

BRANDY SINCO'S APPENDICES AND REFERENCES FOR:

“USING PATH ANALYSIS TO TEST A HYPOTHESIS ON THE THEORY OF CHANGE IN HEMOGLOBIN A1C (HBA1C) AMONG CLIENTS IN A CULTURALLY TAILORED DIABETES INTERVENTION FOR AFRICAN AMERICANS AND LATINOS”

PRESENTED TO APHA STATISTICS SECTION ON 10/30/2012

Table of Contents

APPENDIX	PAGES
A) SAS Code for SEM Power Calculation	2
B) SAS Code for Assessment of Multivariate Normality	3
C) Derivation of Multivariate Skewness and Kurtosis Formulas for Bernoulli Random Variables	4
D) SAS Code for Missing Data Analysis	5
E) SAS Proc CALIS Code for SEM Analysis	6 - 7
REFERENCES	8 - 10

Appendix A: SAS Code for SEM Power Calculation

```
/* Power calculation for REACH SEM paper */
ods html path="c:\tempfiles";
Proc IML;
alpha=.05; /* significance level */
rmsea0=.05; /* null hyp value */
rmseaa=.08; /* alt hyp value */
d=58; /* degrees of freedom */
n=188; /* sample size */
ncp0=(n-1)*d*(rmsea0**2);
ncpa=(n-1)*d*(rmseaa**2);

if rmsea0<rmseaa then
do;
  cval = cinv(1-alpha, d, ncp0);
  power = 1 - probchi(cval, d, ncpa);
end;

if rmsea0>rmseaa then
do;
  cval = cinv(alpha, d, ncp0);
  power = probchi(cval, d, ncpa);
end;

Print rmsea0 rmseaa alpha d n cval[Format=10.3] power[Format=5.3] ncp0 ncpa;
quit;
ods html close;
```

Appendix B: SAS Code for Assessment of Multivariate Normality

```
ods html path="c:\tempfiles";
ods graphics on;
/* Obtain Mahalanobis distance from principle components */
proc princomp data=SEMDData std out=out_all outstat=outstat noprint;
  var Post_H1c Post_V110 Post_SMB Post_PAID Post_SelfEff_MH
      Pre_H1c Pre_V110 Pre_SMB Pre_PAID Pre_SelfEff_MH
      RaceInd GenderInd Age_BLIW Cohort2 Randomization2 HSGrad
      TotalClasses JrnyHlthGrp SelfMgtGrp FHADrVisitsBin;
run;

/* Compute squares of principle components */
data mahalanobis_all;
  set out_all;
  d2 = uss(of prin:);
run;

/* Histogram and QQ Plot of Mahalanobis Distance */
Title 'Multivariate Diagnostics - All';
Proc Univariate Data=Mahalanobis_all;
  Var d2;
  Label mahalanobis_distance_to_mean="Squared Distance";
  Symbol1 V=Dot;

  Histogram / Gamma(Alpha=10 Sigma=2 Theta=0 Fill)
  CFill=Blue Name="Data W/Post";
  Inset Gamma(KSD KSDPval) / Header='Goodness of Fit Test'
  Position=(95,95) RefPoint=TR;

  QQPlot / Gamma(Alpha=10 Sigma=2 Theta=0 L=1)
  PctlMinor PCTLSCALE Name="Data W/Post";
Run;
/* p = 0.2500 Kolmogorov */
ods graphics off;
ods html close;
```

Appendix C: Derivation of Multivariate Skewness and Kurtosis Formulas for Bernoulli Random Variables

The skewness of a Bernoulli variable, X , with probability of event, π , can be computed from:

- $\mu_3 = E(X - \pi)^3 = \sum_{i=0}^3 \binom{3}{i} E(X^i) (-\pi)^{3-i}$.
- $\mu_3 = -\binom{3}{0} \pi^3 + \binom{3}{1} E(X) \pi^2 - \binom{3}{2} E(X^2) \pi + \binom{3}{3} E(X^3)$.
- $\mu_3 = -\pi^3 + 3\pi^3 - 3\pi^2 + \pi$.
- ✓ To standardize μ_3 , divide by variance^{3/2}, $[\pi(1-\pi)]^{3/2}$, and the standardized skewness is $\frac{(1-2\pi)}{\sqrt{\pi(1-\pi)}}$.

The kurtosis of a binary variable, X , with probability of event, π , can be computed from

- $\mu_4 = E(X - \pi)^4 = \sum_{i=0}^4 \binom{4}{i} E(X^i) (-\pi)^{4-i}$.
- $\mu_4 = \binom{4}{0} \pi^4 - \binom{4}{1} E(X) \pi^3 + \binom{4}{2} E(X^2) \pi^2 - \binom{4}{3} E(X^3) \pi + \binom{4}{4} E(X^4)$.
- $\mu_4 = \pi^4 - 4\pi\pi^3 + 6\pi\pi^2 - 4\pi\pi + \pi = -3\pi^4 + 6\pi^3 - 4\pi^2 + \pi$.
- To standardize, divide by $[\pi(1-\pi)]^2$, subtract 3, and the standardized kurtosis is $\frac{(3\pi^2 - 3\pi + 1)}{\pi(1-\pi)} - 3 \frac{\pi(1-\pi)}{\pi(1-\pi)} = \frac{(3\pi^2 - 3\pi + 1) + (3\pi^2 - 3\pi)}{\pi(1-\pi)} = \frac{1 - 6\pi(1-\pi)}{\pi(1-\pi)}$.

Appendix D: SAS Code for Missing Data Analysis

***** Step 1: Impute with Proc MI ***;**

***** Include WithFlag (Withdrawal as covariate) ***;**

```
Proc MI Data=TestMissing NImpute=20 seed=11292011 out=ImputeSEM;  
Var WithFlag Age_BLIW GenderInd RaceInd Cohort2 Randomization2 HSGrad  
TotalClasses FHADrVisitsBinJrnyHlthGrp SelfMgtGrp  
Pre_V110 Pre_SMB Pre_PAID Pre_SelfEff_MH  
Post_V110 Post_SMB Post_PAID Post_SelfEff_MH  
Pre_H1cPost_H1c ;  
Run;
```

***** Step 2: Combine estimates from Proc CALIS ***;**

```
Proc Calis Covariance Method=ML VARDEF=N Data=ImputeSEM;  
LINEQS ... list line equations;  
VARIANCE List variances;  
VAR List variables;  
by _IMPUTATION_;  
ODS Output LINEQSEQ=LINEQSEQ;  
Run;
```

Appendix E: SAS Proc CALIS Code for SEM Analysis

```
ods html newfile=proc path="c:\tempfiles";
ods graphics on;
Proc Calis Covariance Residual Modification Kurtosis Method=FIML plots=residuals
Data=SEMDData;
LINEQS
Post_V110 = P_PostV110_PreV110 Pre_V110 +
  P_PostV110_TotalClasses TotalClasses + P_PostV110_FHADrVisitsBin FHADrVisitsBin +
  P_PostV110_JrnyHlthGrp JrnyHlthGrp + P_PostV110_SelfMgtGrp SelfMgtGrp +
  E_PostV110,

Post_PAID = P_PostPAID_PrePAID Pre_PAID +
  P_PostPAID_TotalClasses TotalClasses + P_PostPAID_FHADrVisitsBin FHADrVisitsBin +
  P_PostPAID_JrnyHlthGrp JrnyHlthGrp + P_PostPAID_SelfMgtGrp SelfMgtGrp +
  E_PostPAID,

Post_SelfEff_MH = P_PostSelfEff_MH_PreSelfEff_MH Pre_SelfEff_MH +
  P_PostSelfEff_MH_TotalClasses TotalClasses + P_PostSelfEff_FHADrVisitsBin
FHADrVisitsBin +
  P_PostSelfEff_JrnyHlthGrp JrnyHlthGrp + P_PostSelfEff_SelfMgtGrp SelfMgtGrp +
  E_PostSelfEff_MH,

Post_SMB = P_PostSMB_PreSMB Pre_SMB + P_PostSMB_PostV110 Post_V110 +
  P_PostSMB_PostPAID Post_PAID + P_PostSMB_PostSelfEff Post_SelfEff_MH +
  E_PostSMB,

Post_H1c = P_PostH1c_PreH1c Pre_H1c + P_PostH1c_PostSMB Post_SMB +
  P_PostH1c_Age Age_BLIW + P_PostH1c_Gender GenderInd +
  P_PostH1c_RaceInd RaceInd + P_PostH1c_Cohort2 Cohort2 +
  P_PostH1c_Rand Randomization2 + P_PostH1c_HSGrad HSGrad +
  E_Post_H1c;

VARIANCE
E_PostV110 = Var_PostV110,
E_PostSMB = Var_PostSMB,
E_PostPAID = Var_PostPAID,
E_PostSelfEff_MH = Var_PostSelfEff_MH,
E_Post_H1c = Var_PostH1c,
Pre_H1c = Var_PreH1c,
Pre_V110 = Var_PreV110,
Pre_SMB = Var_PreSMB,
Pre_PAID = Var_PrePAID,
Pre_SelfEff_MH = Var_PreSelfEff_MH,
Age_BLIW = Var_AgeBLIW,
GenderInd = Var_GenderInd,
```

```
RaceInd = Var_RaceInd,  
HSGrad = Var_HSGrad,  
Cohort2 = Var_Cohort2,  
Randomization2 = Var_Randomization2,  
JrnyHlthGrp = Var_JrnyHlthGrp,  
SelfMgtGrp = Var_SelfMgtGrp,  
FHADrVisitsBin = Var_FHADrVisitsBin,  
TotalClasses = Var_TotalClasses;
```

```
VAR
```

```
Pre_H1c Pre_V110 Pre_SMB Pre_PAID Pre_SelfEff_MH  
Age_BLIW Genderind RaceInd Cohort2 Randomization2 HSGrad  
TotalClasses FHADrVisitsBin JrnyHlthGrp SelfMgtGrp  
Post_H1c Post_V110 Post_SMB Post_PAID Post_SelfEff_MH;  
ODS Output LINEQSEQ=LINEQSEQ SQMultCorr=SQMultCorr Fit=Fit;  
Run;  
ods graphics off;  
ods html close;
```

REFERENCES

1. Center for Statistical Consultation And Research, University of Michigan. Applied structural equation modeling, may 10 - 14. 2010.
2. Kline RB. *Principles and Practice of Structural Equation Modeling*. 3rd ed. New York: The Guilford Press; 2011.
3. Johnson RA, Wichern DW. *Applied Multivariate Statistical Analysis*. 5th ed. New Jersey: Prentice Hall; 2002.
4. Kenny DA. Mediation. <http://davidakenny.net/cm/mediate.htm>. Accessed 1/6/2012.
5. Bollen KA. *Structural Equations with Latent Variables*. New York, NY: John Wiley & Sons, Inc.; 1989.
6. Joreskog KG, Sorbom D. Recent developments in structural equation modeling. *Journal of Marketing Research*. 1982;19(4):404-416.
7. SAS Institute. The CALIS procedure. http://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#calis_toc.htm. Accessed 7/26, 2011.
8. Gao S, Mokhtarian PL, Johnston RA. Non-normality of data in structural equation models. *Transportation Research Board's 87th Annual Meeting*.
9. Joreskog KG, Sorbom D. LISREL: Structural equation modeling. *Scientific Software International*. Chicago, IL:1996;8.
10. Hatcher L. *A Step-by-Step Guide to using SAS for Factor Analysis and Structural Equation Modeling*. Cary, NC: SAS Institute; 2003.
11. Suhr DD. Exploratory or confirmatory factor analysis? *SAS Global Forum Proceedings*. 2006.
12. Estep D. Course notes for stat 560, Colorado State University. 2011;1:224-248.
13. West BT, Welch KB, Galecki AT. *Linear Mixed Models: A Practical Guide using Statistical Software*. Boca Raton, FL: Chapman Hall / CRC Press; 2007.
14. Bentler PM. Comparative fit indices in structural models. *Psychological Bulletin*. 1990;107(2):238-246.
15. Steiger JH. Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*. 1990;25(2):173-180.

16. Hu L, Bentler PM. Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*. 1999;6:1-55.
17. Loehlin JC. *Latent Variable Models: An Introduction to Factor, Path, and Structural Analysis*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates; 1992.
18. MacCullum RC, Browne MW, Sugawara HM. Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*. 1996;1:130-149.
19. Fitzgerald JT, Davis WK, Connell CM, Hess GE, Funnell MM, Hiss RG. Development and validation of the diabetes care profile. *Eval Health Prof*. 1996;19:208-230.
20. Williams GC, Freedman ZR, Deci EL. Supporting autonomy to motivate patients with diabetes for glucose control. *Diabetes Care*. 1998;21:1644-1651.
21. Polonsky WH, Anderson BJ, Lohrer PA, et al. Assessment of diabetes-related distress. *Diabetes Care*. 1995;18(6):754-760.
22. Polonsky WH, Welch G. Listening to our patients' concerns: Understanding and addressing diabetes-specific emotional distress. *Diabetes Care*. 1996;9:8-11.
23. Toobert DJ, Hampson SE, Glasgow RE. The summary of diabetes self-care activities measure. *Diabetes Care*. 2000;23(7):943-950.
24. Agresti A, Mehta CR, Patel NR. Exact inference for contingency tables with ordered categories. *JASA*. 1990;85:453-458.
25. Anupama N, Watts D. Exact methods in the NPAR1WAY procedure. *SAS Users Group International*. 1996.
26. Balanda KP, MacGillivray HL. Kurtosis: A critical review. *The American Statistician*. 1988;42(2):111-119.
27. Mardia KV. Measures of multivariate skewness and kurtosis with applications. *Biometrika*. 1970;57(3):519-530.
28. SAS Institute. Multivariate analysis concepts. support.sas.com/publishing/pubcat/chaps/56903.pdf. Accessed 2/27/2012.
29. Kolmogorov A. Sulla determinazione empirica di una legge di distribuzione. *Giorn. Ist. Ital. Attuari*. 1933(4):83-91.
30. Smirnov NV. Tables for estimating the goodness of fit of empirical distributions. *Annals of Mathematical Statistics*. 1948;19:279-281.

31. SAS Institute. Proc univariate.
http://support.sas.com/documentation/cdl/en/procstat/63104/HTML/default/viewer.htm#univariate_toc.htm. Accessed 7/27/2011.
32. Peng G, Lilly E. Testing normality of data using SAS, paper PO04. *SUGI*. 2004:1-6.
33. Bentler PM, Chou CP. Practical issues in structural modeling. *Sociological methods research*. 1987;16:78-117.
34. Little RJA. A test of missing completely at random for multivariate data with missing values. *JASA*. 1988;83:1198-1202.
35. Little RJA, Rubin DB. *Statistical Analysis with Missing Data*. 2nd ed. New York: John Wiley; 2002.
36. Geldhof GJ, Selig JP. Using SAS for multiple imputation: The MI and MIANALYZE procedures. *Fall Colloquium*. 2007.
37. Welch K. Introduction to proc MI and proc MIAnalyze for multiple imputation of missing data in SAS. *Michigan SAS Users Group Conference*.
38. Yung YF, Zhang W. Making use of incomplete observations in the analysis of structural equation models: The CALIS procedure's full information maximum likelihood method in SAS/STAT 9.3. *SAS Global Forum Proceedings*. 2011.
39. Enders CK, Bandalos DL. The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling*. 2001;8:430-457.
40. Schafer JL, Olsen MK. Multiple imputation for multivariate missing data problems: A data analyst perspective. *Multivariate Behavioral Research*. 1998;33:545-571.