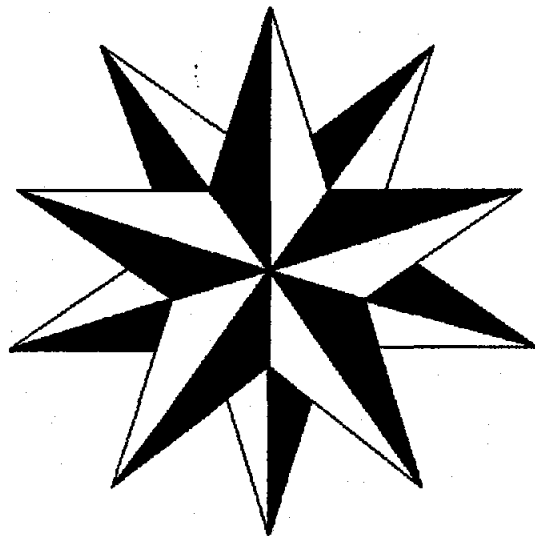


**MONTE CARLO PROBABILITY ANALYSIS
OF CHANGE SCORES**



**David Mangen
Mangen Research Associates, Inc.**

Monte Carlo Probability Analysis of Change Scores

David J. Mangen
Mangen Research Associates, Inc.
Minneapolis, Minnesota 55369
(612) 420-2303

Abstract

This paper demonstrates the use of the SAS® data step in conjunction with PROC REG to perform a Monte Carlo probability analysis of the effect of different data characteristics on the measurement of change. Results indicate that the SAS® system is ideally suited to perform integrated Monte Carlo analyses, and that research that has used simple difference change scores has in all likelihood underestimated correlations with exogenous variables.

Introduction

Issues in understanding processes of change over time are central to almost all fields of scientific inquiry. Methodological developments in the past fifteen years have yielded considerable progress in designing studies that address the complex issues associated with an accurate understanding of change. Longitudinal, cross-sequential, and other methodologies that allow examination of time-based change and decomposition of that change into age, period, and cohort effects are now universally recognized as methodologically necessary conditions for an accurate understanding of change in populations.

Related to this trend, researchers now recognize that early longitudinal research was plagued by a reliance on simple difference change scores (Bohrnstedt, 1969; Cronbach and Furby, 1970). Simple change scores are negatively correlated with with time-one (T_1) scores due to regression to the mean, more commonly known as floor and ceiling effects. The consensus at present is that analysis of simple change scores per se is not appropriate. Analysis of change measures is now accomplished by analyzing time-two (T_2) outcomes after controlling for T_1 origin status.

The net outcome of this fact is that much early research that correlates simple change scores with other characteristics is discounted. The purpose of this paper is to demonstrate how the SAS® system can be used to design a Monte Carlo simulation study to empirically examine the consequences of using simple change scores.

Model Presentation

Consider a simple four variable model including two exogenous characteristics (X_1 and X_2) and one endogenous characteristic measured at two points (T_1 and T_2). Using regression equations, early research examining simple difference change scores yields:

$$(T_2 - T_1) = a + \beta_1 X_1 + \beta_2 X_2 + e \quad [\text{Eq. 1}]$$

Current approaches to measuring change rightly discount this model and frame the analysis as:

$$T_2 = a + \beta_3 T_1 + \beta_4 X_1 + \beta_5 X_2 + e \quad [\text{Eq. 2}]$$

It is readily demonstrated, however, that an analysis of simple difference change scores is appropriate if T_1 origin status is controlled. That is:

$$(T_2 - T_1) = a + \beta_6 T_1 + \beta_7 X_1 + \beta_8 X_2 + e \quad [\text{Eq. 3}]$$

The coefficients of Eq. 2 and Eq. 3 are identical or vary by a constant factor of 1.0, i.e., $\beta_4 = \beta_7$, $\beta_5 = \beta_8$, and $\beta_3 - 1.0 = \beta_6$ (Carlton-Ford, Simmons, and Blyth, 1983). Thus, if researchers are interested in analyzing change scores they can in fact legitimately do so provided that adjustment for origin status is incorporated into the model.

The results yielded by Eq. 2 and Eq. 3 are sample estimates subject to normal sampling fluctuations, the population parameter

correlations among the four variables, measurement reliability, and known and unknown selection factors intervening between T_1 and T_2 (Reichardt, 1979). For purposes of this paper, selection factors are ignored; the analysis focuses on: 1) defining populations free of selection bias factors with known parameter correlations among the four variables in the model, 2) sampling from that population and introducing varying degrees of correlated measurement error, and 3) since the population parameter correlations among the four variables are known, comparing the population regression coefficients to the sample-specific coefficients obtained in both Eq. 1 and Eq. 3. Thus, this analysis addresses: 1) the degree to which studies using simple difference change scores yield biased results under varying conditions, and 2) the degree to which these factors, especially correlated measurement error, bias the coefficients in the covariate adjustment model (Eq. 3).

Method

Monte Carlo probability techniques are used to analyze these issues. Five test factors are used to systematically vary characteristics that influence the population regression coefficients, repeated samples from each population are drawn, and simple difference and covariate-adjustment models of change analyzed. In order to simplify the subscripting of coefficients, throughout the remainder of this presentation T_1 as used in Eq. 1-3 above is henceforth referenced as X_3 and T_2 referenced as X_4 . The five factors and the associated levels of each factor include:

1. Measurement error levels analogous to alpha reliability coefficients for X_3 and X_4 of 0.55, 0.70, and 0.85 are systematically varied. These are referenced as Factor I.
2. The degree of over-time correlation in the measurement error is also systematically varied, with levels of 0.10, 0.40, and 0.70 constituting Factor J.

3. The time-one to time-two correlation (r_{34}) constitutes Factor K. Correlations between X_3 and X_4 of 0.20, 0.40, and 0.60 are used in the analysis.
4. The correlations of the two exogenous variables with the time-one measure (r_{13} and r_{23}) are Factor L. These correlations are varied as a block, with the first level specifying $r_{13} = 0.30$ and $r_{23} = 0.40$, and the second level specifying $r_{13} = 0.40$ and $r_{23} = 0.50$.
5. Factor M is the correlation of the two exogenous variables with the time-two measure (r_{14} and r_{24}). These correlations are also varied as a block, with the first level specifying $r_{14} = 0.30$ and $r_{24} = 0.20$, and the second level specifying $r_{14} = 0.40$ and $r_{24} = 0.30$.

Note that r_{12} never varies and is fixed at 0.25; this is done to simplify the model. Further, perfect reliability of X_1 and X_2 is assumed. The complete cross-classification of these factors yields a $3 \times 3 \times 3 \times 2 \times 2$ matrix of 108 cells. While the levels of these test factors are arbitrarily chosen values, they represent a range of values typical in research.

For each of the 108 cells in the design matrix, a SAS® computer program generates a theoretically infinite population of four true scores with the specified correlational parameters. Each true score is specified to have a mean of 0.0 and a standard deviation of 1.0. From this population, 25 random samples of $n = 300$ are drawn, and error vectors corresponding to the specified level of reliability and correlated measurement error are added to the true scores of X_3 and X_4 . Thus, a total of 2,700 (25×108) random samples of $n = 300$ are drawn for this analysis.¹

For each sample, three regression equations (PROC REG) are computed. First, as a check on the accuracy of the program that generates the data, Eq. 3 above is

tested using the true score data for all variables. Second, a raw change score model (Eq. 1) is estimated. Finally, the covariate adjustment model (Eq. 3) is estimated on the observed scores incorporating correlated measurement error.

The flexibility of the SAS® system in permitting output of summary datasets containing statistics for each model greatly facilitates this analysis. By outputting a dataset of the regression statistics for each random sample of 300, we can then add the population parameters to this dataset. This allows us to simply create the measures of greatest concern to this analysis. Specifically, by simply subtracting the sample coefficients from the population parameter coefficients we obtain measures of inaccuracy in the regression coefficients that have been introduced by the test factors in the experiment. These measures are the dependent variables for this analysis. A *positive* difference implies that the observed regression coefficient is smaller than the population parameter, i.e., the coefficient is attenuated, while a *negative* difference implies that the observed coefficient is greater than the population parameter.

The criterion variables include the following measures of inaccuracy in the regression coefficients: 1) B42DIFF, which references the inaccuracy in the regression coefficient β_{42} , 2) B41DIFF, which references the inaccuracy in the regression coefficient β_{41} , and 3) B43DIFF, computed only in the models controlling for origin status, which references the inaccuracy in the stability regression coefficient β_{43} . The independent variables in the analysis are the five test factors used to generate the data.

Data Analysis

Since the resulting data matrix is a fully-crossed design with equal sample sizes for each cell, analysis of these data uses standard analysis of variance techniques. For each dependent variable, hierarchical testing of main effects and higher-order interactions is done to determine the most parsimonious explanation of the data. Table 1 presents the overall results of the hierarchical testing for the raw change score model

(Eq. 1) and the covariate adjustment model (Eq. 3). The first set of regression equations examining the true scores is not presented since, as expected, any variations in the difference of the observed regression coefficients from the true population parameters are not significant and merely reflect sample-specific fluctuations.

Table 1 About Here

For each model and each dependent variable, the main effects model is clearly the most important and explains at worst 50% of the variance. Each set of higher-order interactions significantly contributes to explanation, although the three through five-way interactions never add more than 2% to the explained variance. Analysis of the total explained variation for each of the coefficients in the two models shows greater predictability of errors in β_{42} than β_{41} , with the greatest predictability for errors in the stability coefficient β_{43} .

Since the two-way interactions yield significant improvements in explanation of the errors in the regression coefficients while the higher-order effects add comparatively little, in the interests of parsimony the remainder of this analysis is restricted to the two-way model, with comparatively greater emphasis placed on the main effects. Table 2 presents the detailed results for the effects tested in the two-way interaction model. Since the sample size for this analysis is quite large, and a relatively large number of effects tested for each dependent variable, the discussion of significant effects in the analysis of variance emphasizes those effects significant at $p < 0.0001$.

Table 2 About Here

Effects on the Simple Difference Model:

Four of the five test factors exhibit strong main effects that influence errors in regression coefficients in the simple difference models. For both B42DIFF and B41DIFF, measurement reliability, the time-one to time-two correlation of the endogenous variables, and the correlations of the inde-

pendent variables with both the time-one and time-two measures strongly influence the accuracy of the coefficients. The degree of correlated measurement error influences the accuracy of the coefficients, but this effect is comparatively weak in the simple difference model.

Of the interaction effects, the two-way interaction $K*L$, which tests the joint effect of varying the time-one to time-two correlation and the correlations of the exogenous variables with the time-one endogenous measure, is a strong predictor of both B41DIFF and B42DIFF. The interactions of measurement reliability with all of the other test factors are determinants of both B41DIFF and B42DIFF, although in only one case is a strong effect exhibited. For B41DIFF, the interaction of correlated measurement error with time-one to time-two correlation is a strong determinant ($J*K$), while for B42DIFF the interaction of correlations of the exogenous measures with the time-one and time-two endogenous measures ($L*M$) is significant.

Effects on the Covariate Adjustment Model:

Strong significant main effects are noted for four of the five test factors in the covariate adjustment model. As expected, measurement reliability, correlated measurement error, the magnitude of the time-one to time-two correlation, and the correlation of exogenous measures with the time-two endogenous measure all significantly influence errors in the regression coefficients. The magnitude of the correlation between exogenous variables and the time-one endogenous measure significantly influences errors in the stability coefficient (β_{43}), but does not strongly influence errors in β_{41} or β_{42} .

Measurement reliability interacts with correlated measurement error ($I*J$), with the magnitude of the time-one to time-two correlation ($I*K$), and with the correlation of exogenous measures with the time-two endogenous measure ($I*M$). The magnitude of the correlated measurement error ($J*L$), the size of the time-one to time-two correlation ($K*L$), and the strength of the correlation between exogenous measures and the time-two endogenous measure ($L*M$) all

interact with the strength of the correlation between exogenous measures and time-one endogenous data to influence the accuracy of regression coefficients.

It is apparent from these results that the test factors used to structure the Monte Carlo analysis strongly influence the accuracy of regression coefficients obtained in any study analyzing change. This is not unexpected; the degree of measurement reliability has long been recognized to influence the accuracy of sample estimates of parameters, and the other test factors included in this analysis may be seen as proxies for the degree of collinearity present in the data. The means and standard deviations for the various levels of the main effects are presented in Table 3.

Table 3 About Here

In Table 3, the mean main effects for test factors on the simple difference and covariate adjustment models reflect the strong pattern of effects noted in Table 2. Recall that all variables in the model have zero mean and unit variance, and thus these differences are close approximations to errors in the standardized regression coefficients. Also, positive mean differences imply coefficients that are attenuated, while negative mean differences imply coefficients that are inflated. As expected, the inaccuracy of the regression coefficients is much greater for coefficients estimated in the simple difference than those estimated in the covariate adjustment model. In all cases, the coefficients estimated in the simple difference model are attenuated, suggesting that any significant results obtained in early longitudinal studies of change are in all likelihood even more significant than previously thought. Thus, discounting the results of these earlier studies is not warranted.

The main effect of reliability on errors in the regression coefficients is not as expected. In general, increasing reliability should yield increased accuracy of coefficients. This is true of all coefficients estimated in the covariate adjustment factor, and is also true of β_{41} in the simple difference model. In con-

trast, however, the accuracy of β_{42} in the simple difference model is actually greater under conditions of poorer reliability.

The main effect for correlated measurement error is noteworthy only for the covariate adjustment model. A low degree of correlated measurement error produces an inflated estimate of the stability coefficient β_{43} , while greater degrees of correlated error lead to attenuation of this coefficient. The accuracy of β_{41} and β_{42} is also influenced by the magnitude of correlated measurement error, with greater attenuation noted for increasing levels of correlation. These results clearly suggest that adjustment for correlated measurement error using procedures such as LISREL (Jöreskog and Sörbom, 1979) is necessary.

The main effect for the magnitude of the time-one to time-two correlation is greater in the simple difference model than the covariate adjustment model. In the simple difference model, increasing time-one to time-two correlations produces substantially decreased attenuation of coefficients. In the covariate adjustment model, a similar pattern is noted for β_{41} , while for β_{42} and β_{43} the highest degree of time-one to time-two correlation produces inflated coefficients.

The effect of the correlations of the exogenous measures on both the time-one and time-two endogenous measures is clear. In the simple difference model, increasing degrees of correlation with both the time-one (Factor L) and time-two (Factor M) measures yields increasing degrees of attenuation in the obtained coefficients. In the covariate adjustment model, varying the correlations with the time-one measure (Factor L) has no effect on β_{41} and β_{42} , and only a small albeit significant effect on the accuracy of β_{43} . Varying the magnitude of correlations with the time-two measure (Factor M) leads to increasing attenuation of all coefficients. This is likely due to collinearity effects.

Table 4 presents the means and standard deviations for all interaction effects tested in the two-way interaction models. Since the two-way interactions add comparatively little to the explanatory power of the model, dis-

cussion of these effects emphasizes those that are substantively strong.

Table 4 About Here

The most noteworthy interaction of reliability with correlated measurement error ($I*J$) is seen on the accuracy of the stability coefficient β_{43} in the covariate adjustment model. Uniformly, a low degree of correlated measurement error produces inflation of stability coefficients, while a high degree of correlated error produces attenuated coefficients. The relative magnitude of this effect is much greater under conditions of poorer reliability. A similar although less pronounced pattern is noted for the accuracy of β_{42} and β_{41} in the covariate adjustment model.

The interaction of reliability and the magnitude of the time-one to time-two correlation ($I*K$) is strong and consistent in the covariate adjustment model, and present but less strong in the simple difference model. In the covariate adjustment model, attenuation declines and, for β_{43} and β_{42} , shifts to inflation with increasing time-one to time-two correlation, but this effect is most pronounced under conditions of worse reliability. In the simple difference model, however, while attenuation declines with increasing time-one to time-two correlation, a slight tendency toward increased attenuation is noted under conditions of greater reliability.

The interaction of reliability with the magnitude of the correlation between exogenous measures and time-two endogenous measures ($I*M$) is also significant. In both the covariate adjustment and simple difference models, the collinearity effect associated with Factor M is less pronounced under conditions of improved reliability, indicating that collinearity problems are less pronounced with good measurement.

The final effect that strongly influences all five criterion measures is the interaction of time-one to time-two correlation with the correlations of exogenous measures with the time-one endogenous measure ($K*L$). In the simple difference model, the increas-

ing attenuation noted with increased levels of Factor L are greatest when the time-one to time-two correlation is small, and disappears when that correlation is strongest. In the covariate adjustment model, under the condition of a low time-one to time-two correlation, increases in exogenous to time-one correlations yield modestly increased attenuation; under the condition of a moderate time-one to time-two correlation, increases in exogenous to time-one correlations have virtually no effect on attenuation, while under conditions of a strong time-one to time-two correlation, increasing exogenous to time-one correlations result in increased inflation of β_{42} and β_{43} , and decreased attenuation for β_{41} .

Discussion and Conclusion

The results of this Monte Carlo analysis have implications for both the credence given to longitudinal studies that have used simple difference change scores as well as current longitudinal research efforts. First, the results of this analysis fairly clearly suggest that studies that examined simple difference change scores without controlling for time-one origin status in the dependent variables have in all likelihood underestimated the significance of possible correlates. Studies that found significant effects should not be completely discounted for flawed methods; rather, the importance of these findings should probably be highlighted.

Published work that yielded inconsistent or nonsignificant findings may well warrant reanalysis. Alternatively, with the results presented here, it may be possible to estimate the actual parameters present in some of this earlier research.

For new longitudinal research analyses, the results presented here suggest that covariance adjustment procedures, even when estimated by ordinary least squares techniques, are reasonably robust to problems in estimation. To the extent that problems are present in OLS models of change, these problems are most severe in estimation of stability coefficients, an important but often less substantively interesting issue. A strong degree of correlated measurement

error can also attenuate coefficients to a considerable degree, as can poor reliability, but techniques such as LISREL are available to address these concerns. Finally, the magnitude of the time-one to time-two correlation in the change variable of interest also strongly influences effect coefficients in longitudinal analysis. Researchers who are examining models of change in their longitudinal data are encouraged to carefully address these issues in subsequent analyses carried out with their data.

FOOTNOTES

1. The SAS® data step that generates one specific sample includes the following statements. For the actual analysis, the data step and variables were converted into a macro to facilitate operation.

```
DATA CHANGE;
  DO I=1 TO 300;

    /* DEFINE THE CORRELATION MATRIX,
       RELIABILITY, AND CORRELATED ERROR.
       ALL CHANGES IN PROGRAM OCCUR
       HERE */

    RELIAB=0.85;
    R12=0.25;
    R13=0.30;
    R14=0.30;
    R23=0.40;
    R24=0.20;
    R34=0.40;
    RERROR=0.70;

    /* DETERMINE THE POPULATION
       PARAMETERS IN THE EQUATIONS */

    BETA31=(R13-(R12*R23))/(1-(R12**2));
    BETA32=(R23-(R13*R12))/(1-(R12**2));
    RSQ3=R13*BETA31+R23*BETA32;
    DET=1-(R23**2)-
      (R12**2)+(R12*R23*R13)+(R13*R12
        *R23)-(R13**2);
    BETA43=(1/DET)*(R34-(R24*R23)-
      (R12*R12*R34)+(R12*R24*R13)+
      (R14*R12*R23)-(R14*R13));
    BETA42=(1/DET)*(R24-(R23*R34)-
      (R14*R12)+(R14*R23*R13)+(R13*R1
        2*R34)-(R13*R24*R13));
```

```

BETA41=(1/DET)*(R14-(R14*R23*R23)-
(R12*R24)+(R12*R23*R34)+(R13*R2
4*R23)-(R13*R34));
RSQ4=R14*BETA41+R24*BETA42+R34*
BETA43;

/* RESIDUALS IN EQUATIONS */

RESID1=SQRT(1-(R12**2));
RESID2=SQRT(1-RSQ3);
RESID3=SQRT(1-RSQ4);
RELERR=SQRT(1-(RELIAB**2));
RELERR2=SQRT(1-(RERROR**2));

/* DEFINE TRUE SCORE MEASURES WITHOUT
MEASUREMENT ERROR */

VAR1=RANNOR(0);
VAR2=R12*VAR1+RESID1*RANNOR(0);
VAR3=BETA31*VAR1+BETA32*VAR2+RE
SID2*RANNOR(0);
VAR4=BETA41*VAR1+BETA42*VAR2+BE
TA43*VAR3+RESID3*RANNOR(0);

/* MEASUREMENT ERROR VECTORS */

ERROR1=RANNOR(0);
ERROR2=RERROR*ERROR1+RELERR2*
RANNOR(0);
ERROR3=RELERR*ERROR1;
ERROR4=RELERR*ERROR2;

/* CREATE THE OBSERVED SCORE
MEASURES WITH ERROR */

X3=RELIAB*VAR3+ERROR3;
X4=RELIAB*VAR4+ERROR4;

/* CREATE THE TRUE AND OBSERVED
DIFFERENCE SCORES */

DIFF1=VAR4-VAR3;
DIFF2=X4-X3;
OUTPUT;
END;
RUN;

/* ESTIMATE REGRESSION EQUATIONS. MODEL 1 IS
TRUE SCORE. MODEL 2 IS SIMPLE
DIFFERENCE. MODEL 3 IS COVARIATE
ADJUSTED. */

PROC REG DATA=CHANGE OUTEST=OUT1
NOPRINT;
MODEL DIFF1=VAR1 VAR2 VAR3;

```

```

MODEL DIFF2=VAR1 VAR2;
MODEL DIFF2=VAR1 VAR2 X3;
RUN;

/* REPEAT THE ABOVE STEPS FOR AS MANY TIMES
AS NECESSARY FOR THE SIMULATION. IN THIS
ANALYSIS, REPEAT 25 TIMES AND APPEND
OUT1 TO A SUMMARY DATA FILE CONTAINING
RESULTS OF ALL TESTS FOR THIS CELL OF THE
DESIGN MATRIX. */

```

REFERENCES

- Bohrnstedt, G. "Observations on the Measurement of Change." Pages 113-133 in E.F. Borgatta (ed.), *Sociological Methodology 1969*. San Francisco: Jossey-Bass, 1969.
- Carlton-Ford, S., R. Simmons, and D. Blyth. "Analyzing Longitudinal Data From Quasi-Experimental Designs: The Analysis of Change." Paper presented to the Annual Meeting of the American Sociological Association, Detroit, MI, 1983.
- Cronbach, L. and L. Furby. "How Should We Measure 'Change'-- Or Should We?" *Psychological Bulletin*, Vol. 74(1): 68-80, 1970.
- Jöreskog, K. and D. Sörbom. *Advances in Factor Analysis and Structural Equation Models*. Cambridge, Massachusetts: Abt Books, 1979.
- Reichardt, C. "The Statistical Analysis of Data from Non-Equivalent Group Designs." Pages 147-206 in T. Cook and D. Campbell (eds.), *Quasi-Experimentation*. Chicago: Rand McNally, 1979.

Table 1
Summary of Analysis of Variance Results
Monte Carlo Analysis

	F (df)	p	R ²
<u>Model 1: Raw Change Scores</u>			
B42DIFF			
Direct Effects	673.71 (8,2691)	< 0.001	0.667
Two-Way Interactions	182.43 (33,2666)	< 0.001	0.693
Three-Way Interactions	103.86 (59,2640)	< 0.001	0.699
Four-Way Interactions	69.21 (89,2610)	< 0.001	0.702
All Effects	57.84 (107,2592)	< 0.001	0.705
B41DIFF			
Direct Effects	335.29 (8,2691)	< 0.001	0.499
Two-Way Interactions	91.72 (33,2666)	< 0.001	0.532
Three-Way Interactions	52.78 (59,2640)	< 0.001	0.541
Four-Way Interactions	35.75 (89,2610)	< 0.001	0.549
All Effects	29.92 (107,2592)	< 0.001	0.553
<u>Model 2: Covariate Adjustment</u>			
B42DIFF			
Direct Effects	506.65 (8,2691)	< 0.001	0.601
Two-Way Interactions	165.07 (33,2666)	< 0.001	0.671
Three-Way Interactions	93.39 (59,2640)	< 0.001	0.676
Four-Way Interactions	62.00 (89,2610)	< 0.001	0.679
All Effects	51.55 (107,2592)	< 0.001	0.680
B41DIFF			
Direct Effects	424.25 (8,2691)	< 0.001	0.558
Two-Way Interactions	121.38 (33,2666)	< 0.001	0.600
Three-Way Interactions	68.73 (59,2640)	< 0.001	0.606
Four-Way Interactions	46.02 (89,2610)	< 0.001	0.611
All Effects	38.51 (107,2592)	< 0.001	0.614
B43DIFF			
Direct Effects	1824.35 (8,2691)	< 0.001	0.844
Two-Way Interactions	1119.10 (33,2666)	< 0.001	0.933
Three-Way Interactions	631.16 (59,2640)	< 0.001	0.934
Four-Way Interactions	424.15 (89,2610)	< 0.001	0.935
All Effects	354.82 (107,2592)	< 0.001	0.936

Table 2
Analysis of Variance Results
Two-Way Interaction Models

		Simple Difference				Covariate Adjustment					
		B42Diff		B41Diff		B42Diff		B41Diff		B43Diff	
Source	DF	F	Prob	F	Prob	F	Prob	F	Prob	F	Prob
I	2	215.76	0.0001	37.74	0.0001	46.40	0.0001	532.89	0.0001	173.81	0.0001
J	2	4.05	0.0175	3.47	0.0313	565.85	0.0001	251.51	0.0001	8808.72	0.0001
K	2	2319.52	0.0001	1086.61	0.0001	1528.89	0.0001	848.86	0.0001	7402.99	0.0001
L	1	177.61	0.0001	176.83	0.0001	1.74	0.1872	3.85	0.0500	19.45	0.0001
M	1	537.30	0.0001	409.27	0.0001	592.00	0.0001	450.69	0.0001	641.54	0.0001
I*J	4	3.61	0.0061	2.83	0.0236	17.21	0.0001	3.21	0.0123	442.36	0.0001
I*K	4	2.28	0.0587	3.70	0.0052	62.46	0.0001	31.54	0.0001	361.56	0.0001
I*L	2	5.08	0.0063	3.65	0.0261	1.44	0.2376	0.13	0.8779	1.35	0.2592
I*M	2	17.98	0.0001	5.64	0.0036	41.18	0.0001	17.65	0.0001	19.96	0.0001
J*K	4	1.64	0.1618	6.20	0.0001	1.61	0.1690	3.24	0.0117	0.32	0.8677
J*L	2	1.85	0.1573	1.01	0.3640	13.24	0.0001	5.53	0.0040	8.01	0.0003
J*M	2	0.84	0.4335	0.44	0.6439	0.42	0.6574	0.90	0.4080	0.07	0.9348
K*L	2	56.74	0.0001	51.60	0.0001	54.78	0.0001	38.71	0.0001	91.89	0.0001
K*M	2	1.39	0.2491	2.94	0.0528	1.86	0.1553	1.31	0.2709	0.05	0.9508
L*M	1	28.77	0.0001	3.48	0.0620	20.32	0.0001	3.96	0.0466	38.60	0.0001

Table 3
Means and Standard Deviations for Main Effects

		Simple Difference Model				Covariate Adjustment Model					
		B42Diff		B41Diff		B42Diff		B41Diff		B43Diff	
Factor											
I	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	900	0.17	0.11	0.21	0.09	0.04	0.10	0.12	0.08	0.08	0.26
2	900	0.21	0.11	0.20	0.09	0.03	0.09	0.08	0.07	0.06	0.20
3	900	0.24	0.11	0.18	0.09	0.02	0.07	0.04	0.06	0.04	0.12
J											
1	900	0.21	0.12	0.20	0.10	-0.01	0.09	0.05	0.08	-0.11	0.15
2	900	0.21	0.12	0.20	0.09	0.04	0.09	0.08	0.08	0.06	0.14
3	900	0.20	0.10	0.19	0.08	0.07	0.08	0.11	0.07	0.23	0.16
K											
1	900	0.31	0.09	0.26	0.08	0.10	0.08	0.13	0.08	0.21	0.17
2	900	0.21	0.08	0.20	0.07	0.03	0.07	0.08	0.07	0.06	0.15
3	900	0.10	0.07	0.12	0.06	-0.04	0.07	0.03	0.06	-0.09	0.16
L											
1	1350	0.19	0.10	0.18	0.08	0.03	0.08	0.08	0.07	0.06	0.19
2	1350	0.22	0.12	0.21	0.10	0.03	0.10	0.08	0.09	0.07	0.22
M											
1	1350	0.18	0.11	0.17	0.09	0.01	0.09	0.06	0.08	0.03	0.20
2	1350	0.24	0.11	0.22	0.09	0.06	0.09	0.10	0.08	0.09	0.20

Table 4
Means and Standard Deviations for Interaction Effects

			Simple Difference Model				Covariate Adjustment Model					
			B42Diff		B41Diff		B42Diff		B41Diff		B43Diff	
Factor												
I	J	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	1	300	0.18	0.12	0.21	0.10	-0.00	0.10	0.09	0.09	-0.14	0.18
1	2	300	0.17	0.11	0.21	0.09	0.04	0.10	0.12	0.08	0.08	0.18
1	3	300	0.17	0.10	0.20	0.09	0.09	0.09	0.15	0.07	0.31	0.18
2	1	300	0.21	0.12	0.20	0.10	-0.01	0.09	0.05	0.07	-0.11	0.14
2	2	300	0.21	0.12	0.19	0.09	0.03	0.09	0.08	0.07	0.06	0.14
2	3	300	0.21	0.11	0.20	0.08	0.08	0.08	0.12	0.06	0.24	0.14
3	1	300	0.24	0.12	0.18	0.10	-0.01	0.07	0.02	0.07	-0.07	0.10
3	2	300	0.24	0.11	0.19	0.09	0.03	0.07	0.04	0.06	0.05	0.10
3	3	300	0.22	0.09	0.17	0.08	0.04	0.06	0.06	0.06	0.13	0.08
I K												
1	1	300	0.28	0.08	0.28	0.08	0.13	0.07	0.18	0.07	0.29	0.20
1	2	300	0.18	0.07	0.21	0.07	0.04	0.07	0.12	0.06	0.08	0.19
1	3	300	0.07	0.06	0.13	0.07	-0.05	0.07	0.05	0.06	-0.12	0.19
2	1	300	0.32	0.08	0.27	0.08	0.11	0.07	0.14	0.06	0.22	0.16
2	2	300	0.21	0.07	0.19	0.07	0.04	0.07	0.08	0.06	0.07	0.15
2	3	300	0.10	0.06	0.13	0.06	-0.04	0.07	0.03	0.06	-0.10	0.15
3	1	300	0.33	0.09	0.24	0.09	0.06	0.07	0.07	0.06	0.13	0.09
3	2	300	0.24	0.08	0.19	0.08	0.02	0.06	0.04	0.06	0.04	0.10
3	3	300	0.14	0.06	0.11	0.06	-0.02	0.06	0.01	0.05	0.05	0.10
I L												
1	1	450	0.16	0.10	0.19	0.08	0.05	0.09	0.12	0.07	0.08	0.24
1	2	450	0.19	0.12	0.22	0.10	0.04	0.12	0.12	0.09	0.09	0.27
2	1	450	0.19	0.10	0.18	0.08	0.04	0.08	0.09	0.06	0.06	0.19
2	2	450	0.22	0.13	0.21	0.10	0.03	0.11	0.08	0.08	0.07	0.22
3	1	450	0.22	0.10	0.16	0.08	0.02	0.07	0.04	0.06	0.03	0.12
3	2	450	0.26	0.12	0.20	0.10	0.02	0.08	0.04	0.07	0.04	0.13
I M												
1	1	450	0.14	0.10	0.17	0.09	0.01	0.10	0.09	0.08	0.05	0.25
1	2	450	0.21	0.11	0.24	0.09	0.08	0.10	0.15	0.08	0.11	0.26
2	1	450	0.18	0.11	0.18	0.09	0.01	0.09	0.06	0.07	0.04	0.20
2	2	450	0.24	0.11	0.22	0.09	0.06	0.09	0.10	0.07	0.09	0.20
3	1	450	0.22	0.11	0.16	0.09	0.01	0.07	0.03	0.06	0.02	0.12
3	2	450	0.26	0.11	0.20	0.09	0.03	0.07	0.06	0.06	0.05	0.12

Continued on Following Page

Table 4 (Continued)
Means and Standard Deviations for Interaction Effects

Simple Difference Model							Covariate Adjustment Model					
			B42Diff		B41Diff		B42Diff		B41Diff		B43Diff	
Factor												
J	K	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	1	300	0.31	0.09	0.27	0.09	0.06	0.07	0.11	0.07	0.04	0.07
1	2	300	0.21	0.09	0.19	0.08	-0.01	0.07	0.05	0.07	-0.10	0.07
1	3	300	0.11	0.08	0.12	0.07	-0.08	0.07	0.00	0.06	-0.26	0.10
2	1	300	0.32	0.09	0.27	0.08	0.10	0.07	0.13	0.07	0.22	0.09
2	2	300	0.21	0.08	0.20	0.07	0.04	0.06	0.08	0.06	0.07	0.06
2	3	300	0.10	0.07	0.12	0.06	-0.04	0.06	0.03	0.05	-0.09	0.07
3	1	300	0.30	0.07	0.25	0.08	0.14	0.08	0.15	0.08	0.38	0.14
3	2	300	0.21	0.07	0.20	0.06	0.07	0.06	0.11	0.06	0.23	0.09
3	3	300	0.10	0.06	0.12	0.05	0.01	0.05	0.06	0.05	0.07	0.06
J L												
1	1	450	0.19	0.10	0.18	0.09	-0.00	0.08	0.06	0.07	-0.11	0.14
1	2	450	0.22	0.14	0.21	0.11	-0.02	0.10	0.05	0.09	-0.11	0.16
2	1	450	0.19	0.10	0.18	0.08	0.04	0.07	0.08	0.07	0.06	0.13
2	2	450	0.23	0.13	0.22	0.10	0.03	0.10	0.08	0.08	0.07	0.16
3	1	450	0.19	0.10	0.18	0.07	0.07	0.07	0.11	0.07	0.22	0.14
3	2	450	0.22	0.11	0.20	0.09	0.08	0.09	0.11	0.08	0.24	0.17
J M												
1	1	450	0.18	0.12	0.17	0.10	-0.04	0.08	0.03	0.08	-0.13	0.15
1	2	450	0.24	0.12	0.22	0.10	0.01	0.09	0.08	0.08	-0.08	0.15
2	1	450	0.18	0.11	0.17	0.09	0.01	0.08	0.06	0.07	0.04	0.14
2	2	450	0.24	0.11	0.22	0.09	0.06	0.08	0.10	0.08	0.09	0.14
3	1	450	0.18	0.10	0.17	0.08	0.05	0.08	0.09	0.07	0.20	0.16
3	2	450	0.23	0.10	0.21	0.08	0.10	0.08	0.13	0.07	0.25	0.16
K L												
1	1	450	0.28	0.08	0.23	0.08	0.09	0.07	0.12	0.07	0.19	0.16
1	2	450	0.34	0.08	0.30	0.08	0.11	0.08	0.14	0.08	0.23	0.18
2	1	450	0.19	0.07	0.18	0.07	0.04	0.06	0.08	0.07	0.06	0.15
2	2	450	0.23	0.08	0.21	0.07	0.03	0.08	0.08	0.07	0.07	0.16
3	1	450	0.10	0.06	0.12	0.06	-0.02	0.06	0.04	0.06	-0.08	0.15
3	2	450	0.10	0.07	0.12	0.06	-0.05	0.07	0.02	0.06	-0.10	0.16

Continued on Following Page

Table 4 (Continued)
Means and Standard Deviations for Interaction Effects

Simple Difference Model						Covariate Adjustment Model						
		B42Diff		B41Diff		B42Diff		B41Diff		B43Diff		
Factor												
K M	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
1 1	450	0.28	0.08	0.24	0.08	0.07	0.07	0.11	0.07	0.19	0.17	
1 2	450	0.34	0.08	0.29	0.08	0.13	0.08	0.15	0.08	0.24	0.17	
2 1	450	0.18	0.07	0.17	0.06	0.01	0.06	0.06	0.06	0.04	0.15	
2 2	450	0.24	0.07	0.23	0.07	0.06	0.07	0.11	0.07	0.09	0.15	
3 1	450	0.08	0.07	0.10	0.05	-0.06	0.07	0.01	0.06	-0.12	0.16	
3 2	450	0.13	0.06	0.15	0.06	-0.01	0.06	0.05	0.06	-0.07	0.15	
L M												
1 1	675	0.17	0.10	0.16	0.08	0.01	0.07	0.06	0.07	0.04	0.19	
1 2	675	0.21	0.10	0.20	0.08	0.05	0.08	0.10	0.07	0.08	0.19	
2 1	675	0.19	0.12	0.18	0.10	0.00	0.10	0.06	0.08	0.03	0.21	
2 2	675	0.26	0.12	0.24	0.10	0.06	0.10	0.10	0.09	0.10	0.22	