

MIXED_RELIABILITY: A SAS Macro for Estimating Lambda and Assessing the Trustworthiness of Random Effects in Multilevel Models

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ABSTRACT

When estimating multilevel models (also called hierarchical models, mixed models, and random effect models), researchers are often interested not only in the regression coefficients but also in the fit of the overall model to the data (e.g., -2LL, AIC, BIC). Whereas both model fit and regression coefficient estimates are important to examine when estimating multilevel models, the reliability of multilevel model random effects should also be examined. However, neither PROC MIXED nor PROC GLIMMIX produce estimates of lambda, the statistic often used to represent reliability. As a result, this important metric is often not examined by researchers who estimate their multilevel models in SAS. The macro presented in this paper will provide analysts estimating multilevel models with a readily-available method for generating reliability estimates within SAS *PROC MIXED*.

Keywords: MULTILEVEL MODELS, PROC MIXED, RANDOM EFFECTS.

INTRODUCTION

When estimating multilevel models (also called hierarchical models, mixed models, and random effect models), researchers are often interested not only in the regression coefficients but also in the fit of the overall model to the data (e.g., -2LL, AIC, BIC). Whereas both model fit and regression coefficient estimates are important to examine when estimating multilevel models, the reliability of multilevel model random effects should also be examined. However, neither PROC MIXED nor PROC GLIMMIX produce estimates of lambda, the statistic often used to represent reliability. As a result, this important metric is often not examined by researchers who estimate their multilevel models in SAS. This section provides a brief overview of the statistical details of why the reliability of multilevel regression coefficients is important.

Multilevel estimates of regression coefficients are weighted averages of the individual ordinary least squared (OLS) group mean estimate ($\bar{Y}_j$), and the generalized least squared (GLS) grand mean estimate ($\hat{\gamma}_{00}$) for all similar groups. The optimal weighted average of these two possible estimators is called a Bayes estimator, β^*_{qj} (Raudenbush & Bryk, 2002); and for each of q level-1 β -coefficients in a multilevel model, it incorporates a weight, λ_{qj} , equal to the reliability of the least squares estimator, $\bar{Y}_j$, for each level-2 unit.

$$\beta^*_{qj} = \lambda_j \bar{Y}_j + (1 - \lambda_j) \hat{\gamma}_{00}$$

The first alternative estimator which factors into the weighted average of the Bayes estimator is based on the level-1 model (below) and models $\bar{Y}_j$ as an unbiased estimator of β_{qj} , with within-group variance V_{qqj} .

$$\bar{Y}_j = \beta_{qj} + \bar{r}_j,$$

The second alternative, based on the level-2 model, defines β_{qj} in terms of the grand mean across level-2 units, with between-group variance σ^2_{uq} .

$$\beta_{qj} = \hat{\gamma}_{00} + u_{qj},$$

This reliability of any Bayes estimator, β^*_{qj} , ρ_{qj} , measures the ratio of the true variance of β_{qj} across groups, σ^2_{uq} , relative to the total variance (σ^2/n_j) observed for each group's mean estimate, $\bar{Y}_j$. In general, the reliability of any level-1 β -coefficient can be defined by the following expressions:

$$\rho_{qj} = \frac{Var(u_{qj})}{Var(u_{qj} + \bar{r}_j)} = \frac{\sigma^2_{uq}}{\sigma^2_{uq} + (\sigma^2/n_j)}$$

The weight used to determine the *Bayes estimator*, β_{qj}^* , for all level-1 β -coefficients is equivalent to the reliability of each group's contribution to the estimation:

$$\lambda_j = \rho_{qj}$$

As the reliability of a group's estimate of β_{qj} approaches unity, the *Bayes estimator*, β_{qj}^* , is heavily weighted on $\bar{Y}_j$ causing the multilevel parameter estimate $\hat{\beta}_{qj}$ to be pulled toward the individual OLS regression coefficients. On the other hand, when a group's estimate of β_{qj} is highly unreliable, more weight is placed on $\hat{y}_{oo}$ when generating the Bayes estimator. As a result, the regression coefficient is shrunk back toward the overall mean, $\hat{y}_{oo}$. Because of the shrinkage effect, empirical Bayes estimates are often called *shrinkage estimators*. They tend to be biased toward the overall mean; however they usually have high precision (i.e., smaller standard errors) in estimating β_{qj} (Hox, 2010).

The reliability of a multilevel regression coefficient is a function of (1) group sample size, (n_j) and (2) the difference between group estimates and the overall estimate (Hox, 2010). Estimates for small groups are less reliable, and shrink more than estimates for large groups. When group sample size is small, the contribution of $\hat{\beta}_{qj}$ to β_{qj}^* is small, and the multilevel parameter estimate is shrunk toward the grand mean, $\hat{y}_{oo}$. Moreover, given a fixed group size, group estimates that are very far from the overall estimate are assumed less reliable and thus shrink more than estimates that are close to the overall mean.

Although SAS analysts do not often report the reliability of $\hat{\beta}_{qj}$, this measure is important in multilevel model parameter estimation as it is used to obtain shrinkage estimates via *empirical Bayes estimation*. With this approach, information is borrowed from all groups to support the statistical estimation for groups with insufficient information (e.g. small sample size). SAS PROC MIXED does not provide estimates for the reliabilities of level-1 β -coefficients. The macro presented in this paper will provide analysts estimating multilevel models with a readily-available method for generating reliability estimates within SAS PROC MIXED. Given that reliability estimates are provided when researchers estimate multilevel models in the HLM software, it is important for SAS analysts to be able to provide the same estimates for their models.

MACRO MIXED_RELIABILITY DETAILS

OVERVIEW & ARGUMENTS

The MIXED_RELIABILITY macro was developed to calculate lambda and assess the trustworthiness of random effects in linear multilevel models that are estimated using PROC MIXED. Written using both SAS IML and SAS/STAT, the macro utilizes Base SAS routines including PROC SQL and data steps and the SAS GRAPH routine PROC SGPLOT to generate summary graphical representations. MIXED_RELIABILITY makes use of PROC MIXED within SAS/STAT for the estimation of the model of interest, and uses the PROC GLIMMIX OUTDESIGN command to generate the multilevel design matrix necessary for the calculation of lambda. SAS IML is necessary for the manipulation of the matrices required to calculate lambda for both random intercepts and slopes. A complete copy of the MIXED_RELIABILITY macro can be obtained by emailing the second author (babell@sc.edu). All examples presented in this paper make use of a subset of the High School and Beyond data (HSB; NCES, 1982) with 7,185 level-1 units nested within 160 level-2 (school) units.

Specifically, the MIXED_RELIABILITY output includes (a) summary table of variance parameter estimates, ICC values, ICC 95% confidence intervals, and lambda estimates for random intercepts and slopes, (b) a forest plot of random effect ICCs, (c) scatterplots of each random effect's level-2 unit reliability (lambda) as a function of level-1 sample size, and (d) boxplots of the distribution of level-2 unit reliability estimates for each random effect.

Macro inputs, in addition to the inclusion of PROC MIXED code for model specification include:

- path: folder location where the data file for analysis resides
- data: this argument is the name of the data file containing the data to be analyzed and simulated.
- dv: the criterion or dependent variable
- lv1iv: the list of level-1 predictors separated by a space (centering of variables should occur before submitting to macro)
- lv2iv: the list of level-2 predictors separated by a space
- interact: the interaction effects, separated by a space
- random: the list of random effects to be modeled separated by a space (list random intercept as "intercept")
- lv2id: the variable denoting cluster or subject id
- ddfm: degrees of freedom calculation method, default=kenward roger

cov: covariance structure (only variance components [vc] or unstructured [un] are acceptable entries)

ci: desired confidence interval for intra-class correlations (e.g. .95 for 95% confidence intervals)

MACRO EXECUTION

The following is a sample call to the MIXED_RELIABILITY macro that generated the results presented throughout the paper using a subset of the HSB data set. The random effects model includes a single predictor at level-1 (group-mean centered ses) and no predictors at level-2, and random effects for the intercept and the group-mean centered ses slope. The level-2 identifier is schoolid, the default degrees of freedom are used, and the random effect covariance matrix has been specified as unstructured (un). Finally, 95% confidence intervals will be calculated for the ICC estimates.

```
%mLm_reLiab(path=%str(C:\Users\Jason\sesug_2015\),
  data=hsb,
  dv=mathach,
  lvl1iv=grp_mn_ses,
  lvl2iv=,
  interact=,
  random=intercept grp_mn_ses,
  lvl2id=schoolid,
  ddfm=,
  cov=un,
  ci=.95);
```

LAMBDA CALCULATIONS

After the user enters the macro input information and specifies her/his PROC MIXED model, %SCAN and %INDEX functions are used to search across the values entered in the RANDOM macro argument, compiling an ordered list and generating macro calls for each random effect. The sample code below creates calls to the %LAM_MAC sub-macro that calculates lambda values for each level-2 unit. The result for a random intercept model would appear as:

```
%lam_mac(intercept, 1);

**the following handles random effects;
%let m=1;
%let ran=%scan(&random, &m);
%let intpres=%index(%sysfunc(lowcase(&random)), intercept);
%do %while (&ran^=);
  **create macro calls to cycle through random effects;
  %let lam_mac&m=%nrstr(%lam_mac)%str((&ran%nrstr(,)&m));
  %let m=%eval(&m + 1);
  %let ran=%scan(&random, &m);
  %let ran_n=%eval(&m - 1);
%end;
```

MIXED_RELIABILITY uses PROC MIXED to estimate the specified multilevel model and obtain variance component estimates. MIXED_RELIABILITY then uses PROC GLIMMIX with the same multilevel model specification to obtain the design matrix using the OUTDESIGN command. Figure 1 displays a snapshot of a design matrix from a model with a random intercept (_Z1) and a group-mean centered, continuous variable modeled as a random slope (_Z2).

	SCHOOLID	_SubjectID_	_X1	_X2	_Z1	_Z2
1	1224	1	1	0.35	1	0.35
2	1224	1	1	-0.25	1	-0.25
3	1224	1	1	-1.1	1	-1.1
4	1224	1	1	-0.46	1	-0.46
5	1224	1	1	0.57	1	0.57
6	1224	1	1	1.18	1	1.18
7	1224	1	1	-0.24	1	-0.24
8	1224	1	1	0.8	1	0.8
9	1224	1	1	0.27	1	0.27

Figure 1. Snapshot of GLIMMIX Design Matrix from Model with Random Intercept and Slope.

Using PROC CONTENTS to obtain the variable names within the outputted design matrix, MIXED_RELIABILITY creates code to retain the necessary variables inside both a PROC SQL statement (requiring a list to be separated by commas and each variable preceded by a prefix denoting the parent table) and inside PROC IML. Below is the code used to create the list of variables to be retained inside a PROC SQL statement. Note we are only interested in the default `_SubjectID_` variable, any random effects (denoted by `_Z`), and the user-specified `&lvl2id` variable. This yields a macro argument named `des_mat_keep` set equal to: `a.school_id, a._subjectID_, a.Z1, a.Z2`.

```
**retain only the columns of interest in the design matrix;
**one set up for sql listing, one for the iml keep statement;
proc sql noprint;
select compress(cat("a.",name)) into :des_mat_keep separated by ','
  from des_mat_vars
  where name='_SubjectID_' or (substr(name,1,2)="_Z") or name=%upcase("&lvl2id");
```

MIXED_RELIABILITY then examines each random effect to determine the number of categories present in the data. This step became necessary when we attempted to use the variable 'female' denoting student gender. There are some schools in the HSB data set, due to sampling, that are represented by a single gender. A short sub-macro was written using PROC SQL to count distinct values of the dependent variable and each random predictor for each user-specified `&lvl2id` variable. As you can see in Figure 2 below, under the female column, school 1308 was a single-gender school. A subsequent ARRAY statement is used to search across all of the random effects and DELETE any record with a value less than two. Note that the count of distinct categories is replicated across each individual record within a level-2 unit, ensuring all reliability estimates are calculated only for level-2 units that have the necessary data available for all random effects specified in the user's model (and is consistent with practices in other specialty software). Subsequent PROC SQL statements are used to calculate a revised number of level-2 units and create a new `_SubjectID_` variable to account for the deletion of records with single category predictors.

	SCHOOLID	_SubjectID_	_Z1	_Z2	intercept	female
116	1296	3	1	0	47	2
117	1296	3	1	1	47	2
118	1296	3	1	1	47	2
119	1296	3	1	0	47	2
120	1296	3	1	1	47	2
121	1308	4	1	0	20	1
122	1308	4	1	0	20	1
123	1308	4	1	0	20	1
124	1308	4	1	0	20	1

Figure 2. Snapshot of Design Matrix with Random Effect Category Counts by Level-2 ID.

The next step in the MIXED_RELIABILITY macro is to compile a sub-macro that will calculate λ_j values for each random effect, for each level-2 unit (j). The first step in this sub-macro is to populate a macro argument with the variance component value from the covparm ODS table generated from PROC MIXED. The PROC SQL statement below accomplishes this when the covariance matrices are specified by the user as unstructured, as seen in Figure 3, when both a random intercept and random slope (a group-mean centered predictor representing student Socio-Economic Status) are specified using the HSB data set as `random = intercept grp_mn_ses`. Because the random intercept is specified first in the macro call, the sub-macro will process that random effect first with a `&ranef_order` equal to 1. The SELECT statement will take the maximum value from the estimate variable in the covparm table when the value of the covparm variable is equal to 'UN(1,1)', or 8.6769 in Figure 3. When the sub-macro processes `grp_mn_ses`, with a `&ranef_order` equal to 2, it will populate the `tau_&ranef_order` argument with the value of .6940.

```
**this subset processes models with unstructured covariance matrices;
%if "&cov" = "un" %then %do;
  proc sql noprint;
    /*populate argument with variance component for specified random effects*/
    select max(case when(covparm=cat("UN(",&ranef_order,"",&ranef_order,""))
    then strip(put(estimate,8.4 -L)) end) into : tau_&ranef_order
      from covparm;
    /*populate argument for residual*/
    select max(case when (covparm="Residual") then strip(put(estimate,8.4 -L)) end)
    into : sigma
      from covparm;
    quit;
%end;
```

	Cov Pam	Subject	Estimate	Standard Error	Z Value	Pr Z
1	UN(1,1)	SCHOOLID	8.6769	1.0786	8.04	<.0001
2	UN(2,1)	SCHOOLID	0.05075	0.4062	0.12	0.9006
3	UN(2,2)	SCHOOLID	0.6940	0.2808	2.47	0.0067
4	Residual		36.7006	0.6258	58.65	<.0001

Figure 3. Unstructured Covariance Matrix.

Once the variance estimates are populated in the macro argument for each random effect, PROC IML is used to calculate the lambda-j values for each level-2 unit. The formula for lambda-j is

$$\lambda_{qj} = \frac{\tau_{qq}}{\tau_{qq} + v_{qqj}}$$

where v_{qqj} is the diagonal element of $\sigma^2(X_j^T X_j)^{-1}$. After reading the design matrix into IML, the procedures for calculating lambda-j are repeated for each level-2 unit. Once the subset of the design matrix associated with the random effect is multiplied by the transpose of itself, the inverse of the resulting matrix is calculated. The appropriate cell of this resulting matrix (e.g cell 1-1 for the random intercept) is then multiplied by the residual variance.

```
proc iml;
  use des_matrix;
  do i=1 to &n2_count;
    read all var {&des_mat_keep_uml} where (_SubjectID=i) into x;
    lambda_j_&ran_eff.=&tau_&ran_eff_order./
      (&tau_&ran_eff_order. + (inv(x[,3:3+&ran_n-1]`*x[,3:3+&ran_n-1])
        [&ran_eff_order.,&ran_eff_order.]*&sigma.));
    to_sas=x[1,1]||lambda_j_&ran_eff;
    if (i = 1) then lambda_j_&ran_eff._all=to_sas;
    if (i > 1) then lambda_j_&ran_eff._all=lambda_j_&ran_eff._all//to_sas;
  end;
  cname={"&lvl2id" "&z_&ran_eff_order" };
  create lambda_j_&ran_eff from lambda_j_&ran_eff._all[colname=cname];
  append from lambda_j_&ran_eff._all;
quit;
```

As an example, the first level-2 unit in the HSB data set contains 47 level-1 units. When processing the random intercept (with a random effect order of 1), the first three rows of the subset of the design matrix appear as the first matrix labeled 'sub_des' in Figure 4. Once the full 47-row by 2-column matrix is multiplied by its transpose, the result is the 2-by-2 matrix labeled 'sub_des_by_t'. Using the INV function in IML, the inverse of 'sub_des_by_t' is calculated, reflected as 'inv_sub_des_by_t'. Because we are interested in the random intercept, we multiply the value in cell 1-1 (.0212788) by the level-1 residual from PROC MIXED (36.7006) to arrive at lambda-j for the first level-2 unit equal to .91743.

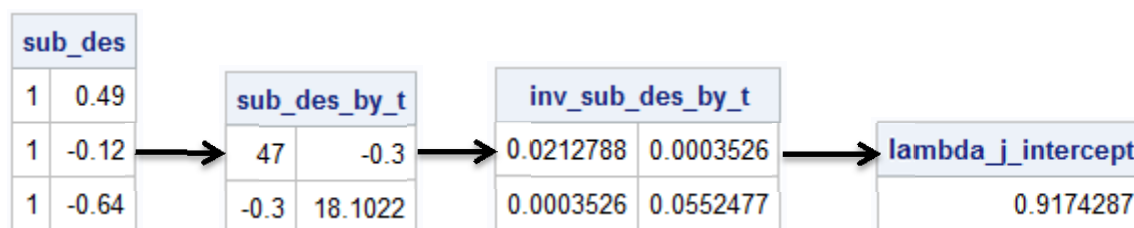


Figure 4. Lambda-j Calculation Matrices.

Once MIXED_RELIABILITY calculates a lambda-j table for each random effect, PROC SQL is used to calculate the number of level-1 units within each level-2 unit and merge that result with the individual lambda-j estimates. Subsequently, the mean value across all of the lambda-j values is calculated as the overall lambda. Once this is completed for each random effect specified by the user, comprehensive lambda-j and lambda tables including all random effects are created.

ICC CALCULATIONS

The MIXED_RELIABILITY macro also provides intra-class correlation (ICC) estimates for each random effect. The ICC for a random intercept is the same as is typically reported from an unconditional multilevel model, where only the dependent variable is specified with no predictors. The unconditional model partitions the variance in the dependent

variable into within and between level-2 unit pieces, and provides an estimate of the proportion of variance explained by the nesting of level-1 units within level-2 units. Alternatively, this value can be thought of as the correlation among two randomly identified level-1 units within the same level-2 unit. The ICC is calculated as

$$\rho = \frac{\sigma_{\mu_0}^2}{\sigma_{\mu_0}^2 + \sigma_e^2}$$

where $\sigma_{\mu_0}^2$ is estimated random intercept variance and σ_e^2 is the estimated level-1 residual variance. For random slopes, the predictor variables are entered into PROC MIXED as the dependent variable in the MODEL statement with no predictors, partitioning the variance in these variables to within and between level-2 units.

In addition to the ICC for each random effect, MIXED_RELIABILITY also provides an approximate confidence interval based on ICC variability estimation formulas documented in Donner (1986) and Shoukri, Donner and El-Dali (2013) as

$$var(\hat{\rho}) = \frac{2(1-\rho)^2(1+(n_0-1)\rho)^2}{n_0^2(k-1)(1-\frac{k}{N})}$$

where ρ is the estimated ICC, k is the number of level-2 units and n_0 is

$$n_0 = \frac{1}{k-1} [N - \sum_{i=1}^k n_i^2 / N]$$

and N is the total number of level-1 units in the model and n_i^2 is the number of level-1 units in each level-2 unit, squared. These calculations are accomplished using the PROC SQL statements below. The first step calculates the total number of level-1 and level-2 units in the user-specified data file. The second step creates a table containing the information from step 1, plus the sum of the squared number of level-1 units across all level-2 units, that value divided by the total number of level-1 units in the data file and n_0 as specified above. Figure 5 contains a snapshot of this table for the random intercept calculated using the HSB data.

```

**calculate parameters for icc variance and confidence interval calculation;
proc sql noprint;
/*calculate total number of level-1 and level-2 units*/
create table &raneff._n_count as
select count(a.&lvl2id) as level1_n, count(distinct a.&lvl2id) as level2_n
  from mlm_raw as a;
/*calculate sum of squared level-1 units, value divided by level-1 units
and n0*/
create table &raneff._n2i_div as
select "&raneff" as parameter length=20, a.level1_n, a.level2_n, b.sum_n2i,
      b.sum_n2i /a.level1_n as n2i_div,
      (1/(a.level2_n-1))*(a.level1_n - calculated n2i_div) as n0
  from &raneff._n_count as a
 left join
      (select sum(level1_nj) as level1_n, sum(n2i) as sum_n2i
        from
          (select count(&lvl2id) as level1_nj,
                 count(&lvl2id)**2 as n2i
            from mlm_raw
             %if "&raneff" = "intercept" %then %do;
               where &dv ne .
             %end;
             %else %do;
               where &raneff ne .
             %end;
            group by &lvl2id)
        )as b on a.level1_n=b.level1_n;

quit;

```

	parameter	level1_n	level2_n	sum_n2i	n2i_div	n0
1	intercept	7185	160	344997	48.016283925	44.886690038

Figure 5. Snapshot of Table with ICC Variability Components.

MIXED_RELIABILITY then combines the ICC variability information with the random effect between-group variance estimate and the lambda estimates calculated previously. In addition, we calculate the ICC variance using the formula from above and the confidence limits, again using PROC SQL. The summary output table for the model with a random intercept and slope for the group-mean centered SES variable using the HSB data is shown in Figure 6. Note the between-group variance estimate for the group-mean centered SES variable. The strategy of group-mean centering variables effectively removes the between-group variance and yields values uncorrelated with level-2 variables (see Enders & Tofighi, 2007 for an excellent discussion). To calculate an ICC for this variable, the uncentered version would have to be entered in the appropriate MIXED_RELIABILITY macro arguments.

```

**calculate confidence intervals for iccs and compile all reporting
information into single file per random effect;
proc sql noprint;
create table &raneff._icc as
select a.parameter length=20, a.tau format=8.3 label="Between Variance",
a.sigma format=8.3 label="Within Variance",
  a.icc format=8.3 label='ICC',
  b.level1_n, b.level2_n, b.sum_n2i, b.n2i_div, b.n0,
  (2*((1-icc)**2) * ((1+ (b.n0-1)*icc)**2) ) /
  ((b.n0**2)*(level2_n-1)*(1-(level2_n/level1_n))) as icc_var,
  icc - abs(probit((1-&ci)/2))*sqrt(calculated icc_var) as icc_lcl
  format=8.3 label="ICC Lower &ci% Limit",
  icc + abs(probit((1-&ci)/2))*sqrt(calculated icc_var) as icc_ucl
  format=8.3 label="ICC Upper &ci% Limit",
  c.lambda format=8.3 label='Reliability'
from &raneff.cov as a
left join &raneff._n2i_div as b on a.parameter=b.parameter
left join lambda as c on a.parameter=c.parameter
where a.icc ne .;
quit;

```

Parameter	Between Variance	Within Variance	ICC	ICC Lower 95% Limit	ICC Upper 95% Limit	Reliability
intercept	8.610	39.149	0.180	0.144	0.216	0.908
grp_mn_ses	0.000	0.436	0.000	-0.005	0.005	0.264

Figure 6. Random Effect Variance Partitions, ICC, Confidence Intervals and Reliability Table.

MIXED_RELIABILITY GRAPHICAL OUTPUT

MIXED_RELIABILITY also provides a number of graphical outputs. The first graph is a forest plot of the ICC estimates and the corresponding confidence limits using PROC SGPLOT. Figure 7 displays this forest plot for the model that included a random intercept and random slope for the group-mean centered SES variable in the HSB data set. The x-axis is set dynamically using the minimum and maximum values found in the comprehensive table created above.

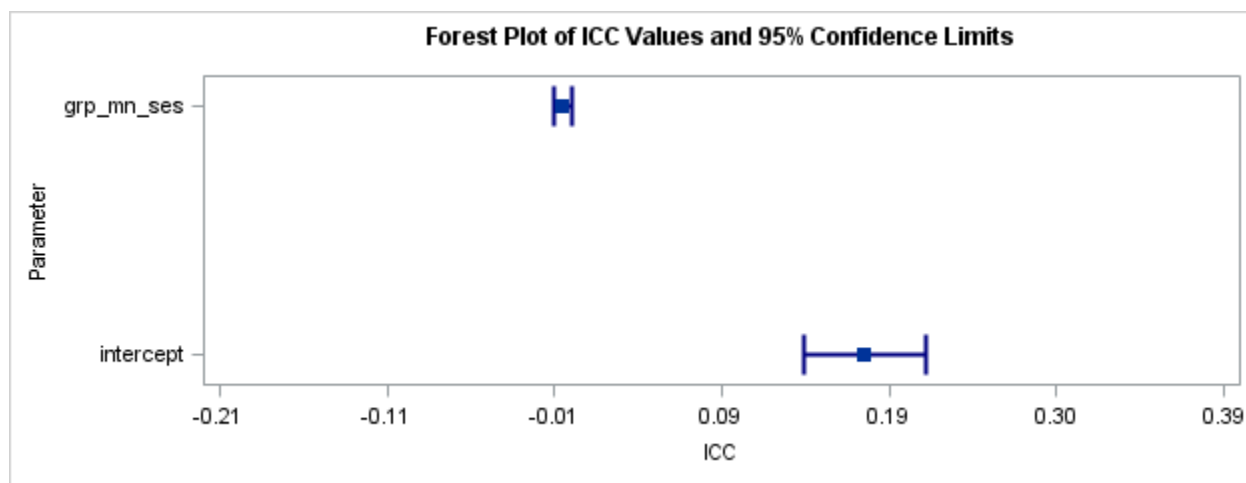


Figure 7. Forest Plot of ICC Values and Confidence Limits.

The next set of graphs depict different approaches to examining lambda-j estimates. First, Figure 8 displays the scatterplot for the group-mean centered SES random slope reliability as a function of level-1 sample size of each level-2 unit. In general, we can see that as the level-1 sample size associated with a level-2 unit increases, the reliability estimate for that level-2 unit tends to increase. Figure 9 displays the distribution of reliability estimates for each level-2 unit for all random effect specified in the model. Clearly, the random intercepts have higher reliability estimates when compared with the estimates for the group-mean centered SES random slope. Figure 9 also shows us a greater deal of variability among level-2 unit random slope reliability estimates compared to the distribution of random intercept reliability estimates.

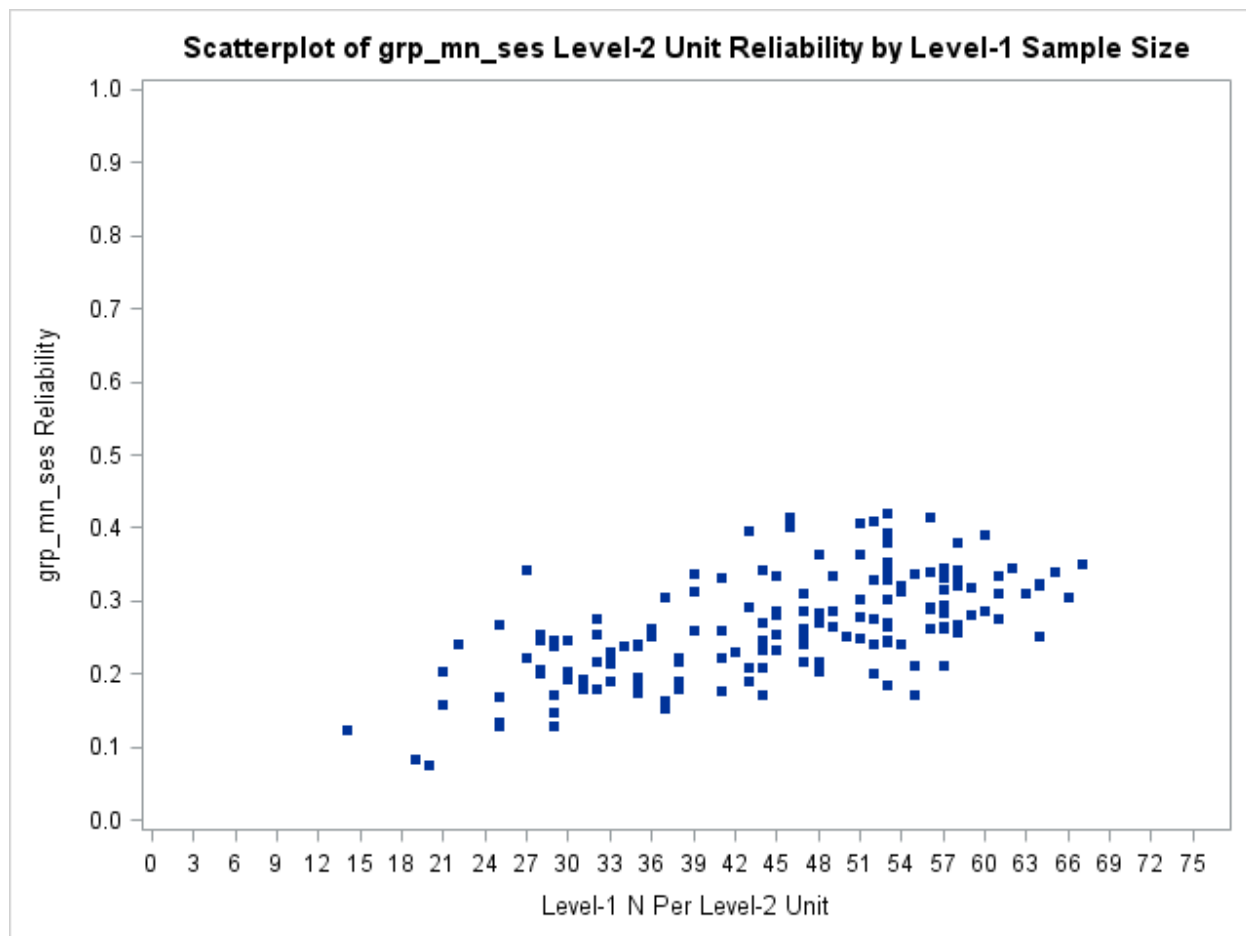


Figure 8. Scatterplot of Lambda-j Estimates by Level-1 Sample Size.

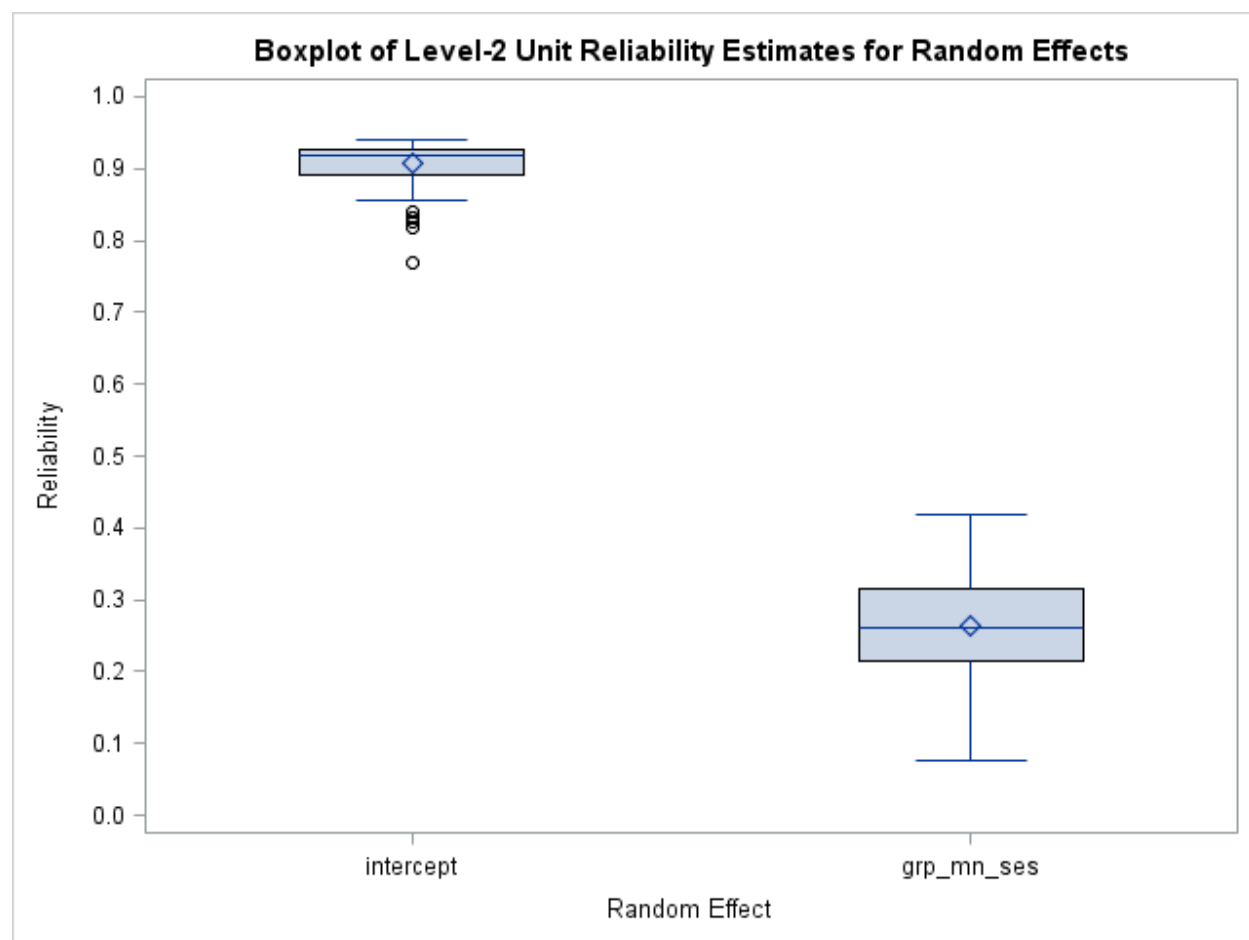


Figure 9. Boxplots of Level-2 Unit Reliability Estimates.

CONCLUSION

The macro presented in this paper provides the user with the ability to assess the trustworthiness of random effects in two-level, linear multilevel models estimated with PROC MIXED. MIXED_RELIABILITY estimates lambda and provides users with shrinkage estimates associated with random effects via empirical Bayes estimation. Level-2 units with smaller reliability estimates for a particular random effect will be shrunk toward the overall mean of that same effect. Further, a small lambda estimate for a random effect would suggest that the individual random effects are not contributing much information to the overall model, and may suggest the random effect be treated as fixed or removed from the model altogether. In addition, intraclass correlation coefficients and corresponding confidence intervals are calculated for each random effect. By default, SAS PROC MIXED does not provide lambda estimates for random, level-1 β -coefficients. MIXED_RELIABILITY provides analysts with the ability to report reliability estimates as is done in the HLM software.

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