330	146	1.54	0.1249
age0*BGENDER	1		0	.	.	.	.
age0*LGMFPU			0.01123	0.05165	146	0.22	0.8282
age0*LGMFPU*BGENDER	0		0.2336	0.09411	146	2.48	0.0142
age0*LGMFPU*BGENDER	1		0	.	.	.	.
age0*age0			-0.04338	0.008049	146	-5.39	<.0001
age0*age0*BGENDER	0		-0.03073	0.01442	146	-2.13	0.0347
age0*age0*BGENDER	1		0	.	.	.	.
age0*age0*LGMFPU			-0.00118	0.005457	146	-0.22	0.8295
age0*age0*LGMF*BGEND	0		-0.02590	0.01024	146	-2.53	0.0125
age0*age0*LGMF*BGEND	1		0	.	.	.	.

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
POVERTY	1	15	5.60	0.0319
age0	1	146	11.35	0.0010
age0*BGENDER	1	146	2.38	0.1249
age0*LGMFPU	1	146	7.31	0.0077
age0*LGMFPU*BGENDER	1	146	6.16	0.0142
age0*age0	1	146	63.07	<.0001
age0*age0*BGENDER	1	146	4.54	0.0347
age0*age0*LGMFPU	1	146	7.58	0.0067
age0*age0*LGMF*BGEND	1	146	6.40	0.0125

Contrasts

Num DF	Den DF	Chi-Square	F Value	Pr > ChiSq	Pr > F
1	146	2.38	2.38	0.1227	0.1249

Linear Mixed Model Output

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	CHILD	0.02565

UN(2,1)	CHILD	-0.02899
UN(2,2)	CHILD	0.02694
UN(3,1)	CHILD	-0.02851
UN(3,2)	CHILD	0.01051
UN(3,3)	CHILD	0.04493
Residual	CHILD	0.2158

Fit Statistics

-2 Log Likelihood	267.1
AIC (smaller is better)	301.1
AICC (smaller is better)	304.4
BIC (smaller is better)	327.1

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	2.37	0.8828

Solution for Fixed Effects

Effect	BGENDER	POVERTY	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept			0.7844	0.08242	15	9.52	<.0001
POVERTY		0	-0.1866	0.07885	15	-2.37	0.0319
POVERTY		1	0	.	.	.	.
age0			0.1348	0.07834	146	1.72	0.0875
age0*BGENDER	0		0.2052	0.1330	146	1.54	0.1249
age0*BGENDER	1		0	.	.	.	.
age0*LGMFPU			0.01123	0.05165	146	0.22	0.8282
age0*LGMFPU*BGENDER	0		0.2336	0.09411	146	2.48	0.0142
age0*LGMFPU*BGENDER	1		0	.	.	.	.
age0*age0			-0.04338	0.008049	146	-5.39	<.0001
age0*age0*BGENDER	0		-0.03073	0.01442	146	-2.13	0.0347
age0*age0*BGENDER	1		0	.	.	.	.
age0*age0*LGMFPU			-0.00118	0.005457	146	-0.22	0.8295
age0*age0*LGMF*BGEND	0		-0.02590	0.01024	146	-2.53	0.0125
age0*age0*LGMF*BGEND	1		0	.	.	.	.

Solution for Random Effects

Effect	CHILD	POVERTY	Estimate	Std Err Pred	DF	t Value	Pr > |t|
Intercept	1		-0.01012	0.1591	146	-0.06	0.9494
POVERTY	1	0	-0.04245	0.1505	146	-0.28	0.7783
POVERTY	1	1	0.01441	0.1976	146	0.07	0.9419
Intercept	2		-0.00622	0.1597	146	-0.04	0.9690
POVERTY	2	0	-0.04020	0.1439	146	-0.28	0.7804
POVERTY	2	1	0.03574	0.2000	146	0.18	0.8584
Intercept	3		-0.02073	0.1597	146	-0.13	0.8969
POVERTY	3	0	-0.1341	0.1438	146	-0.93	0.3529
POVERTY	3	1	0.1192	0.2000	146	0.60	0.5521
Intercept	4		-0.03673	0.1594	146	-0.23	0.8181
POVERTY	4	0	-0.06660	0.1551	146	-0.43	0.6683
POVERTY	4	1	-0.1143	0.1991	146	-0.57	0.5670
Intercept	5		0.004516	0.1591	146	0.03	0.9774
POVERTY	5	0	0.002764	0.1638	146	0.02	0.9866
POVERTY	5	1	0.02438	0.1884	146	0.13	0.8972
Intercept	6		0.03093	0.1591	146	0.19	0.8461
POVERTY	6	0	0.06536	0.1504	146	0.43	0.6644
POVERTY	6	1	0.07859	0.1975	146	0.40	0.6913
Intercept	7		-0.00960	0.1597	146	-0.06	0.9522

POVERTY	7	0	-0.06208	0.1446	146	-0.43	0.6682
POVERTY	7	1	0.05518	0.2004	146	0.28	0.7834
Intercept	8		-0.00265	0.1591	146	-0.02	0.9868
POVERTY	8	0	-0.00162	0.1638	146	-0.01	0.9921
POVERTY	8	1	-0.01428	0.1881	146	-0.08	0.9396
Intercept	9		0.02005	0.1591	146	0.13	0.8999
POVERTY	9	0	0.01227	0.1638	146	0.07	0.9404
POVERTY	9	1	0.1082	0.1879	146	0.58	0.5656
Intercept	10		-0.01241	0.1592	146	-0.08	0.9380
POVERTY	10	0	-0.03501	0.1593	146	-0.22	0.8264
POVERTY	10	1	-0.01481	0.1927	146	-0.08	0.9388
Intercept	11		0.001938	0.1591	146	0.01	0.9903
POVERTY	11	0	0.001187	0.1638	146	0.01	0.9942
POVERTY	11	1	0.01046	0.1879	146	0.06	0.9557
Intercept	12		-0.00896	0.1597	146	-0.06	0.9554
POVERTY	12	0	-0.05792	0.1434	146	-0.40	0.6868
POVERTY	12	1	0.05149	0.1997	146	0.26	0.7969
Intercept	13		0.02676	0.1590	146	0.17	0.8666
POVERTY	13	0	0.02050	0.1540	146	0.13	0.8942
POVERTY	13	1	0.1366	0.1948	146	0.70	0.4844
Intercept	14		0.04175	0.1592	146	0.26	0.7935
POVERTY	14	0	0.01491	0.1592	146	0.09	0.9255
POVERTY	14	1	0.2456	0.1930	146	1.27	0.2051
Intercept	15		0.01880	0.1597	146	0.12	0.9064
POVERTY	15	0	0.1216	0.1436	146	0.85	0.3984
POVERTY	15	1	-0.1081	0.1998	146	-0.54	0.5893
Intercept	16		0.01102	0.1593	146	0.07	0.9450
POVERTY	16	0	0.1064	0.1475	146	0.72	0.4719
POVERTY	16	1	-0.1302	0.1990	146	-0.65	0.5140
Intercept	17		0.002235	0.1597	146	0.01	0.9889
POVERTY	17	0	0.01446	0.1434	146	0.10	0.9198
POVERTY	17	1	-0.01285	0.1997	146	-0.06	0.9488
Intercept	18		-0.01799	0.1590	146	-0.11	0.9101
POVERTY	18	0	-0.04484	0.1586	146	-0.28	0.7778
POVERTY	18	1	-0.03271	0.1920	146	-0.17	0.8650
Intercept	19		0.000851	0.1597	146	0.01	0.9958
POVERTY	19	0	0.005504	0.1444	146	0.04	0.9696
POVERTY	19	1	-0.00489	0.2003	146	-0.02	0.9805
Intercept	20		0.01618	0.1597	146	0.10	0.9194
POVERTY	20	0	0.1047	0.1458	146	0.72	0.4741
POVERTY	20	1	-0.09304	0.2011	146	-0.46	0.6443
Intercept	21		-0.00418	0.1592	146	-0.03	0.9791
POVERTY	21	0	-0.00256	0.1638	146	-0.02	0.9876
POVERTY	21	1	-0.02254	0.1897	146	-0.12	0.9056
Intercept	22		0.002580	0.1590	146	0.02	0.9871
POVERTY	22	0	-0.02621	0.1542	146	-0.17	0.8653
POVERTY	22	1	0.06682	0.1951	146	0.34	0.7325
Intercept	23		-0.01130	0.1591	146	-0.07	0.9435
POVERTY	23	0	-0.06545	0.1542	146	-0.42	0.6718
POVERTY	23	1	0.05043	0.1952	146	0.26	0.7964
Intercept	24		0.01649	0.1591	146	0.10	0.9176
POVERTY	24	0	0.1135	0.1546	146	0.73	0.4638
POVERTY	24	1	-0.1079	0.1956	146	-0.55	0.5819
Intercept	25		0.01590	0.1597	146	0.10	0.9208
POVERTY	25	0	0.1029	0.1448	146	0.71	0.4786
POVERTY	25	1	-0.09143	0.2005	146	-0.46	0.6491
Intercept	26		-0.02626	0.1593	146	-0.16	0.8693
POVERTY	26	0	-0.09083	0.1473	146	-0.62	0.5384
POVERTY	26	1	0.000557	0.1989	146	0.00	0.9978
Intercept	27		-0.02334	0.1590	146	-0.15	0.8835
POVERTY	27	0	0.002500	0.1541	146	0.02	0.9871
POVERTY	27	1	-0.1580	0.1950	146	-0.81	0.4193
Intercept	28		0.004993	0.1590	146	0.03	0.9750
POVERTY	28	0	-0.02011	0.1538	146	-0.13	0.8962
POVERTY	28	1	0.07105	0.1951	146	0.36	0.7162
Intercept	29		0.01072	0.1597	146	0.07	0.9466
POVERTY	29	0	0.06936	0.1445	146	0.48	0.6320
POVERTY	29	1	-0.06166	0.2003	146	-0.31	0.7587
Intercept	30		-0.02743	0.1590	146	-0.17	0.8633

POVERTY	30	0	-0.02106	0.1585	146	-0.13	0.8945
POVERTY	30	1	-0.1399	0.1921	146	-0.73	0.4674
Intercept	31		0.002497	0.1591	146	0.02	0.9875
POVERTY	31	0	0.001528	0.1638	146	0.01	0.9926
POVERTY	31	1	0.01348	0.1879	146	0.07	0.9429
Intercept	32		0.001597	0.1592	146	0.01	0.9920
POVERTY	32	0	0.000978	0.1638	146	0.01	0.9952
POVERTY	32	1	0.008622	0.1888	146	0.05	0.9636
Intercept	33		0.01139	0.1592	146	0.07	0.9431
POVERTY	33	0	0.006973	0.1638	146	0.04	0.9661
POVERTY	33	1	0.06149	0.1898	146	0.32	0.7465
Intercept	34		-0.02330	0.1590	146	-0.15	0.8837
POVERTY	34	0	-0.05631	0.1586	146	-0.36	0.7231
POVERTY	34	1	-0.04575	0.1917	146	-0.24	0.8117

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
POVERTY	1	15	5.60	0.0319
age0	1	146	11.35	0.0010
age0*BGENDER	1	146	2.38	0.1249
age0*LGMFPU	1	146	7.31	0.0077
age0*LGMFPU*BGENDER	1	146	6.16	0.0142
age0*age0	1	146	63.07	<.0001
age0*age0*BGENDER	1	146	4.54	0.0347
age0*age0*LGMFPU	1	146	7.58	0.0067
age0*age0*LGMF*BGEND	1	146	6.40	0.0125