## Supplementary materials for:

Tang TS, Funnell MM, Sinco B, Spencer MS, Heisler M. Peer-led, empowerment-based approach to self-management efforts in diabetes (PLEASED): a randomized controlled trial in an African-American community. *Ann Fam Med*. 2015;13:S27-S35. Doi: 10.1370/afm.1819.

# Appendix: Using the Multivariate Delta Method to Report Logistic Regression Results with Repeated Measures

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#### **Generalized Estimating Equation With Repeated Measures**

Note: This example uses time points, but could easily be extended to the four time points in this paper.

- Let i = 0 for control and 1 for treatment.
- Let j = 1 for pre-intervention and 2 for post-intervention.
- Let k = k<sup>th</sup> subject.
- Let R = 0 for control and 1 for treatment.
- Let T = 0 for baseline and 1 for first follow-up.
- Let  $\pi$  = probability of success.

Generalized Estimating Equation for a Binary Outcome. logit( $\pi_{ijk}$ ) = ln( $\pi_{ijk}$ /(1 -  $\pi_{ijk}$ )) = ( $\beta_0$  +  $\beta_1$ R +  $\beta_2$ T +  $\beta_3$ RT +  $\epsilon_{ijk}$ ,  $\epsilon_{ijk}$  = error term. The  $\beta$  terms are assumed to be multivariate normal.

Estimated Mean:  $ln(\pi_{iik}/(1 - \pi_{iik})) = \beta_0 + \beta_1 R + \beta_2 T + \beta_3 RT$ .

The mean percentages for the control group are  $\exp(\beta_0)/(1+\exp(\beta_0))$  at preintervention and  $\exp(\beta_0+\beta_2)/(1+\exp(\beta_0+\beta_2))$  at post-intervention. The means for the treatment group are  $\exp(\beta_0+\beta_1)/(1+\exp(\beta_0+\beta_1))$  at preintervention and  $\exp(\beta_0+\beta_1+\beta_2+\beta_3)/(1+\exp(\beta_0+\beta_1+\beta_2+\beta_3))$  at post-intervention.

#### The Univariate Delta Method<sup>1</sup>

- Let Y ~ Normal( $\mu$ ,  $\sigma^2$ ),  $\mu$ ,  $\sigma^2 \neq 0$ ; n = sample size.
- Let g(Y) be a differentiable function of Y with non-zero first derivative.
- Then, a first-order Taylor series for  $g(Y) = g(\mu) + g'(\mu)(Y \mu)$ .
- Mean of  $g(Y) \approx g(\mu)$  and Variance of  $(g(Y)) \approx (g'(\mu))^2 \sigma^2$ .
- Delta Method Theorem:  $\lim_{n\to\infty} \sqrt{n} (g(Y) g(\mu)) \xrightarrow{D} Normal (0, \sigma^2 (g'(\mu))^2).$
- I.E., asymptotic distribution of  $g(Y) = Normal(g(\mu), (g'(\mu))^2 \sigma^2)$ .
- Example: Let Y ~ Normal( $\mu$ ,  $\sigma^2$ ). Let W = g(Y) =  $e^Y$ .
- $g'(\mu) = e^{\mu}$ .
- Using the delta method, mean of W =  $g(\mu)$  =  $e^{\mu}$  and
- Variance of W =  $(g'(\mu))^2 \sigma^2 = e^{2\mu} \sigma^2$ ; Standard deviation of W =  $e^{\mu} \sigma$ .
- Asymptotic distribution of W = Normal( $e^{\mu}$ ,  $e^{2\mu}\sigma^2$ ).

### The Multivariate Delta Method<sup>2</sup>

- Let Y be a multivariate vector of m normal variables, Y = [Y<sub>1</sub> Y<sub>2</sub> ... Y<sub>m</sub>].
- $Y \sim N(\mu, \Sigma)$ , where  $\Sigma$  is a m × m covariance matrix.
- Let g(Y) be a differentiable function of Y with non-zero first derivative.

- The multivariate delta method states that if  $\lim_{n \to \infty} \sqrt{n} (Y \mu) \xrightarrow{D} N(0, \Sigma)$ , then  $\lim_{n\to\infty} \sqrt{n} \left( g(Y) - g(\mu) \right) \xrightarrow{D} N \left( 0, J_g(\mu) \Sigma J_g^T(\mu) \right).$
- Where  $J_q(\mu)$  is the Jacobian matrix, evaluated at Y =  $\mu$ .

• Where 
$$J_g(\mu)$$
 is the Jacobian matrix, evaluated at  $Y = \mu$ .

•  $J_g(\mu) = \begin{bmatrix} \frac{\partial g_1(Y)}{\partial Y_1} & \frac{\partial g_1(Y)}{\partial Y_2} & \dots & \frac{\partial g_1(Y)}{\partial Y_m} \\ \frac{\partial g_2(Y)}{\partial Y_1} & \frac{\partial g_2(Y)}{\partial Y_2} & \dots & \frac{\partial g_2(Y)}{\partial Y_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial g_m(Y)}{\partial Y_1} & \frac{\partial g_m(Y)}{\partial Y_2} & \dots & \frac{\partial g_m(Y)}{\partial Y_m} \end{bmatrix}$  evaluated at  $Y = \mu$ .

Application of the Multivariate Delta Method to Report the Outcomes of a Generalize Estimating Equation for a Binary Variable As Percentages Instead of As Odds Ratios<sup>2</sup>.

(Note: Reference shows how to apply the delta method to the log transform when used with a linear mixed model. The same methodology can be used to calculate percentages from a logistic model.)

- The  $\beta$ 's are assumed to be multivariate normal, with covariance matrix  $\Sigma_{\beta}$ .
- Percent success of control group at time  $1 = \exp(\beta_0)/(1 + \exp(\beta_0))$ .
- $g_1(\beta) = \exp(\beta_0)/(1 + \exp(\beta_0))$ .
- Note that  $\partial g_1(\beta)/\partial \beta_0 = \exp(\beta_0)/(1+\exp(\beta_0))^2$  and  $\partial g_1(\beta)/\partial \beta_i = 0$  if i>0.
- Percent success of control group at time 2 =  $\exp(\beta_0 + \beta_2)/(1 + \exp(\beta_0 + \beta_2))$ .
- Let  $g_2(\beta) = \exp(\beta_0 + \beta_2)/(1 + \exp(\beta_0 + \beta_2))$ . Note that  $\partial g_2(\beta)/\partial \beta_0 = \partial g_2(\beta)/\partial \beta_2 = \partial g_2(\beta)/\partial \partial$  $\exp(\beta_0 + \beta_2)/(1 + \exp(\beta_0 + \beta_2))^2$  and  $\partial g_2(\beta)/\partial \beta_i = 0$  for  $i \neq 0$  and  $i \neq 2$ .
- Same property holds for g<sub>3</sub> and g<sub>4</sub> derivatives with respect to the β's.
- Percent success of treatment group at time  $1 = \exp(\beta_0 + \beta_1)/(1 + \exp(\beta_0 + \beta_1))$ .
- $q_3(\beta) = \exp(\beta_0 + \beta_1)/(1 + \exp(\beta_0 + \beta_1)).$
- $\partial g_3(\beta)/\partial \beta_0 = \partial g_3(\beta)/\partial \beta_1 = \exp(\beta_0 + \beta_1)/(1 + \exp(\beta_0 + \beta_1))^2$ , and  $\partial g_3(\beta)/\partial \beta_i = 0$  for i>1.
- Percent success of treatment group at time 2 =  $\exp(\beta_0 + \beta_1 + \beta_2 + \beta_3)/(1 + \exp(\beta_0 + \beta_1 + \beta_2 + \beta_3))$  $+ \beta_1 + \beta_2 + \beta_3)$ ).
- $g_4(\beta) = \exp(\beta_0 + \beta_1 + \beta_2 + \beta_3)/(1 + \exp(\beta_0 + \beta_1 + \beta_2 + \beta_3))$
- $\partial g_4(\beta)/\partial \beta_i = \exp(\beta_0 + \beta_1 + \beta_2 + \beta_3)/(1 + \exp(\beta_0 + \beta_1 + \beta_2 + \beta_3))^2$ ,  $0 \le i \le 3$ .

Jacobian Matrix for  $q(\beta)$ .

Jacobian Matrix for g(
$$\beta$$
). 
$$\begin{bmatrix} \frac{\exp(\beta_0)}{(1 + \exp(\beta_0))^2} & 0 & 0 & 0 \\ \frac{\exp(\beta_0 + \beta_2)}{(1 + \exp(\beta_0 + \beta_2))^2} & 0 & \frac{\exp(\beta_0 + \beta_2)}{(1 + \exp(\beta_0 + \beta_2))^2} & 0 \\ \frac{\exp(\beta_0 + \beta_1)}{(1 + \exp(\beta_0 + \beta_1))^2} & \frac{\exp(\beta_0 + \beta_1)}{(1 + \exp(\beta_0 + \beta_1))^2} & 0 & 0 \\ \frac{\exp(\sum_{i=0}^3 \beta_i)}{(1 + \exp(\sum_{i=0}^3 \beta_i))^2} & \frac{\exp(\sum_{i=0}^3 \beta_i)}{(1 + \exp(\sum_{i=0}^3 \beta_i))^2} & \frac{\exp(\sum_{i=0}^3 \beta_i)}{(1 + \exp(\sum_{i=0}^3 \beta_i))^2} & \frac{\exp(\sum_{i=0}^3 \beta_i)}{(1 + \exp(\sum_{i=0}^3 \beta_i))^2} \end{bmatrix}$$
 In simpler form,  $J_g(\beta) = \begin{bmatrix} W_1 & 0 & 0 & 0 \\ W_2 & 0 & W_2 & 0 \\ W_3 & W_3 & 0 & 0 \\ W_4 & W_4 & W_4 & W_4 \end{bmatrix}$ .

Define the covariance matrix for the 
$$\beta$$
's as  $\Sigma_{\beta} = \begin{bmatrix} \sigma_{\beta00}^2 & \sigma_{\beta01} & \sigma_{\beta02} & \sigma_{\beta03} \\ \sigma_{\beta01} & \sigma_{\beta11}^2 & \sigma_{\beta12} & \sigma_{\beta13} \\ \sigma_{\beta02} & \sigma_{\beta12} & \sigma_{\beta22}^2 & \sigma_{\beta23} \\ \sigma_{\beta03} & \sigma_{\beta13} & \sigma_{\beta23} & \sigma_{\beta33}^2 \end{bmatrix}$ 

The covariance matrix for W (estimates for each group at each time point) will be  $\Sigma_{W} = J_{a}(\beta) \times \Sigma_{\beta} \times (J_{a}(\beta))^{T}$ .

#### **Example SAS Code to Compute Covariance Matrix With Four Time Points** (Other software could be used. The delta method can be applied with any statistical software.)

\*\*\* PHQ Bin, Minimally Depressed or Greater \*\*\*;

ods html; ods graphics on;

Proc Genmod Data=AcrossTimeLong Ypsi Descending:

Class REACHID TimepointN RandomizationN;

Model PHQBin=TimepointN RandomizationN TimepointN\*RandomizationN / dist=bin: Repeated Subject=REACHID / Type=UN Modelse ECOVB;

ODS OUTPUT GEEModPEst=RegBinPHQ GEERCov=CovBPHQ;

Run;

ods graphics off; ods html close;

```
/* PHQBin: Compute standard errors for difference scores via the delta method */
ods html path="c:\temp";
Proc IML:
/* Input beta vector; begin at B1 instead of B0 because SAS numbers parameters
starting at 1 */
use regbinphq; read all var {'Estimate'} into B; close regbinphq;
/* B5=B7=B9=B11=B13=B14=B15=0 reference levels */
B00 = B[1]; /* B00 = control group at baseline */
B10 = B[1] + B[6]; /* B10 = peer group at baseline */
B01 = B[1] + B[4]; /* B01 = control group at 3 months */
B11 = B[1] + B[4] + B[6] + B[12]; /* B11 = peer group at 3 months */
B02 = B[1] + B[3]; /* B02 = control group at 9 months */
B12 = B[1] + B[3] + B[6] + B[10]; /* B12 = peer group at 9 months */
B03 = B[1] + B[2]; /* B03 = control group at 15 months */
B13 = B[1] + B[2] + B[6] + B[8]; /* B12 = peer group at 15 months */
/* Convert to exp scale */
\exp B00 = \exp(B00)/((1 + \exp(B00))^{**}2);
expB10=exp(B10)/((1+exp(B10))**2);
expB01=exp(B01)/((1+exp(B01))**2);
expB11=exp(B11)/((1+exp(B11))**2);
\exp B02 = \exp(B02)/((1+\exp(B02))^{**}2);
expB12=exp(B12)/((1+exp(B12))**2);
\exp B03 = \exp(B03)/((1+\exp(B03))^{**}2);
expB13=exp(B13)/((1+exp(B13))**2);
/* Input covariance matrix, 8x8 matrix */
use CovBPHQ; read all var{'Prm1' 'Prm2' 'Prm3' 'Prm4' 'Prm6' 'Prm8' 'Prm10' 'Prm12'}
into CovB; close CovBPHQ; print CovB;
/* Contruct W, 8x8 matrix */
W=i(8,8,0);
W[1,1]=expB00;
z=\{1 5\};
W[2,z]=expB10:
z=\{1,4\}:
W[3, z]=expB01;
z=\{1458\};
W[4,z]=expB11;
z=\{1\ 3\};
```

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\label{eq:weighted_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_continuous_c
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#### **REFERENCES**

<sup>&</sup>lt;sup>1</sup>Multivariate Delta Method: Reference: Casella G, Berger RL. Statistical inference. 2nd ed. Pacific Grove, CA: Duxbury; 2002.

<sup>&</sup>lt;sup>2</sup>Sinco B., Kieffer E., Spencer M. Using the Delta Method to generate means and confidence intervals from a Linear Mixed Model on the original scale, when the analysis is done on the log scale. Presented at the American Statistical Association's Conference on Statistical Practice in New Orleans, 2/20/2015.