ABSTRACT
A longitudinal data set is defined as a data set in which the response for each experimental unit is observed on two or more occasions. In the paper I will present different types of Longitudinal Data Analysis, and review the traditional approaches to longitudinal data analysis including mixed models and repeated measures analysis of variance. I will concentrate on random coefficient models showing their greater power and other advantages over traditional methods. I will try to show the similarities and differences between the repeated measures and random coefficient analyses by comparing their results using the same data set. I will use simulated data with high dropout rate to evaluate the missing data effect on these approaches. I will also present the SAS code for MIXED procedure for each method and when we have to use the time as fixed effect and when as random effect as I will try to show the differences between the time as a class variable and the time as a continuous variable.

KEYWORDS: Longitudinal data, Repeated measures, Random coefficients, Mixed Model

INTRODUCTION
The repeated measures for the same subject are correlated, and this correlation must be taken into account in a repeated measures analysis. We need to specify a covariance structure for the repeated measurements of an individual subject. The same covariance structure is used for all subjects. Questions we may want to answer in a repeated measures analysis may be whether main effect influences the response, whether time, the repeated factor, influences the response, and whether there is a main effect by time interaction. This task uses the mixed models approach for analyzing repeated measures.

Another method to analyze the longitudinal data is the random coefficient regression models (Rao [4], Swamy [5]), which are generalizations of the classical Gauss-Markov model, where the parameters are allowed to be random quantities. The regression coefficients for one or more covariates are assumed to be a random sample from some population of possible coefficients, hence the term random coefficients. Random coefficient models are sensible whenever the data arise from independent subjects or clusters and the regression model for each subject or cluster can be assumed to be a random deviation from some population regression model. The standard random coefficient model (Littell [3]) involves a random intercept and slope for each subject.

The aim of this paper is to compare the above mentioned methods, and investigate which application is best suited for our data sets.

In the 1st section we will present the mixed models theory, repeated measures analysis, and the random coefficient models. In the 2nd we will show the SAS code for MIXED procedure and the use of repeated and random statements for each method. At the end we will present an example and the results.

LONGITUDINAL DATA ANALYSIS
There are different approaches to analyze the longitudinal data including:
- Univariate
- Split-plot designs
- Multivariate:
- Mixed Model Analysis

In this paper we will consider the Mixed Model Approach as a preferred method.

MIXED MODELS

General Linear Mixed Model (GLMM) defined as:

\[ Y_i = X_i \beta + Z_i u_i + e_i \]

where
Y_i represents the observed data for subject i, 1 ≤ i ≤ N, N is the number of subjects.

X_i and Z_i are (n×p) and (n×q) the known design matrices

β (p × 1) represents the fixed effects

u_i (q × I) represents the random effects

ε_i represents the residual error

The mixed models state that observed data consist of two parts:
1- Fixed effects
2- Random effects.

Where the fixed effects define the expected values of the observations,
And the random effects define the variance and covariances of the observations.

REPEATED MEASURES ANALYSIS

Repeated measures are response outcomes measured on the same subject. Most of the times, these measurements are made over a period of time, such as pain score measured once a day for a week. However, repeated measures can also refer to multiple measurements on an experimental unit under different conditions or in different places.

Time is called a within-subject effect because there are different measurements at different times on the same subject. Explanatory variables such as race or sex are called between-subject effects because their values change only from subject to subject; there is not a different value for them at different times for the same subject.

The effects of interest in repeated measures analysis are:
Between-subject effects (the effect of TREATMENT on different patients in clinical trials),
Within-subject effects (the effect of TIME on the same patient), and
the interactions between the two types of effects (TREATMENT*TIME).

Figure 1:

Plot of response scores over time (repeated measures) for selected patients

RANDOM COEFFICIENTS MODELS

The regression model for each subject can be assumed to be a random deviation from some population regression model; the standard random coefficient model involves a random intercept and slope for each subject. Random coefficient models are sensible whenever the data arise from independent subjects.
THE MODEL

• $y_{ij} = a_i + x_{ij}b_i + e_{ij}$ …………………..(1)
• Where

• $y_{ij}$ = the measurement on the $j$th observation on the $i$th subject
• Model (1) can be expressed as

• $y_{ij} = a + \hat{a}_i + bX_{ij} + \hat{b}_i X_{ij} + e_{ij}$ ………………..(2)
• Where

• $\hat{a}_i = a_i - a$
• $\hat{b}_i = b_i - b$
• Model (2) can be expressed in terms of a mixed model as

• $y_{ij} = a + bX_{ij} + \hat{a}_i + \hat{b}_i X_{ij} + e_{ij}$ ………………..(3)
• Where

• $a + bX_{ij}$ is the fixed effects part of the model.
• $\hat{a}_i + \hat{b}_i X_{ij} + e_{ij}$ is the random effects part of the model.
• Finally the model (3) can be expressed as

• $y_{ij} = a + bX_{ij} + e_{ij}$……………..(3)

FIGURE 2:
Several simple linear regression models from a random sample of patients

RANDOM AND REPEATED STATEMENTS
The RANDOM statement specifies which effects in the model are random.
The following SAS code specifies the time as random effect and as continuous variable as well as estimates the deviations of the subjects’ intercepts from the population mean intercept.

```
random intercept time /type=un sub=subject solution;
```
The option type=UN in the random statement provides estimates of the variances of the slopes and of the intercepts and the covariance between the slopes and the intercepts. The option sub=subject in the random statement specifies that the intercept and slope of one subject are independently distributed from the intercepts and slopes of the other subjects, but the intercept and the slope within each subject are correlated. The solution option in the random statement requests the printout of the predicted values for the deviations of the subjects’ intercepts and slopes from the population mean intercept and the population mean slope.

The REPEATED statement allows us to test hypotheses about the measurement factors (often called within-subject factors) as well as the interaction of within-subject factors with independent variables in the model statement (often called between-subject factors).

The following SAS code specifies the time as repeated effect and as a class variable to inform the PROC MIXED of the time level of the current observation.

```
repeated time /type=un sub=subject r rcorr;
```

The TYPE= UN with SUB= subject defines an unstructured variance-covariance structure for each subject. The R option requests the printout of the covariance matrix corresponding to the first level of subject, and RCORR prints this matrix in correlation form.

**EXAMPLES AND RESULTS**

```
%macro mix (ds=,mod=,rand=,rep=,class=,tit=,model= );
   proc mixed data=effw&ds ;
      title1 "Mixed Model Results/ study &ds";
      title2 "&tit";
      class &class;
      model &mod /outp=predicted solution;
      &rand ;
      &rep ;
      %if &ds=1 %then %do;
         lsmeans rxgrp/pdiff cl;
         estimate 'Trt1 - PBO' rxgrp -1 1 0 0 / cl ;
         estimate 'Trt2 - PBO' rxgrp -1 0 1 0 / cl ;
         estimate 'Control - PBO' rxgrp -1 0 0 1 / cl ;
         estimate 'Treatment vs Placebo' rxgrp -2 1 1 0 / divisor=2;
         estimate 'Treatment vs Control' rxgrp 0 1 1 -2 / divisor=2;
         estimate 'All vs Placebo' rxgrp -3 1 1 1 / divisor=3;
      %end;
      %else %if &ds=2 %then %do;
         lsmeans rxgp/pdiff cl;
         estimate 'Treatment-PBO' rxgp -1 1 / cl ;
      %end;
      ods output LSMEANS=LSM&model;
      ods output SolutionF=fixed&model;
      ods output SolutionR=rand&model;
      ods output FitStatistics=fitinfo&model;
      ods output estimates=estimate&model;
      ods output TESTS3=TYPE&model;
   run;
%macro dat (tab=, model=, ds=);
   data &tab&model;
   set &tab&model;
   model=&model;
   if &model=&ds.1 then modeff='Only FIXED EFFECT';
   if &model=&ds.2 then modeff='REPEATED MASUR';
   if &model=&ds.3 then modeff='RANDOM and FIXED';
   if &model=&ds.4 then modeff='RAN and FIX/AR(1)';
   if &model=&ds.5 then modeff='REPEATED MASU/AR(1)';
   if &model=&ds.6 then modeff='RAN & REP';
   if &model=&ds.7 then modeff='RAN & REP/AR(1) ';
```

RUN;
%MEND DAT;
%MEND DAT (TAB=TYPE, MODEL=&MODEL, DS=&DS);
%MEND DAT (TAB=LSM, MODEL=&MODEL, DS=&DS);
%MEND DAT (TAB=ESTIMATE, MODEL=&MODEL, DS=&DS);
%MEND DAT (TAB=FITINFO, MODEL=&MODEL, DS=&DS);

%if &ds=1 %then %do;
    proc append base=estimateall_1 data=estimate&model force ;
    run;
    proc append base=LSMall_1 data=LSM&model force ;
    run;
    proc append base=fitinfoall_1 data=fitinfo&model force ;
    run;
    proc append base=TYPEall_1 data=TYPE&model force ;
    run;
%END;

%if &ds=2 %then %do;
    proc append base=estimateall_2 data=estimate&model force ;
    run;
    proc append base=LSMall_2 data=LSM&model force ;
    run;
    proc append base=fitinfoall_2 data=fitinfo&model force ;
    run;
    proc append base=TYPEall_2 data=TYPE&model force ;
    run;
%END;

%mend mix;

%mix (ds=1,
    class=ptid rxgrp week,
    mod=hamatot=week cluster rxgrp hamabl,
    model=ll,
    tit=Random intercept and time as continues variable / type un
    );

RESULTS OF MIXED MODELS USING DIFFERENT EFFECTS
TABLE 1: LEAST SQUARES MEAN

<table>
<thead>
<tr>
<th>EFFECT</th>
<th>RXGRP</th>
<th>ESTIMATE</th>
<th>LOWER</th>
<th>UPPER</th>
<th>MODEFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>RXGRP</td>
<td>Placebo</td>
<td>17.4400</td>
<td>16.7862</td>
<td>18.0938</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT1</td>
<td>14.8684</td>
<td>14.2005</td>
<td>15.5362</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT2</td>
<td>14.1474</td>
<td>13.4862</td>
<td>14.8086</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>RXGRP</td>
<td>CONTROL</td>
<td>14.9858</td>
<td>14.3292</td>
<td>15.6423</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>RXGRP</td>
<td>Placebo</td>
<td>17.5713</td>
<td>16.3943</td>
<td>18.7482</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT1</td>
<td>14.8873</td>
<td>13.6786</td>
<td>16.0960</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT2</td>
<td>14.6721</td>
<td>13.5076</td>
<td>15.8366</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>RXGRP</td>
<td>CONTROL</td>
<td>16.0012</td>
<td>14.8626</td>
<td>17.1398</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>RXGRP</td>
<td>Placebo</td>
<td>17.2220</td>
<td>16.0684</td>
<td>18.3757</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT1</td>
<td>14.7958</td>
<td>13.6120</td>
<td>15.9797</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>RXGRP</td>
<td>TRT2</td>
<td>14.3806</td>
<td>13.2395</td>
<td>15.5216</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>RXGRP</td>
<td>CONTROL</td>
<td>16.0607</td>
<td>14.9415</td>
<td>17.1800</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>RXGRP</td>
<td>Placebo</td>
<td>17.4441</td>
<td>16.2854</td>
<td>18.6028</td>
<td>REPEATED MASU/AR(1)</td>
</tr>
</tbody>
</table>
TABLE 2: TREATMENTS DIFFERENCES

<table>
<thead>
<tr>
<th>LABEL</th>
<th>ESTIMATE</th>
<th>PROBT</th>
<th>LOWER</th>
<th>UPPER</th>
<th>MODEL EFFECT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trt1 - PBO</td>
<td>-2.5716</td>
<td>0.0000</td>
<td>-3.5085</td>
<td>-1.6348</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>Trt2 - PBO</td>
<td>-3.2926</td>
<td>0.0000</td>
<td>-4.2217</td>
<td>-2.3635</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>Control - PBO</td>
<td>-2.4542</td>
<td>0.0000</td>
<td>-3.3825</td>
<td>-1.5260</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>Treatment vs Placebo</td>
<td>-2.9321</td>
<td>0.0000</td>
<td>-3.7382</td>
<td>-2.1261</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>Treatment vs Control</td>
<td>-0.4779</td>
<td>0.2452</td>
<td>-1.2842</td>
<td>0.3284</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>All vs Placebo</td>
<td>-2.7728</td>
<td>0.0000</td>
<td>-3.5317</td>
<td>-2.0140</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>Trt1 - PBO</td>
<td>-2.4262</td>
<td>0.0034</td>
<td>-4.0456</td>
<td>-0.8068</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>Trt2 - PBO</td>
<td>-2.8415</td>
<td>0.0005</td>
<td>-4.4232</td>
<td>-1.2598</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>Control - PBO</td>
<td>-1.1613</td>
<td>0.1467</td>
<td>-2.7314</td>
<td>0.4088</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>Treatment vs Placebo</td>
<td>-2.6338</td>
<td>0.0002</td>
<td>-4.0183</td>
<td>-1.2494</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>Treatment vs Control</td>
<td>-1.4725</td>
<td>0.0328</td>
<td>-2.8239</td>
<td>-0.1212</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>All vs Placebo</td>
<td>-2.1430</td>
<td>0.0013</td>
<td>-3.4445</td>
<td>-0.8415</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>Trt1 - PBO</td>
<td>-2.6840</td>
<td>0.0017</td>
<td>-4.3590</td>
<td>-1.0090</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>Trt2 - PBO</td>
<td>-2.8992</td>
<td>0.0005</td>
<td>-4.5367</td>
<td>-1.2616</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>Control - PBO</td>
<td>-1.5701</td>
<td>0.0580</td>
<td>-3.1935</td>
<td>0.0534</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>Treatment vs Placebo</td>
<td>-2.7916</td>
<td>0.0001</td>
<td>-4.2242</td>
<td>-1.3590</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>Treatment vs Control</td>
<td>-1.2215</td>
<td>0.0865</td>
<td>-2.6185</td>
<td>0.1754</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>All vs Placebo</td>
<td>-2.3844</td>
<td>0.0005</td>
<td>-3.7309</td>
<td>-1.0379</td>
<td>RANDOM and FIXED</td>
</tr>
<tr>
<td>Trt1 - PBO</td>
<td>-2.4838</td>
<td>0.0033</td>
<td>-4.1361</td>
<td>-0.8316</td>
<td>REPEATED /AR(1)</td>
</tr>
<tr>
<td>Trt2 - PBO</td>
<td>-2.9608</td>
<td>0.0004</td>
<td>-4.5813</td>
<td>-1.3402</td>
<td>REPEATED /AR(1)</td>
</tr>
<tr>
<td>Control - PBO</td>
<td>-2.0094</td>
<td>0.0147</td>
<td>-3.6222</td>
<td>-0.3966</td>
<td>REPEATED /AR(1)</td>
</tr>
<tr>
<td>Treatment vs Placebo</td>
<td>-2.7223</td>
<td>0.0002</td>
<td>-4.1380</td>
<td>-1.3067</td>
<td>REPEATED /AR(1)</td>
</tr>
<tr>
<td>Treatment vs Control</td>
<td>-0.7129</td>
<td>0.3139</td>
<td>-2.1029</td>
<td>0.6770</td>
<td>REPEATED /AR(1)</td>
</tr>
<tr>
<td>All vs Placebo</td>
<td>-2.4847</td>
<td>0.0003</td>
<td>-3.8165</td>
<td>-1.1529</td>
<td>REPEATED /AR(1)</td>
</tr>
</tbody>
</table>

TABLE 3: FIT STATISTICS

<table>
<thead>
<tr>
<th>DESCR</th>
<th>VALUE</th>
<th>MODEFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2 Res Log Likelihood</td>
<td>12252.6</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>AIC (smaller is better)</td>
<td>12254.6</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>AICC (smaller is better)</td>
<td>12254.6</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>BIC (smaller is better)</td>
<td>12260.1</td>
<td>Only FIXED EFFECT</td>
</tr>
<tr>
<td>-2 Res Log Likelihood</td>
<td>11017.6</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>AIC (smaller is better)</td>
<td>11047.6</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>AICC (smaller is better)</td>
<td>11047.8</td>
<td>REPEATED MASUR</td>
</tr>
<tr>
<td>BIC (smaller is better)</td>
<td>11107.7</td>
<td>REPEATED MASUR</td>
</tr>
</tbody>
</table>
FIT MODEL WITH UNEQUAL SLOPES
FOR EACH LEVEL OF BASELINE SCORE
ESTIMATE STATEMENT CODE

estimate 'placebo at 25%=23' intercept 1 rxgrp 1 0 0 0 hamabl*rxgrp 23 0 0 0;
estimate 'placebo at 50%=26' intercept 1 rxgrp 1 0 0 0 hamabl*rxgrp 26 0 0 0;
estimate 'placebo at 75%=30' intercept 1 rxgrp 1 0 0 0 hamabl*rxgrp 30 0 0 0;
estimate 'placebo at mean' intercept 1 rxgrp 1 0 0 0 hamabl*rxgrp 26.7 0 0 0;
estimate 'trt1 at 25%=23' intercept 1 rxgrp 0 1 0 0 hamabl*rxgrp 0 23 0 0;
estimate 'trt1 at 50%=26' intercept 1 rxgrp 0 1 0 0 hamabl*rxgrp 0 26 0 0;
estimate 'trt1 at 75%=30' intercept 1 rxgrp 0 1 0 0 hamabl*rxgrp 0 30 0 0;
estimate 'trt1 at mean' intercept 1 rxgrp 0 1 0 0 hamabl*rxgrp 0 26.7 0 0;
estimate 'trt2 at 25%=23' intercept 1 rxgrp 0 0 1 0 hamabl*rxgrp 0 0 23 0;
estimate 'trt2 at 50%=26' intercept 1 rxgrp 0 0 1 0 hamabl*rxgrp 0 0 26 0;
estimate 'trt2 at 75%=30' intercept 1 rxgrp 0 0 1 0 hamabl*rxgrp 0 0 30 0;
estimate 'trt2 at mean' intercept 1 rxgrp 0 0 1 0 hamabl*rxgrp 0 0 26.7 0;
estimate 'Control at 25%=23' intercept 1 rxgrp 0 0 0 1 hamabl*rxgrp 0 0 0 23;
estimate 'Control at 50%=26' intercept 1 rxgrp 0 0 0 1 hamabl*rxgrp 0 0 0 26;
estimate 'Control at 75%=30' intercept 1 rxgrp 0 0 0 1 hamabl*rxgrp 0 0 0 30;
estimate 'Control at mean' intercept 1 rxgrp 0 0 0 1 hamabl*rxgrp 0 0 0 26.7;
estimate 'trt1 - Placebo at 25%=23' rxgrp -1 1 0 0 baseline*rxgrp -23 23 0 0;
estimate 'trt1 - Placebo at 50%=26' rxgrp -1 1 0 0 baseline*rxgrp -26 26 0 0;
estimate 'trt1 - Placebo at 75%=30' rxgrp -1 1 0 0 baseline*rxgrp -30 30 0 0;
estimate 'trt1 - Placebo at mean' rxgrp -1 1 0 0 baseline*rxgrp -26.7 26.7 0 0;
estimate 'trt2 - Placebo at 25%=23' rxgrp -1 0 1 0 baseline*rxgrp -23 0 23 0;
estimate 'trt2 - Placebo at 50%=26' rxgrp -1 0 1 0 baseline*rxgrp -26 0 26 0;
estimate 'trt2 - Placebo at 75%=30' rxgrp -1 0 1 0 baseline*rxgrp -30 0 30 0;
estimate 'trt2 - Placebo at mean' rxgrp -1 0 1 0 baseline*rxgrp -26.7 0 26.7 0;
estimate 'Control - Placebo at 25%=23' rxgrp -1 0 0 1 baseline*rxgrp -23 0 0 23;
estimate 'Control - Placebo at 50%=26' rxgrp -1 0 0 1 baseline*rxgrp -26 0 0 26;
estimate 'Control - Placebo at 75%=30' rxgrp -1 0 0 1 baseline*rxgrp -30 0 0 30;
estimate 'Control - Placebo at mean' rxgrp -1 0 0 1 baseline*rxgrp -26.7 0 0 26.7;
**FIT MODEL WITH UNEQUAL SLOPES**

**FOR EACH WEEK (POINT OF TIME)**

**ESTIMATE STATEMENT CODE**

```plaintext
estimate 'Placebo at week=1'   intercept 1 rxgrp 1 0 0 0 week*rxgrp 1 0 0 0;
estimate 'Placebo at week=3'   intercept 1 rxgrp 1 0 0 0 week*rxgrp 3 0 0 0;
estimate 'Placebo at week=6'   intercept 1 rxgrp 1 0 0 0 week*rxgrp 6 0 0 0;
estimate 'trt1 at week=1'   intercept 1 rxgrp 0 1 0 0 week*rxgrp 0 1 0 0;
estimate 'trt1 at week=3'   intercept 1 rxgrp 0 1 0 0 week*rxgrp 0 3 0 0;
estimate 'trt1 at week=6'   intercept 1 rxgrp 0 1 0 0 week*rxgrp 0 6 0 0;
estimate 'trt2 at week=1'   intercept 1 rxgrp 0 0 1 0 week*rxgrp 0 0 1 0;
estimate 'trt2 at week=3'   intercept 1 rxgrp 0 0 1 0 week*rxgrp 0 0 3 0;
estimate 'trt2 at week=6'   intercept 1 rxgrp 0 0 1 0 week*rxgrp 0 0 6 0;
estimate 'trt1 - Placebo at week=1'   rxgrp -1 1 0 0 week*rxgrp -1 1 0 0;
estimate 'trt1 - Placebo at week=3'   rxgrp -1 1 0 0 week*rxgrp -3 3 0 0;
estimate 'trt1 - Placebo at week=6'   rxgrp -1 1 0 0 week*rxgrp -6 6 0 0;
estimate 'trt2 - Placebo at week=1'   rxgrp -1 0 1 0 week*rxgrp -1 0 1 0;
estimate 'trt2 - Placebo at week=3'   rxgrp -1 0 1 0 week*rxgrp -3 0 3 0;
estimate 'trt2 - Placebo at week=6'   rxgrp -1 0 1 0 week*rxgrp -6 0 6 0;
estimate 'Control - Placebo at week=1'   rxgrp -1 0 0 1 week*rxgrp -1 0 0 1;
estimate 'Control - Placebo at week=3'   rxgrp -1 0 0 1 week*rxgrp -3 0 0 3;
estimate 'Control - Placebo at week=6'   rxgrp -1 0 0 1 week*rxgrp -6 0 0 6;
```
CONCLUSION
The repeated measures analysis of variance and the random coefficient models are two different approaches to analyze the longitudinal data.

The repeated measures allow us to test hypotheses about the within-subject factors as well as the interaction of within-subject factors with independent variables in the model statement.

In the Random coefficient models, the regression model for each subject can be assumed to be a random deviation from a certain population regression model; the standard random coefficient model involves a random intercept and slope for each subject.

The traditional repeated measures analysis includes the time as class variable. On the other hand the random coefficient models include the time as a continuous variable.

The results of the analysis of the clinical trials data shows that the estimated means for treatments and control groups are different between the two approaches as well as for the estimated differences between treatments and control group. Also the results from using the common mixed model including only fixed effects in the model are different from the two mentioned approaches. Significant differences were found between the approaches in the means of the control group and in the estimated differences between the control group and the placebo.

The random coefficient models show different levels of treatment change with different levels of baseline scores and different time points.

REFERENCES

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