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# Development Of Efficient Simultaneous Confidence Bounds For Linear Mixed Models With Applications In Alcohol Research

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DEVELOPMENT OF EFFICIENT SIMULTANEOUS CONFIDENCE BOUNDS FOR LINEAR MIXED MODELS WITH APPLICATIONS IN ALCOHOL RESEARCH

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# DEVELOPMENT OF EFFICIENT SIMULTANEOUS CONFIDENCE BOUNDS FOR LINEAR MIXED MODELS WITH APPLICATIONS IN ALCOHOL RESEARCH

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# Chapter 1

# Introduction

## 1.1 The Need for Multiplicity Corrections

Multiplicity corrections are an integral part of any study under consideration. Whenever multiple inferences are made simultaneously, whether through statistical testing or interval estimation, multiple comparisons or simultaneous confidence bounds (SCB) should be carried out to ensure the accuracy of conclusions made. Multiple comparisons enable one to control the error rate of a family of tests to the prescribed amount, while SCBs help to accurately estimate the limits of the bounds for such families of comparisons. While the terms multiple comparisons and simultaneous confidence bounds might be used interchangeably, the term multiple comparisons specifically applies to data with discrete end-points, while simultaneous confidence bounds apply to data with continuous end-points.

## 1.2 Longitudinal Studies

Multiplicity corrections are incredibly important in longitudinal studies where multiple observations are repeated on the same subjects over an extended period. These studies are highly prevalent in social fields like psychology and sociology and aim to track changes in certain characteristics of the subjects over time. The responses in longitudinal studies are therefore highly correlated due to them being performed on the same subjects multiple times. Simultaneous confidence bounds used to make inferences in these studies should, therefore, account for this high degree of correlation when they are created.

## 1.3 Motivating Example

One such longitudinal study from the field of psychology will serve as a motivating example for this thesis. The study involves testing the moderation effect of mental health indicators such as suicidal thoughts and behaviors and injury-related post-traumatic stress disorder (PTSD) on the efficacy of three brief alcohol intervention strategies. As described in detail in [1], after screening injured patients from three Level I trauma centers for alcohol abuse, 596 of them were randomly assigned to one of three interventions, brief advice (BA), brief motivational intervention (BMI), and brief motivational intervention with a telephone booster (BMI-B). Five levels of suicidal thoughts and behaviors, ranging from none to executing a prepared suicide plan, were measured, while PTSD was diagnosed in a yes/no format. Measurements were carried out at baseline, three months and six months, and the response variables were three alcohol outcomes. Chapter 3 describes the results of the motivating example.

The data in this motivating example was modeled using generalized estimating equations (GEEs). The response curves were modeled as piecewise growth curves with endpoints being the response measurement times, namely baseline, three months, and six months. Multiplicity correcting SCBs were also needed for the longitudinal data presented in the motivational example, to more accurately detect differences in the responses due to the different interventions. As discussed, since the data-points were highly correlated, a modified approach to determining the SCBs was needed. This thesis proposes a new method for estimating SCBs using graph-theory based results. The application of the graph-theory results helps determine SCBs that are less conservative than Bonferroni confidence bounds, while still maintaining the desired confidence levels, to control the overall family-wise error rate. Similar to [6], the described graph-theory based SCBs will be applicable to a large domain of time intervals including finite intervals (continuous) and finite points (discrete). The next chapter describes the theory of Linear Mixed Models (LMMs) and how they can be used in the motivating example to come up with SCBs for the data.

# Chapter 2

# Linear Mixed Models (LMMs)

## 2.1 Introduction to LMMs

Linear Mixed Models (LMMs) are a very widely used subset of linear models in data modeling. LMMs consist of two parts: a fixed effects part and a random effects part. In this chapter, we provide a brief introduction to LMMs and briefly derive the estimation of fixed effects of an LMM and its covariance structure, following the methodology described in [4].

The general form of an LMM is expressed with the help of an $\mathbf{X}\boldsymbol{\beta}$ term to denote the fixed effects in the model, where $\mathbf{X}$ is a known model matrix, and a $\mathbf{Zu}$ term to describe the random effects in the model. By conditioning the model on the unobservable but realized random effect values, we express the LMM as follows:

$$E\left[\mathbf{y}|\mathbf{u}\right] = \mathbf{X}\boldsymbol{\beta} + \mathbf{Zu},$$

where

$$\mathbf{u} \sim \left(\mathbf{0}, \mathbf{D}\right).$$

Now, setting

$$\text{var}(\mathbf{y}|\mathbf{u}) = \mathbf{R},$$

we get

$$\mathbf{y} \sim \left(\mathbf{X}\boldsymbol{\beta}, \mathbf{ZDZ}^{'} + \mathbf{R}\right).$$

In order to simplify notation $\mathbf{ZDZ}^{'} + \mathbf{R}$ is renamed as $\mathbf{V}$, the covariance matrix whose

structure accounts for both the fixed effects and random effects. This gives,

$$\mathbf{y} \sim (\mathbf{X}\boldsymbol{\beta}, \mathbf{V}) .$$

One can, as a result of this, notice that the fixed effects only affect the mean of $\mathbf{y}$, while the components of the random effects only affect the variance of $\mathbf{y}$.

## 2.2 Random Intercept Models

A particular form of the LMM in single predictor regression is called the Random Intercept Model, where the intercepts are random variables themselves, in addition to the randomness of error.

In order to present the model, as in [4], for $\mathbf{y_i}$ with $i = 1, 2, \ldots, m$, we define

$$\mathbf{y} = \{\mathbf{y_i}\}_{i=1}^{m} \text{ and } \mathbf{a} = \{a_i\}_{i=1}^{m} .$$

Here, the $\mathbf{y_i}$'s are all the response variables, and the $\mathbf{a_i}$'s are the random effects, where each $a_i$ is taken to be normally distributed with mean 0 and variance $\sigma_\alpha^2$. That is,

$$a_i \sim \mathbf{N}\left(0, \sigma_a^2\right) .$$

Then, from [4], the model is written as,

$$E\left[\mathbf{y}|\mathbf{a}\right] = \mathbf{X}\begin{pmatrix}\mu \\ \beta\end{pmatrix} + \mathbf{Za}$$

and

$$E\left[\mathbf{y}\right] = \mathbf{X}\begin{pmatrix}\mu \\ \beta\end{pmatrix}$$

In the above equation,

$$\mathbf{X} = \mathbf{1}_m \otimes \mathbf{X}_0 \text{ and } \mathbf{Z} = \mathbf{I}_m \otimes \mathbf{Z}_0.$$

Here, $\otimes$ signifies the direct (or Kronecker) product for matrices.

## 2.3 Estimating Fixed Effects for Unknown Covariance Matrix V in an LMM

As noted from [4], since the variance matrix of $\mathbf{y}$, $\mathbf{V}$, is unknown, one has to estimate it with a calculated $\hat{\mathbf{V}}$, which is obtained by maximizing the likelihood function of $\mathbf{y}$ with respect to the parameters in $\mathbf{V}$. Regardless of the $\hat{\mathbf{V}}$ obtained, the ML estimator of $\boldsymbol{\mu} = \mathbf{X}\boldsymbol{\beta}$ is,

$$\mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{y}$$

When, var($\mathbf{y}$), $\mathbf{V}$ is known and expressed in terms of a weight matrix $\mathbf{W}$, as in [4], which is the inverse of $\mathbf{V}$ up to a scalar multiple, that is, $\mathbf{V} = \sigma^2\mathbf{W}^{-1}$, testing the null hypothesis $H_0 : \mathbf{K}'\mathbf{X}\boldsymbol{\beta} = \mathbf{m}$, where $\mathbf{K}'$ is of full row rank ($r_{\mathbf{K}} \leq r_{\mathbf{X}}$) can be carried out using the uniformly most powerful invariant test with the following statistic:

$$F = \frac{(\mathbf{K}'\mathbf{X}\boldsymbol{\beta}^{\mathbf{0}} - \mathbf{m})' \left[\mathbf{K}'\mathbf{X}(\mathbf{X}'\mathbf{W}\mathbf{X})^{-}\mathbf{X}'\mathbf{K}\right]^{-1} (\mathbf{K}'\mathbf{X}\boldsymbol{\beta}^{\mathbf{0}} - \mathbf{m})}{r_{\mathbf{K}}\hat{\sigma}^2}$$

where

$$\hat{\sigma}^2 = \frac{\mathbf{y}' \left[\mathbf{W} - \mathbf{W}\mathbf{X}(\mathbf{X}'\mathbf{W}\mathbf{X})^{-}\mathbf{X}'\mathbf{W}\right] \mathbf{y}}{N - r_{\mathbf{X}}}.$$

Under this null hypothesis, F has an $\mathbf{F}$-distribution with $r_{\mathbf{K}}$ and $N - r_{\mathbf{X}}$ degrees of freedom.

However, since the knowledge of $\mathbf{V}$ is not assumed, one cannot deduce the $\mathbf{F}$-distribution and thus an approximation must be obtained. With a substitution of the ML estimate $\hat{\boldsymbol{\beta}}$ in $\mathbf{K}'\mathbf{X}\boldsymbol{\beta}^{\mathbf{0}}$ to get $\mathbf{K}'\mathbf{X}\hat{\boldsymbol{\beta}}$, and $\hat{\mathbf{V}}$ for $\mathbf{V}$ in $F$, the resulting statistic called $\hat{F}$ can be assumed to be approximately $\mathbf{F}$-distributed. This approximation can be accomplished by assuming

$$\lambda\hat{F} \sim \mathbf{F}_d^r,$$

where

$$r = r_{\mathbf{K}} \text{ for } \mathbf{K} \text{ in } H_0 : \mathbf{K}'\mathbf{X}\boldsymbol{\beta} = \mathbf{m}.$$

Using a matching of moments method similar to [5], $\lambda$ and $d$ are obtained to be

$$\lambda = \frac{d}{(d-2)E[\hat{F}]}$$

and

$$d = \frac{1 + \frac{2}{r}}{var\left(\frac{\hat{F}}{2\left[E[\hat{F}]\right]^2}\right) - \frac{1}{r}}$$

## 2.4 Covariance Structure for Fixed Effects

As known from [4], when $\text{var}(\mathbf{y}) = \mathbf{V}$ is known, using the ML estimate of $\mathbf{X}\boldsymbol{\beta}$,

$$\mathbf{X}\boldsymbol{\beta}^0 = \mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{y},$$

one can quickly arrive at the conclusion that

$$\text{var}(\mathbf{X}\boldsymbol{\beta}^0) = \mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'.$$

However, since the knowledge of $\mathbf{V}$ is again not assumed, using the ML expression for $\mathbf{X}\hat{\boldsymbol{\beta}}$, and substituting the estimate of $\mathbf{V}$, $\hat{\mathbf{V}}$ for $\text{var}(\mathbf{y})$, we can see that

$$\text{var}(\mathbf{X}\hat{\boldsymbol{\beta}}) = \mathbf{X}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\mathbf{V}}^{-1}\hat{\mathbf{V}}\hat{\mathbf{V}}^{-1}\mathbf{X}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'$$

which simplifies to

$$\text{var}(\mathbf{X}\hat{\boldsymbol{\beta}}) = \mathbf{X}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'$$

giving a similar result as before

$$\text{var}(\mathbf{X}\hat{\boldsymbol{\beta}}) = \mathbf{X}(\mathbf{X}'\hat{\mathbf{V}}^{-1}\mathbf{X})^{-1}\mathbf{X}'.$$

## 2.5 Linear Model for Growth and Response Curves

As in [6], assume data is obtained from $n$ individuals on each of whom $p$ measurements are carried out. If the response of measurement $j$ for person $i$ is given by $Y_{ij}$ where $i = 1, \ldots, n$ and $j = 1, \ldots, p_i$ then

$$Y_{ij} = f(t_{ij}) + \epsilon_{ij}$$

where $f(t) = \sum_{k=0}^{q} \beta_k x_k(t)$, for some smooth functions of $t$, $x_0(t), \ldots, x_q(t)$.

Letting $\mathbf{Y}_i = (Y_{i1}, \ldots, Y_{ip_i})'$, $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_q)'$, $\boldsymbol{\epsilon} = (\epsilon_{i1}, \ldots, \epsilon_{ip_i})'$ with $\boldsymbol{\epsilon}_1, \ldots, \boldsymbol{\epsilon}_n$ iid multivariate normal with mean $\mathbf{0}$ and covariance matrix $\boldsymbol{V}_i$, and the $p_i \times (q+1)$ matrix $\mathbf{X}_i$ with elements $x_k(t_{ij})$, then the model has, for $i = 1, \ldots, n$, the form

$$\mathbf{Y}_i = \mathbf{X}_i\boldsymbol{\beta} + \boldsymbol{\epsilon}_i$$

Further, if, $N = \sum_{i=1}^{n} p_i$, $\mathbf{Y} = (\mathbf{Y}_1, \ldots, \mathbf{Y}_n)'$is an $N$ vector, $\mathbf{X}' = (\mathbf{X}_1', \ldots, \mathbf{X}_n')$ is an $N \times (q+1)$ matrix and $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}_1', \ldots, \boldsymbol{\epsilon}_n')'$, then the model can be expressed in the readily known form

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where $\boldsymbol{\epsilon}$ has an N-dimensional normal distribution with mean zero and block diagonal covariance $\boldsymbol{V} = \{\mathbf{V}_1, \mathbf{V}_2, \ldots, \mathbf{V}_n\}$

## 2.6 Using Generalized Estimating Equations (GEEs)

To obtain more stable standard errors in the models used in Chapter 3, generalized estimating equations (GEEs), proposed in [3], were used. GEEs, as described in [7], require only the correct specification of univariate marginal distributions so long as assumptions made about the association structure are acceptable to the users. In practice, this means that

one specifies a correlation matrix which, along with the variances, results in the creation of a hypothesized covariance matrix for the model. In general, however, the equations to be solved are not first-order derivatives of a likelihood function, and thus no maximum likelihood estimates are found. Rather, solving the equations is done iteratively with a constant updating of the assumed correlation matrix using moment-based estimators. [7] also emphasizes how [3] enabled the carrying out of classical Wald-type inferences to be possible, by showing that $\hat{\beta}$ was asymptotically normally distributed with mean $\beta$ and with an easily estimated covariance matrix. Thus, although generalized linear models can be fit to longitudinal data, more efficiency can be gained in the results if an appropriate correlation structure is assumed and a GEE methodology followed.

# Chapter 3

# Proposed Method: Using Graph Theory to Obtain Improved Simultaneous Confidence Bounds (SCBs)

## 3.1 Theoretical Background

Using the methodology described in [6], alongside the minimal spanning tree algorithm used by Hunter in [2] and the improved Bonferroni inequality determined by Worsley in [8], a simulation was conducted to calculate empirical error rates for obtained improved simultaneous confidence bounds (SCB) and compare them to those of the Bonferroni confidence bounds for multiple comparisons. For a 95% SCB, Bonferroni's method guarantees at least 95% confidence, but the actual confidence level increases as the dependency between covariates in a model increases. The improved SCB, which also guarantees at least 95% confidence, aims to bring the actual confidence level to a value closer to 95%, thereby tightening the bounds for more accurate inferences about model parameters.

As in [8], the Bonferroni Inequality used to provide upper and lower bounds for the probability of a union of a sequence of events $A_1, A_2, \ldots, A_n$ is given by

$$\sum_{i=1}^{n} P(A_i) - \sum_{i=1}^{n} \sum_{j>i}^{n} P(A_i \cap A_j) \leq P\left(\bigcup_{i=1}^{n} A_i\right) \leq \sum_{i=1}^{n} P(A_i)$$

[2] and [8] provided a means with which to tighten the upper bound in the above equation with the help of a spanning tree. This obtained

$$P\left(\bigcup_{i=1}^{n} A_i\right) \leq \sum_{i=1}^{n} P\left(A_i\right) - \sum_{(i,j)\in\tau} P\left(A_i \cap A_j\right)$$

where $\tau$ is a tree in a family of graphs G. G is formed by the set of nodes $A_i$, $i = 1, \ldots, n$ and the set of branches is given by the intersections $(A_i \cap A_j)$. In order to utilize this tightened upper bound in the creation of the more efficient SCBs, a constant $c$ that equates the right hand side to $\alpha$ has to be chosen. Since equality is not always a possibility, for a single optimal spanning tree $\tau$, different values of $c$ have to be evaluated and the value that makes the right hand side as close to $\alpha$ as possible is chosen.

Using the setup discussed in section 2.5, [6] describes the estimation of $\hat{\boldsymbol{\beta}}$ for a known $\boldsymbol{\theta}$, a $q \times 1$ vector of unknown parameters, using the least-squares estimator,

$$\hat{\boldsymbol{\beta}} \equiv \hat{\boldsymbol{\beta}}\left(\boldsymbol{\theta}\right) = \left(\mathbf{X}'\mathbf{V}(\boldsymbol{\theta})^{-\mathbf{1}}\mathbf{X}\right)^{-\mathbf{1}}\mathbf{X}'\mathbf{V}(\boldsymbol{\theta})^{-\mathbf{1}}\mathbf{Y}$$

Also, $f(t)$ can be estimated through

$$\hat{f}(t) = \sum_{k=0}^{q} \hat{\beta}_k x_k(t) = \mathbf{x}(t)\hat{\boldsymbol{\beta}}\left(\boldsymbol{\theta}\right) \equiv \mathbf{l}\left(t, \boldsymbol{\theta}\right)'\mathbf{Y} = \sum_{i=1}^{n} \mathbf{l}_i\left(t, \boldsymbol{\theta}\right)'\mathbf{Y}_i$$

From this, $\mathrm{Var}\{\hat{f}(t)\} = \mathbf{l}\left(t, \boldsymbol{\theta}\right)'\boldsymbol{V}\mathbf{l}\left(t, \boldsymbol{\theta}\right) = \|\mathbf{l}^V\left(t, \boldsymbol{\theta}\right)\|^2$, where $\mathbf{l}^V\left(t, \boldsymbol{\theta}\right) = \mathbf{L}'\left(\boldsymbol{\theta}\right)\mathbf{l}\left(\mathbf{t}, \boldsymbol{\theta}\right)$. Here, $\mathbf{L}\left(\boldsymbol{\theta}\right)$ is obtained from $\mathbf{L}\left(\boldsymbol{\theta}\right)\mathbf{L}'\left(\boldsymbol{\theta}\right) = \mathbf{V}\left(\boldsymbol{\theta}\right)$, the Cholesky decomposition of $\mathbf{V}$. Finally,

$$\|\mathbf{l}^V\left(t, \boldsymbol{\theta}\right)\|^2 = \mathbf{l}\left(t, \boldsymbol{\theta}\right)'\mathbf{V}\left(\boldsymbol{\theta}\right)\mathbf{l}\left(t, \boldsymbol{\theta}\right) = \mathbf{x}(t)'\{\mathbf{X}'\mathbf{V}(\boldsymbol{\theta})^{-\mathbf{1}}\mathbf{X}\}^{-1}\mathbf{x}(t)$$

An SCB suited to the model with known parameters described would be of the form,

$$\left(\hat{f}(t) - c\sigma\|\mathbf{l}^V\left(t, \boldsymbol{\theta}\right)\|, \hat{f}(t) + c\sigma\|\mathbf{l}^V\left(t, \boldsymbol{\theta}\right)\|\right)$$

We are resigned to the fact that parameters in models are unknown, so for unknown

$\sigma^2$ and $\boldsymbol{\theta}$ replacement with MLE or REML estimators $\hat{\sigma}^2$ and $\hat{\boldsymbol{\theta}}$ is warranted. The SCB shown above then becomes,

$$\left(\hat{f}(t) - c\hat{\sigma}\|\mathbf{l}^V(t,\hat{\boldsymbol{\theta}})\|, \hat{f}(t) + c\hat{\sigma}\|\mathbf{l}^V(t,\hat{\boldsymbol{\theta}})\|\right)$$

## 3.2 Simulation: Compound Symmetry

In order to compare the more efficient minimal spanning tree SCBs with those of Bonferroni, a mixed effects model with a compound symmetric correlation structure was simulated and empirical error rates obtained. In a similar fashion to [6], evenly spaced time points $t_{ij}$ from $(-0.50, 0.50)$ were used for $n = 20$ patients simulated giving $p = 5$. $\beta_0 = 1, \beta_1 = 10$ were parameter values to be estimated for the growth curve $f(t_{ij}) = \beta_0 + \beta_1 t_{ij}$. Also as in [6], setting $\mathbf{Z}_i = \mathbf{1}_p$ gave a $\mathbf{V}_i = \sigma^2\mathbf{I}_p + \sigma_a^2\mathbf{1}_p\mathbf{1}_p'$ with $\sigma^2 = 1$, $\sigma_a^2$ the variance of the random intercept, and $R = \frac{\sigma_a^2}{\sigma^2} = 1$. Here $\mathbf{1}_p$ is a vector of ones and $\mathbf{I}_p$ is a $p \times p$ identity matrix. The overall covariance matrix $\mathbf{V}$ is given by the following form for a compound symmetric covariance structure:

$$\mathbf{V} = \begin{pmatrix} \sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 \\ & \sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 \\ & & \sigma^2 & \sigma_a^2+\sigma^2 & \sigma_a^2+\sigma^2 \\ & & & \sigma^2 & \sigma_a^2+\sigma^2 \\ & & & & \sigma^2 \end{pmatrix}$$

An LMM was fitted to randomly generated multivariate normal data with mean $\mathbf{0}$ and covariance matrix $\mathbf{V}$ in each of 1000 simulations, to estimate the $\beta$ coefficients for data with covariance matrices obtained using correlation values $\rho = \{0.0, 0.5, 0.9\}$. The LMM used time as a fixed effect predicting factor and used variation between subjects as the random effects. Using the estimated coefficients and extracted standard errors from the models, confidence bounds were created for each of the coefficients using both the Bon-

ferroni technique for multiple comparisons as well as the minimal spanning tree method derived by [2] and [8]. A variable was created to calculate the number of times the true coefficient was captured by the confidence bounds in both instances. Next, the percentage of times the confidence bounds captured all five of the true coefficients using either method was calculated. Empirical error rates were obtained by subtracting the percentage of complete coverage from 100%. In order to determine values that are statistically equivalent to 0.95, confidence bounds must be created around the value 0.95. These bounds are given by the standard confidence bound calculations for population proportions, i.e. $0.95 \pm z_{0.025}\sqrt{\frac{(0.95)(0.05)}{1000}} = (0.936, 0.963)$.

A table containing the empirical coverage rate results for the LMM method is shown below. All of the multiplicity corrected bounds below are conservative in nature.

Table 3.1: Comparing Bonferroni v/s Hunter-Worsley SCB (LMM)

| $\rho$ | 0.0 | 0.5 | 0.9 |
|---|---|---|---|
| Bonferroni | 98.8 | 98.0 | 97.9 |
| Hunter-Worsley | 98.8 | 97.8 | 97.2 |

In a similar fashion, the GEE methodology was also employed with an assumed exchangeable correlation structure, and the empirical error rates calculated. Using GEEs, all SCBs' empirical coverage rates except for the Bonferroni SCB at the correlation value of 0.9 are within the bounds created for 0.95. The empirical coverage rates for the GEE method are as follows:

Table 3.2: Comparing Bonferroni v/s Hunter-Worsley SCB (GEE)

| $\rho$ | 0.0 | 0.5 | 0.9 |
|---|---|---|---|
| Bonferroni | 96.2 | 95.8 | 97.2 |
| Hunter-Worsley | 96.0 | 94.8 | 96.2 |

## 3.3 Conclusions for Hunter-Worsley Simulations

The Hunter-Worsley SCBs do not perform significantly better than Bonferroni SCBs for both the LMM and GEE methods at lower correlation values but have an advantage over Bonferroni at the correlation value of 0.9. An important observation is that a reduction in the conservative nature of the bounds can be observed from using the GEE method. The robust standard errors obtained using the GEE method help bring the empirical error rates much closer to the desired value of 0.95. Thus, GEE models should be utilized, when a need for multiplicity correcting SCBs in longitudinal data analysis exists.

# Chapter 4

# Application of Improved SCBs to Alcohol Research

In this chapter, a description of the application of the efficient SCBs to current alcohol research being conducted within the Latino Alcohol & Health Disparities Research (LAHDR) Center is described. The moderation effect between mental health indicators (MHIs) such as injury-related PTSD and suicidal tendencies on the efficacy of three brief alcohol interventions (BA: Brief Advice, BMI: Brief Motivational Intervention, BMI-B: BMI with telephone booster session) to help treat alcohol abuse was investigated. Further, comparisons were made to evaluate if significant differences, between the treatment groups, could be observed in the alcohol consumption of participants.

## 4.1 Background

LAHDR is actively involved in a variety of alcohol-based research and is in the continual pursuit of excellence in helping curb problematic alcohol consumption within the community. The data used in this study was obtained from $n = 596$ injured patients who were treated within three Level I trauma centers in the United States. [1] describes all of the following selection criteria and assignment to groups in the study. The patients were screened for heavy drinking and then randomly assigned to one of the three treatments described above. 200 patients were assigned to the BA group, 203 to the BMI group, and 193 to the BMI-B group. 76.51% of the patients were male, and 28.86% of them were Latino. The efficacies of the interventions were assessed for three drinking outcomes: The average

number of drinks consumed in a week (ADW), the maximum number of drinks consumed on one drinking occasion (MAXD), and the percentage of days of heavy drinking (PDH). Measurements were carried out at baseline, three months, and six months.

In order to classify patients as having injury-related PTSD, patients were asked two questions relating to the symptoms of the extreme trauma they experienced after their injury. If the patient answered positively to both questions, he or she was assessed to be showing symptoms of injury-related PTSD. For the data analysis, injury-related PTSD was classified as a binary covariate. 318 participants were diagnosed as having injury-related PTSD in this study.

Similarly, four questions in the survey were concerned with determining the extent of a patient's suicidal tendencies. Based on the number of positive answers, the patient's suicidal tendencies were classified. If a patient answered no to the first question he/ she was determined to have no suicidal tendencies. Similarly in incremental levels, suicide level 1 was determined if the patient ever thought he/ she would be better off dead, and suicide level 2 was determined if the patient ever though of committing suicide. Suicide level 3 was determined if the patient ever made a suicide plan, and level 4 was determined if the patient ever executed the suicide plan. Patients who answered "don't know"or those who refused to answer a question were assigned a value of NA for that particular question. The counts of the various levels of suicide are given below in table 4.1. Since levels 3 and 4 of suicidal tendencies had small counts compared to those of levels 0, 1, & 2, they were combined into a single level for more robustness of the statistical model's capability to detect differences between the various treatments considered.

Table 4.1: Frequencies of Suicidal Tendency Levels

| Suicidal Tendency | Frequency |
|---|---|
| 0 | 1526 |
| 1 | 105 |
| 2 | 70 |
| 3 | 40 |
| 4 | 47 |

Using input from the head of the LAHDR group, Dr. Craig Field, controlled covariates for all of the models run were chosen. Fixed effects in the models were chosen from covariates such as the number of prior injuries and demographics such as age, gender, and ethnicity. Random variation between patients and the sites of recruitment were treated as random effects in the models. For each of the models used to determine effects on drinking outcomes, an incremental approach was used to add covariates into them. At each step, the model with the smallest AIC was chosen, and an additional covariate added. When no further covariates could be added without increasing the AIC, the process stopped, and the final model for data analysis was picked. Also added into each of the models were the effects of time interacting with the treatments, to allow for a changing slope of the lines connecting the response values at the three different time-points. All comparisons and testing were carried out at the 0.05 significance level. Furthermore, contrasts for differences were created by eliminating the values for gender, ethnicity and the number of prior injuries, to enable the comparisons to be carried out over all genders, ethnicities and injury values.

## 4.2 Describing the Comparison Contrasts

The contrast matrix for the comparison of differences between treatments at the various time-points was calculated by conducting differences between estimates of the means of the model parameters. An example is as follows: In order to compare the differences between the BMI-B and the BMI group for a patient having PTSD at the 3 month time-point, the following calculation was carried out: $\mu_{(3Mo,PTSD,BMI-B)} - \mu_{(3Mo,PTSD,BMI)}$

$= (\beta_0 + \beta_{3Mo} + \beta_{PTSD} + \beta_{BMI-B} + \beta_{3Mo*BMI-B} + \beta_{PTSD*BMI-B}) -$

$(\beta_0 + \beta_{3Mo} + \beta_{PTSD} + \beta_{BMI} + \beta_{3Mo*BMI} + \beta_{PTSD*BMI})$

$= (\beta_{BMI-B} - \beta_{BMI}) + (\beta_{3Mo*BMI-B} - \beta_{3Mo*BMI}) + (\beta_{PTSD*BMI-B} - \beta_{PTSD*BMI})$

The parameters $\mu_{(3Mo,PTSD,BMI-B)}$ and $\mu_{(3Mo,PTSD,BMI)}$ can be estimated using their corresponding model estimates, $\hat{\mu}_{(3Mo,PTSD,BMI-B)}$ and $\hat{\mu}_{(3Mo,PTSD,BMI)}$.

Contrasts for the suicidal tendencies and for PTSD were also designed in order to

facilitate the comparison to a control group (a patient in the BA group at each of the time-points with no suicidal tendencies / no PTSD) in order to reduce the number of possible comparisons and determine how much of an effect time had on the efficacy of the treatments alongside the effects of the mental health indicators. An example of one of the contrasts comparing the difference in a drinking outcome for patient with PTSD in the BMI-B group at 3 months with control group (Patient in BA at 3 months with no PTSD) is as follows:

$$\mu_{(3Mo,PTSD,BMI-B)} - \mu_{(3Mo,NoPTSD,BA)}$$
$$= (\beta_0 + \beta_{3Mo} + \beta_{PTSD} + \beta_{BMI-B} + \beta_{3Mo*BMI-B} + \beta_{PTSD*BMI-B}) - (\beta_0 + \beta_{3Mo})$$
$$= (\beta_{PTSD} + \beta_{BMI-B} + \beta_{3Mo*BMI-B} + \beta_{PTSD*BMI-B}).$$

## 4.3 Efficacy of Treatments on Average Number of Drinks per Week (ADW)

### 4.3.1 Effect of PTSD on Treatments for ADW

In the model analyzing the effect of PTSD on the treatments for average number of drinks consumed in a week, a model predicted by gender and ethnicity obtained the smallest AIC. To determine the moderation effect of PTSD on the treatments for ADW, a term involving the study groups' interactions with the binary PTSD variable was also included. The model showed no significant interaction between PTSD and the treatments at the 0.05 level. Since no significant interaction was observed, the term corresponding to the interaction was removed from the model and the model rerun, thereby obtaining the following results.

No significant differences were found in table 4.2 for any of the treatments at any time-points.

When comparing to the control group (patients in the BA group at each time-point with no PTSD) in table 4.3, no significant differences were observed for any of the treatments at any of the time-points.

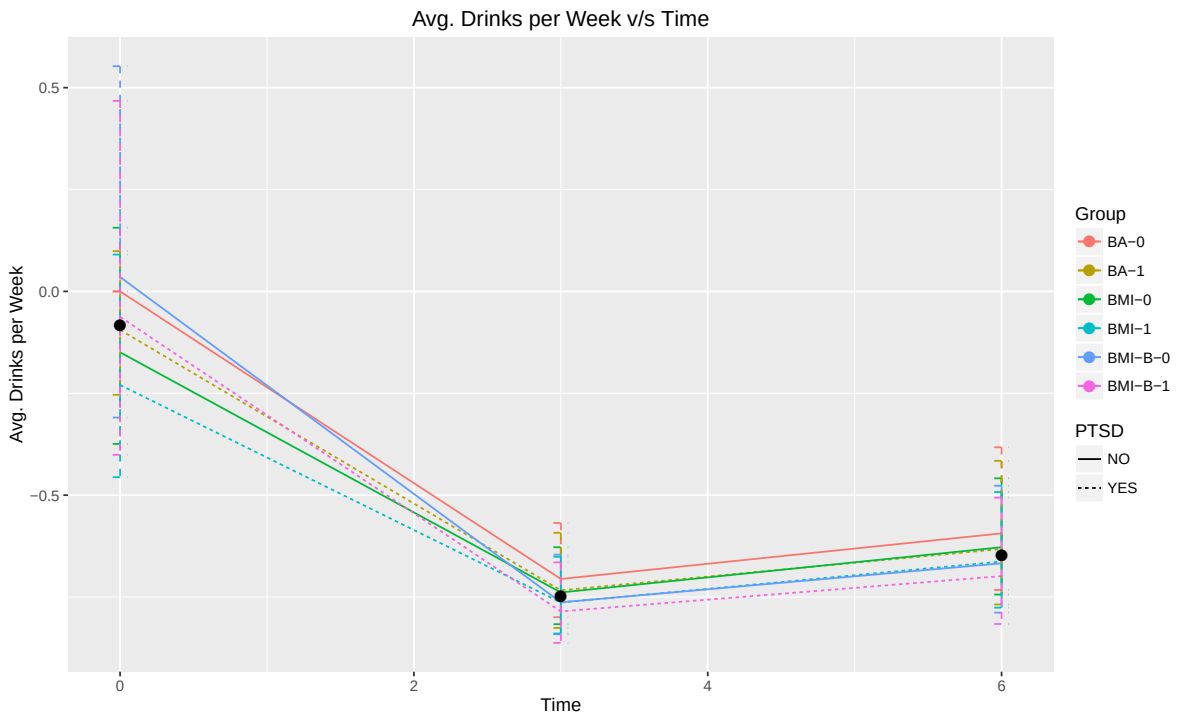


Figure 4.1: ADW Growth Curves for Levels of PTSD

Table 4.2: Differences in ADW for PTSD

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.149 | 0.103 | -0.374 | 0.156 | -0.375 | 0.158 | 0 | BMI-BA(0) | |
| 2 | 0.035 | 0.135 | -0.310 | 0.553 | -0.311 | 0.555 | 0 | BMIB-BA(0) | |
| 3 | 0.217 | 0.129 | -0.172 | 0.789 | -0.173 | 0.791 | 0 | BMIB-BMI(0) | |
| 4 | -0.149 | 0.103 | -0.374 | 0.156 | -0.375 | 0.158 | 0 | BMI-BA(1) | |
| 5 | 0.035 | 0.135 | -0.310 | 0.553 | -0.311 | 0.555 | 0 | BMIB-BA(1) | |
| 6 | 0.217 | 0.129 | -0.172 | 0.789 | -0.173 | 0.791 | 0 | BMIB-BMI(1) | |
| 7 | -0.112 | 0.135 | -0.407 | 0.328 | -0.407 | 0.330 | 3 | BMI-BA(0) | |
| 8 | -0.195 | 0.149 | -0.484 | 0.256 | -0.485 | 0.259 | 3 | BMIB-BA(0) | |
| 9 | -0.093 | 0.140 | -0.404 | 0.381 | -0.405 | 0.384 | 3 | BMIB-BMI(0) | |
| 10 | -0.112 | 0.135 | -0.407 | 0.328 | -0.407 | 0.330 | 3 | BMI-BA(1) | |
| 11 | -0.195 | 0.149 | -0.484 | 0.256 | -0.485 | 0.259 | 3 | BMIB-BA(1) | |
| 12 | -0.093 | 0.140 | -0.404 | 0.381 | -0.405 | 0.384 | 3 | BMIB-BMI(1) | |
| 13 | -0.084 | 0.152 | -0.418 | 0.442 | -0.419 | 0.445 | 6 | BMI-BA(0) | |
| 14 | -0.181 | 0.174 | -0.513 | 0.377 | -0.514 | 0.379 | 6 | BMIB-BA(0) | |
| 15 | -0.106 | 0.162 | -0.449 | 0.451 | -0.450 | 0.454 | 6 | BMIB-BMI(0) | |
| 16 | -0.084 | 0.152 | -0.418 | 0.442 | -0.419 | 0.445 | 6 | BMI-BA(1) | |
| 17 | -0.181 | 0.174 | -0.513 | 0.377 | -0.514 | 0.379 | 6 | BMIB-BA(1) | |
| 18 | -0.106 | 0.162 | -0.449 | 0.451 | -0.450 | 0.454 | 6 | BMIB-BMI(1) | |

Table 4.3: Comparison of ADW to Control Group for PTSD

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | -0.149 | 0.103 | -0.374 | 0.156 | 0 | BMI(0)-BA(0) | |
| 2 | 0.035 | 0.135 | -0.310 | 0.553 | 0 | BMIB(0)-BA(0) | |
| 3 | -0.094 | 0.065 | -0.254 | 0.099 | 0 | BA(1)-BA(0) | |
| 4 | -0.230 | 0.116 | -0.456 | 0.090 | 0 | BMI(1)-BA(0) | |
| 5 | -0.062 | 0.150 | -0.401 | 0.468 | 0 | BMIB(1)-BA(0) | |
| 6 | -0.112 | 0.135 | -0.407 | 0.328 | 3 | BMI(0)-BA(0) | |
| 7 | -0.195 | 0.149 | -0.484 | 0.256 | 3 | BMIB(0)-BA(0) | |
| 8 | -0.094 | 0.065 | -0.254 | 0.099 | 3 | BA(1)-BA(0) | |
| 9 | -0.196 | 0.146 | -0.481 | 0.245 | 3 | BMI(1)-BA(0) | |
| 10 | -0.271 | 0.163 | -0.553 | 0.189 | 3 | BMIB(1)-BA(0) | |
| 11 | -0.084 | 0.152 | -0.418 | 0.442 | 6 | BMI(0)-BA(0) | |
| 12 | -0.181 | 0.174 | -0.513 | 0.377 | 6 | BMIB(0)-BA(0) | |
| 13 | -0.094 | 0.065 | -0.254 | 0.099 | 6 | BA(1)-BA(0) | |
| 14 | -0.170 | 0.161 | -0.487 | 0.343 | 6 | BMI(1)-BA(0) | |
| 15 | -0.258 | 0.186 | -0.574 | 0.292 | 6 | BMIB(1)-BA(0) | |

### 4.3.2 Effect of Suicidal Tendencies on Treatments for ADW

In the model analyzing the effect of reduced suicidal tendencies (levels 0,1,2,3) on the treatments for average number of drinks consumed in a week, a model predicted by gender and ethnicity obtained the smallest AIC. To determine the moderation effect of the suicidal tendencies on the treatments for ADW, a term involving the study groups' interactions with the four-level suicidal tendency variable was also included. The model showed no significant interaction between the suicidal tendencies and treatments for ADW at the 0.05 level. Again, the interaction term was dropped and the model rerun, obtaining the results below.

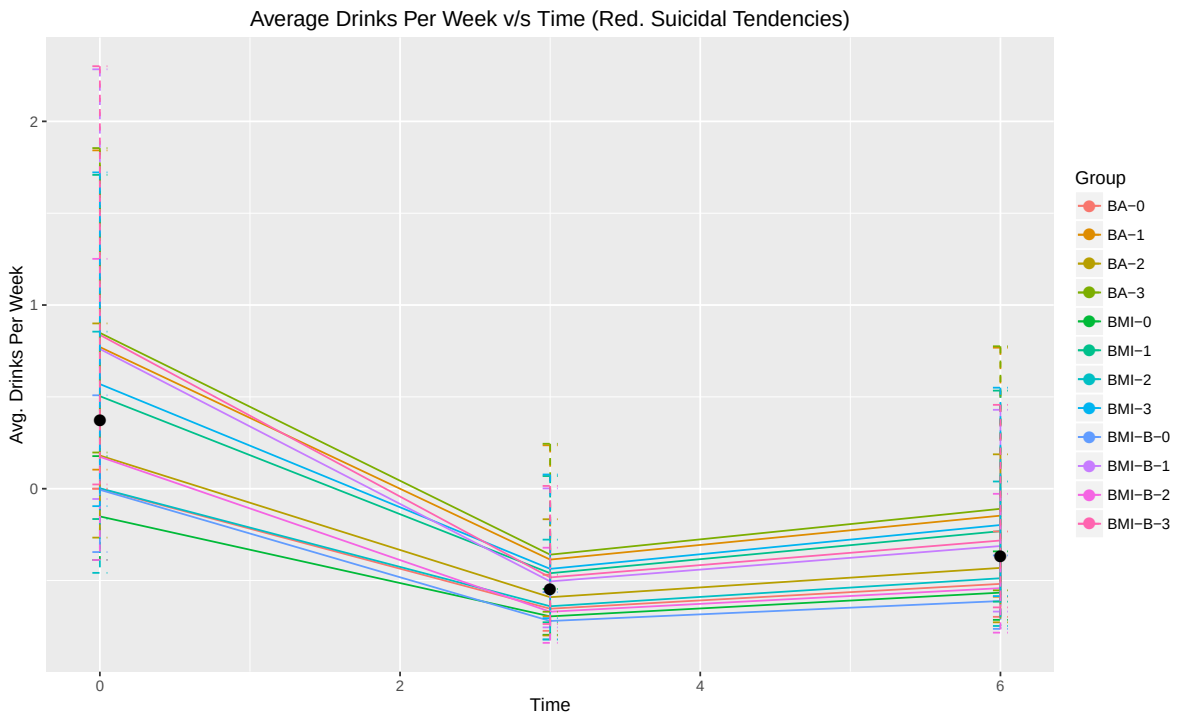


Figure 4.2: ADW Growth Curves for Levels of Suicidal Tendencies

No significant differences were found in table 4.4 between all treatments at all time-points.

When comparing the ADW values to those of the control group (patients in BA at each time-point with no suicidal tendencies) in table 4.5, patients in the BA group at suicide levels 1 and 3 consistently showed significantly higher levels of ADW at all time-points.

Table 4.4: Differences in ADW for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Study Group | Sig. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.151 | 0.102 | -0.388 | 0.177 | -0.389 | 0.179 | 0 | BMI-BA(0) | |
| 2 | -0.006 | 0.130 | -0.345 | 0.509 | -0.346 | 0.511 | 0 | BMIB-BA(0) | |
| 3 | 0.171 | 0.123 | -0.211 | 0.737 | -0.212 | 0.740 | 0 | BMIB-BMI(0) | |
| 4 | -0.151 | 0.102 | -0.388 | 0.177 | -0.389 | 0.179 | 0 | BMI-BA(1) | |
| 5 | -0.006 | 0.130 | -0.345 | 0.509 | -0.346 | 0.511 | 0 | BMIB-BA(1) | |
| 6 | 0.171 | 0.123 | -0.211 | 0.737 | -0.212 | 0.740 | 0 | BMIB-BMI(1) | |
| 7 | -0.151 | 0.102 | -0.388 | 0.177 | -0.389 | 0.179 | 0 | BMI-BA(2) | |
| 8 | -0.006 | 0.130 | -0.345 | 0.509 | -0.346 | 0.511 | 0 | BMIB-BA(2) | |
| 9 | 0.171 | 0.123 | -0.211 | 0.737 | -0.212 | 0.740 | 0 | BMIB-BMI(2) | |
| 10 | -0.151 | 0.102 | -0.388 | 0.177 | -0.389 | 0.179 | 0 | BMI-BA(3) | |
| 11 | -0.006 | 0.130 | -0.345 | 0.509 | -0.346 | 0.511 | 0 | BMIB-BA(3) | |
| 12 | 0.171 | 0.123 | -0.211 | 0.737 | -0.212 | 0.740 | 0 | BMIB-BMI(3) | |
| 13 | -0.121 | 0.133 | -0.426 | 0.347 | -0.427 | 0.350 | 3 | BMI-BA(0) | |
| 14 | -0.193 | 0.148 | -0.498 | 0.295 | -0.499 | 0.298 | 3 | BMIB-BA(0) | |
| 15 | -0.083 | 0.140 | -0.414 | 0.435 | -0.415 | 0.438 | 3 | BMIB-BMI(0) | |
| 16 | -0.121 | 0.133 | -0.426 | 0.347 | -0.427 | 0.350 | 3 | BMI-BA(1) | |
| 17 | -0.193 | 0.148 | -0.498 | 0.295 | -0.499 | 0.298 | 3 | BMIB-BA(1) | |
| 18 | -0.083 | 0.140 | -0.414 | 0.435 | -0.415 | 0.438 | 3 | BMIB-BMI(1) | |
| 19 | -0.121 | 0.133 | -0.426 | 0.347 | -0.427 | 0.350 | 3 | BMI-BA(2) | |
| 20 | -0.193 | 0.148 | -0.498 | 0.295 | -0.499 | 0.298 | 3 | BMIB-BA(2) | |
| 21 | -0.083 | 0.140 | -0.414 | 0.435 | -0.415 | 0.438 | 3 | BMIB-BMI(2) | |
| 22 | -0.121 | 0.133 | -0.426 | 0.347 | -0.427 | 0.350 | 3 | BMI-BA(3) | |
| 23 | -0.193 | 0.148 | -0.498 | 0.295 | -0.499 | 0.298 | 3 | BMIB-BA(3) | |
| 24 | -0.083 | 0.140 | -0.414 | 0.435 | -0.415 | 0.438 | 3 | BMIB-BMI(3) | |
| 25 | -0.099 | 0.150 | -0.443 | 0.456 | -0.444 | 0.460 | 6 | BMI-BA(0) | |
| 26 | -0.194 | 0.172 | -0.535 | 0.399 | -0.537 | 0.402 | 6 | BMIB-BA(0) | |
| 27 | -0.105 | 0.160 | -0.464 | 0.493 | -0.465 | 0.497 | 6 | BMIB-BMI(0) | |
| 28 | -0.099 | 0.150 | -0.443 | 0.456 | -0.444 | 0.460 | 6 | BMI-BA(1) | |
| 29 | -0.194 | 0.172 | -0.535 | 0.399 | -0.537 | 0.402 | 6 | BMIB-BA(1) | |
| 30 | -0.105 | 0.160 | -0.464 | 0.493 | -0.465 | 0.497 | 6 | BMIB-BMI(1) | |
| 31 | -0.099 | 0.150 | -0.443 | 0.456 | -0.444 | 0.460 | 6 | BMI-BA(2) | |
| 32 | -0.194 | 0.172 | -0.535 | 0.399 | -0.537 | 0.402 | 6 | BMIB-BA(2) | |
| 33 | -0.105 | 0.160 | -0.464 | 0.493 | -0.465 | 0.497 | 6 | BMIB-BMI(2) | |
| 34 | -0.099 | 0.150 | -0.443 | 0.456 | -0.444 | 0.460 | 6 | BMI-BA(3) | |
| 35 | -0.194 | 0.172 | -0.535 | 0.399 | -0.537 | 0.402 | 6 | BMIB-BA(3) | |
| 36 | -0.105 | 0.160 | -0.464 | 0.493 | -0.465 | 0.497 | 6 | BMIB-BMI(3) | |

Table 4.5: Comparison of ADW to Control Group for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | -0.151 | 0.102 | -0.388 | 0.177 | 0 | BMI(0)-BA(0) | |
| 2 | -0.006 | 0.130 | -0.345 | 0.509 | 0 | BMIB(0)-BA(0) | |
| 3 | 0.771 | 0.148 | 0.104 | 1.842 | 0 | BA(1)-BA(0) | * |
| 4 | 0.504 | 0.184 | -0.165 | 1.709 | 0 | BMI(1)-BA(0) | |
| 5 | 0.761 | 0.195 | -0.056 | 2.283 | 0 | BMIB(1)-BA(0) | |
| 6 | 0.181 | 0.149 | -0.266 | 0.900 | 0 | BA(2)-BA(0) | |
| 7 | 0.003 | 0.193 | -0.458 | 0.855 | 0 | BMI(2)-BA(0) | |
| 8 | 0.174 | 0.204 | -0.388 | 1.251 | 0 | BMIB(2)-BA(0) | |
| 9 | 0.849 | 0.136 | 0.197 | 1.855 | 0 | BA(3)-BA(0) | * |
| 10 | 0.570 | 0.172 | -0.095 | 1.722 | 0 | BMI(3)-BA(0) | |
| 11 | 0.838 | 0.183 | 0.023 | 2.300 | 0 | BMIB(3)-BA(0) | |
| 12 | -0.121 | 0.133 | -0.426 | 0.347 | 3 | BMI(0)-BA(0) | |
| 13 | -0.193 | 0.148 | -0.498 | 0.295 | 3 | BMIB(0)-BA(0) | |
| 14 | 0.771 | 0.148 | 0.104 | 1.842 | 3 | BA(1)-BA(0) | * |
| 15 | 0.557 | 0.199 | -0.176 | 1.945 | 3 | BMI(1)-BA(0) | |
| 16 | 0.429 | 0.207 | -0.263 | 1.768 | 3 | BMIB(1)-BA(0) | |
| 17 | 0.181 | 0.149 | -0.266 | 0.900 | 3 | BA(2)-BA(0) | |
| 18 | 0.038 | 0.201 | -0.453 | 0.972 | 3 | BMI(2)-BA(0) | |
| 19 | -0.048 | 0.209 | -0.512 | 0.859 | 3 | BMIB(2)-BA(0) | |
| 20 | 0.849 | 0.136 | 0.197 | 1.855 | 3 | BA(3)-BA(0) | * |
| 21 | 0.625 | 0.191 | -0.118 | 1.995 | 3 | BMI(3)-BA(0) | |
| 22 | 0.491 | 0.201 | -0.215 | 1.831 | 3 | BMIB(3)-BA(0) | |
| 23 | -0.099 | 0.150 | -0.443 | 0.456 | 6 | BMI(0)-BA(0) | |
| 24 | -0.194 | 0.172 | -0.535 | 0.399 | 6 | BMIB(0)-BA(0) | |
| 25 | 0.771 | 0.148 | 0.104 | 1.842 | 6 | BA(1)-BA(0) | * |
| 26 | 0.596 | 0.208 | -0.180 | 2.105 | 6 | BMI(1)-BA(0) | |
| 27 | 0.428 | 0.222 | -0.298 | 1.903 | 6 | BMIB(1)-BA(0) | |
| 28 | 0.181 | 0.149 | -0.266 | 0.900 | 6 | BA(2)-BA(0) | |
| 29 | 0.064 | 0.212 | -0.459 | 1.092 | 6 | BMI(2)-BA(0) | |
| 30 | -0.048 | 0.227 | -0.539 | 0.964 | 6 | BMIB(2)-BA(0) | |
| 31 | 0.849 | 0.136 | 0.197 | 1.855 | 6 | BA(3)-BA(0) | * |
| 32 | 0.665 | 0.203 | -0.128 | 2.182 | 6 | BMI(3)-BA(0) | |
| 33 | 0.490 | 0.219 | -0.259 | 1.998 | 6 | BMIB(3)-BA(0) | |

## 4.4 Efficacy of Treatments on Maximum Number of Drinks on a Drinking Occasion (MAXD)

### 4.4.1 Effect of PTSD on Treatments for MAXD

In the model analyzing the effect of PTSD on the treatments for MAXD, a model predicted by gender and number of injuries obtained the smallest AIC. To determine the moderation effect of PTSD on the treatments for MAXD, a term involving the study groups' interactions with the binary PTSD variable was also included. The model showed a significant negative interaction (z=-1.84) between the BMI group and PTSD for MAXD at the 0.05 significance level.

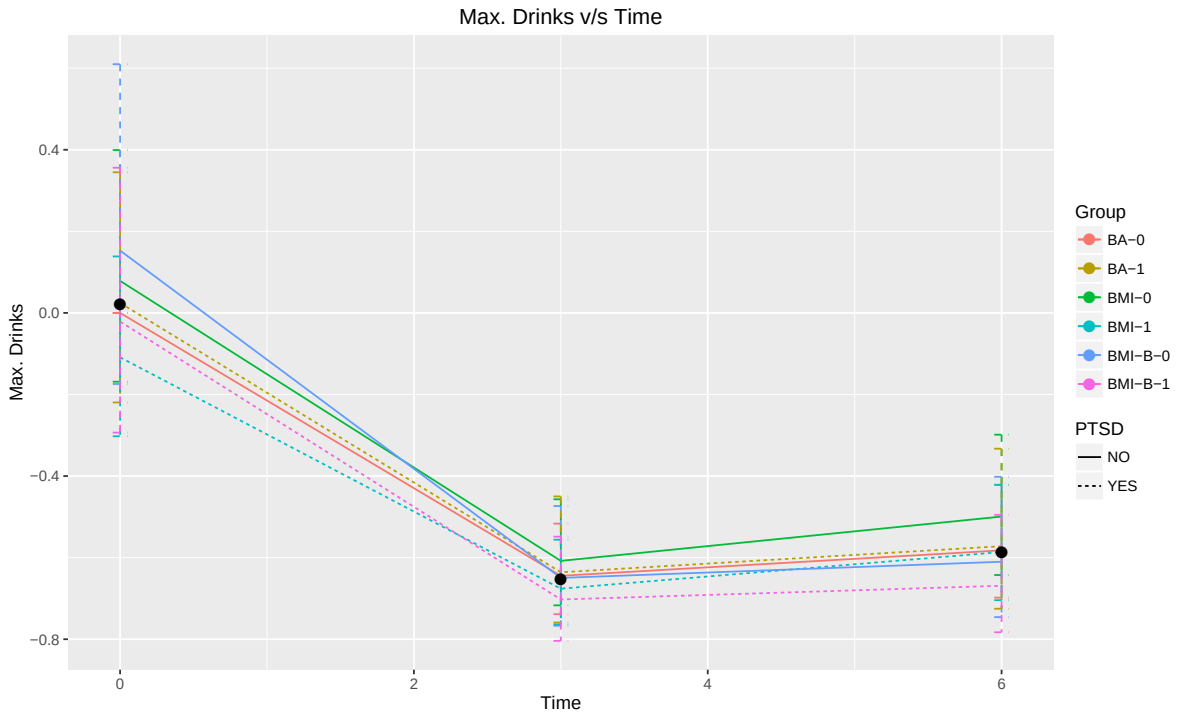


Figure 4.3: MAXD Growth Curves for Levels of PTSD

Table 4.6: Differences in MAXD for PTSD

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Study Group | Significant |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.079 | 0.087 | -0.169 | 0.399 | -0.169 | 0.399 | 0 | BMI-BA(0) | |
| 2 | 0.153 | 0.111 | -0.174 | 0.610 | -0.174 | 0.610 | 0 | BMIB-BA(0) | |
| 3 | 0.069 | 0.108 | -0.227 | 0.479 | -0.227 | 0.479 | 0 | BMIB-BMI(0) | |
| 4 | -0.130 | 0.082 | -0.321 | 0.114 | -0.321 | 0.114 | 0 | BMI-BA(1) | |
| 5 | -0.045 | 0.110 | -0.313 | 0.328 | -0.313 | 0.328 | 0 | BMIB-BA(1) | |
| 6 | 0.098 | 0.101 | -0.189 | 0.487 | -0.189 | 0.487 | 0 | BMIB-BMI(1) | |
| 7 | 0.103 | 0.134 | -0.262 | 0.648 | -0.262 | 0.648 | 3 | BMI-BA(0) | |
| 8 | -0.014 | 0.156 | -0.384 | 0.577 | -0.384 | 0.577 | 3 | BMIB-BA(0) | |
| 9 | -0.107 | 0.149 | -0.429 | 0.397 | -0.428 | 0.397 | 3 | BMIB-BMI(0) | |
| 10 | -0.110 | 0.132 | -0.401 | 0.321 | -0.401 | 0.321 | 3 | BMI-BA(1) | |
| 11 | -0.183 | 0.161 | -0.496 | 0.324 | -0.496 | 0.323 | 3 | BMIB-BA(1) | |
| 12 | -0.082 | 0.148 | -0.412 | 0.433 | -0.412 | 0.433 | 3 | BMIB-BMI(1) | |
| 13 | 0.198 | 0.138 | -0.209 | 0.816 | -0.209 | 0.815 | 6 | BMI-BA(0) | |
| 14 | -0.067 | 0.163 | -0.429 | 0.525 | -0.429 | 0.525 | 6 | BMIB-BA(0) | |
| 15 | -0.221 | 0.157 | -0.514 | 0.249 | -0.514 | 0.249 | 6 | BMIB-BMI(0) | |
| 16 | -0.034 | 0.145 | -0.374 | 0.492 | -0.374 | 0.492 | 6 | BMI-BA(1) | |
| 17 | -0.227 | 0.169 | -0.534 | 0.283 | -0.534 | 0.283 | 6 | BMIB-BA(1) | |
| 18 | -0.200 | 0.155 | -0.497 | 0.274 | -0.497 | 0.274 | 6 | BMIB-BMI(1) | |

No significant differences were found in the MAXD values in table 4.6 between any of the treatments at any time-points.

When comparing to the control group (patient in the BA group at each time-point with no PTSD) in table 4.7, no significant differences were observed for any of the treatments at any of the time-points.

Table 4.7: Comparison of MAXD to Control Group for PTSD

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | 0.079 | 0.087 | -0.168 | 0.398 | 0 | BMI(0)-BA(0) | |
| 2 | 0.153 | 0.111 | -0.173 | 0.607 | 0 | BMIB(0)-BA(0) | |
| 3 | 0.024 | 0.091 | -0.219 | 0.343 | 0 | BA(1)-BA(0) | |
| 4 | -0.109 | 0.082 | -0.302 | 0.137 | 0 | BMI(1)-BA(0) | |
| 5 | -0.021 | 0.108 | -0.292 | 0.354 | 0 | BMIB(1)-BA(0) | |
| 6 | 0.103 | 0.134 | -0.260 | 0.645 | 3 | BMI(0)-BA(0) | |
| 7 | -0.014 | 0.156 | -0.383 | 0.574 | 3 | BMIB(0)-BA(0) | |
| 8 | 0.024 | 0.091 | -0.219 | 0.343 | 3 | BA(1)-BA(0) | |
| 9 | -0.089 | 0.131 | -0.383 | 0.347 | 3 | BMI(1)-BA(0) | |
| 10 | -0.163 | 0.159 | -0.480 | 0.348 | 3 | BMIB(1)-BA(0) | |
| 11 | 0.198 | 0.138 | -0.208 | 0.812 | 6 | BMI(0)-BA(0) | |
| 12 | -0.067 | 0.163 | -0.428 | 0.522 | 6 | BMIB(0)-BA(0) | |
| 13 | 0.024 | 0.091 | -0.219 | 0.343 | 6 | BA(1)-BA(0) | |
| 14 | -0.010 | 0.138 | -0.344 | 0.494 | 6 | BMI(1)-BA(0) | |
| 15 | -0.208 | 0.162 | -0.512 | 0.286 | 6 | BMIB(1)-BA(0) | |

### 4.4.2 Effect of Suicidal Tendencies on Treatments for MAXD

In the model analyzing the effect of reduced suicidal tendencies (levels 0,1,2,3) on the treatments for MAXD, a model predicted by gender and number of injuries obtained the smallest AIC. To determine the moderation effect of the suicidal tendencies on the treatments for MAXD, a term involving the study groups' interactions with the four-level suicidal tendency variable was also included. No significant interaction between the treatment groups and suicidal tendencies were observed for MAXD at the 0.05 significance level.

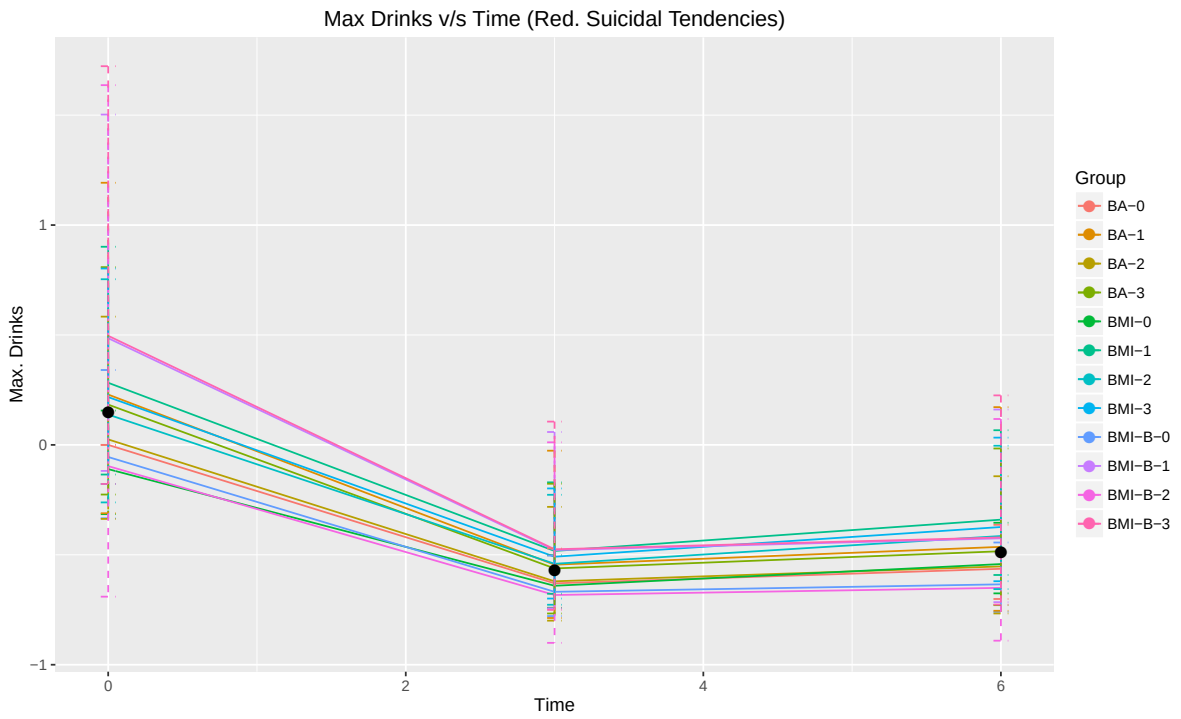


Figure 4.4: MAXD Growth Curves for Levels of Suicidal Tendencies

The treatment comparisons showed no significant differences in table 4.8 for any of the treatment groups at any of the observation time points.

When comparing the MAXD values of the treatments to the control group (patients in the BA group at each time-point with no suicidal tendencies) in table 4.9, no significant differences were observed for any of the treatments at any of the time-points.

Table 4.8: Differences in MAXD for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Study Group | Significant |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.110 | 0.082 | -0.316 | 0.158 | -0.316 | 0.157 | 0 | BMI-BA(0) | |
| 2 | -0.055 | 0.109 | -0.335 | 0.343 | -0.335 | 0.343 | 0 | BMIB-BA(0) | |
| 3 | 0.062 | 0.099 | -0.226 | 0.457 | -0.226 | 0.457 | 0 | BMIB-BMI(0) | |
| 4 | 0.044 | 0.188 | -0.430 | 0.911 | -0.430 | 0.911 | 0 | BMI-BA(1) | |
| 5 | 0.209 | 0.216 | -0.396 | 1.420 | -0.396 | 1.419 | 0 | BMIB-BA(1) | |
| 6 | 0.158 | 0.181 | -0.353 | 1.072 | -0.353 | 1.072 | 0 | BMIB-BMI(1) | |
| 7 | 0.110 | 0.166 | -0.349 | 0.895 | -0.349 | 0.895 | 0 | BMI-BA(2) | |
| 8 | -0.118 | 0.350 | -0.713 | 1.710 | -0.713 | 1.709 | 0 | BMIB-BA(2) | |
| 9 | -0.206 | 0.349 | -0.741 | 1.433 | -0.741 | 1.432 | 0 | BMIB-BMI(2) | |
| 10 | 0.029 | 0.150 | -0.364 | 0.666 | -0.364 | 0.666 | 0 | BMI-BA(3) | |
| 11 | 0.265 | 0.208 | -0.351 | 1.465 | -0.351 | 1.464 | 0 | BMIB-BA(3) | |
| 12 | 0.229 | 0.202 | -0.357 | 1.349 | -0.357 | 1.348 | 0 | BMIB-BMI(3) | |
| 13 | -0.030 | 0.119 | -0.339 | 0.423 | -0.339 | 0.422 | 3 | BMI-BA(0) | |
| 14 | -0.104 | 0.141 | -0.431 | 0.411 | -0.431 | 0.410 | 3 | BMIB-BA(0) | |
| 15 | -0.076 | 0.133 | -0.397 | 0.415 | -0.397 | 0.415 | 3 | BMIB-BMI(0) | |
| 16 | 0.138 | 0.238 | -0.471 | 1.446 | -0.471 | 1.446 | 3 | BMI-BA(1) | |
| 17 | 0.146 | 0.291 | -0.549 | 1.915 | -0.549 | 1.915 | 3 | BMIB-BA(1) | |
| 18 | 0.007 | 0.248 | -0.546 | 1.237 | -0.546 | 1.236 | 3 | BMIB-BMI(1) | |
| 19 | 0.210 | 0.219 | -0.402 | 1.449 | -0.402 | 1.448 | 3 | BMI-BA(2) | |
| 20 | -0.164 | 0.394 | -0.764 | 1.960 | -0.764 | 1.960 | 3 | BMIB-BA(2) | |
| 21 | -0.309 | 0.386 | -0.800 | 1.386 | -0.800 | 1.386 | 3 | BMIB-BMI(2) | |
| 22 | 0.122 | 0.207 | -0.423 | 1.180 | -0.423 | 1.179 | 3 | BMI-BA(3) | |
| 23 | 0.199 | 0.275 | -0.504 | 1.898 | -0.504 | 1.897 | 3 | BMIB-BA(3) | |
| 24 | 0.069 | 0.261 | -0.538 | 1.476 | -0.538 | 1.475 | 3 | BMIB-BMI(3) | |
| 25 | 0.049 | 0.129 | -0.306 | 0.588 | -0.306 | 0.588 | 6 | BMI-BA(0) | |
| 26 | -0.162 | 0.149 | -0.481 | 0.353 | -0.481 | 0.353 | 6 | BMIB-BA(0) | |
| 27 | -0.201 | 0.141 | -0.492 | 0.255 | -0.492 | 0.255 | 6 | BMIB-BMI(0) | |
| 28 | 0.231 | 0.246 | -0.442 | 1.715 | -0.442 | 1.715 | 6 | BMI-BA(1) | |
| 29 | 0.072 | 0.294 | -0.583 | 1.756 | -0.583 | 1.755 | 6 | BMIB-BA(1) | |
| 30 | -0.129 | 0.248 | -0.608 | 0.935 | -0.608 | 0.935 | 6 | BMIB-BMI(1) | |
| 31 | 0.310 | 0.225 | -0.365 | 1.700 | -0.365 | 1.700 | 6 | BMI-BA(2) | |
| 32 | -0.218 | 0.395 | -0.780 | 1.785 | -0.780 | 1.784 | 6 | BMIB-BA(2) | |
| 33 | -0.403 | 0.388 | -0.828 | 1.076 | -0.828 | 1.076 | 6 | BMIB-BMI(2) | |
| 34 | 0.214 | 0.213 | -0.388 | 1.407 | -0.388 | 1.407 | 6 | BMI-BA(3) | |
| 35 | 0.122 | 0.278 | -0.540 | 1.738 | -0.540 | 1.738 | 6 | BMIB-BA(3) | |
| 36 | -0.076 | 0.264 | -0.605 | 1.161 | -0.605 | 1.161 | 6 | BMIB-BMI(3) | |

Table 4.9: Comparison of MAXD to Control Group for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | -0.110 | 0.082 | -0.315 | 0.156 | 0 | BMI(0)-BA(0) | |
| 2 | -0.055 | 0.109 | -0.334 | 0.341 | 0 | BMIB(0)-BA(0) | |
| 3 | 0.229 | 0.181 | -0.311 | 1.192 | 0 | BA(1)-BA(0) | |
| 4 | 0.282 | 0.123 | -0.135 | 0.901 | 0 | BMI(1)-BA(0) | |
| 5 | 0.485 | 0.163 | -0.118 | 1.503 | 0 | BMIB(1)-BA(0) | |
| 6 | 0.025 | 0.136 | -0.337 | 0.583 | 0 | BA(2)-BA(0) | |
| 7 | 0.138 | 0.135 | -0.262 | 0.754 | 0 | BMI(2)-BA(0) | |
| 8 | -0.097 | 0.335 | -0.690 | 1.636 | 0 | BMIB(2)-BA(0) | |
| 9 | 0.183 | 0.133 | -0.226 | 0.809 | 0 | BA(3)-BA(0) | |
| 10 | 0.217 | 0.123 | -0.178 | 0.802 | 0 | BMI(3)-BA(0) | |
| 11 | 0.496 | 0.187 | -0.178 | 1.723 | 0 | BMIB(3)-BA(0) | |
| 12 | -0.030 | 0.119 | -0.337 | 0.420 | 3 | BMI(0)-BA(0) | |
| 13 | -0.104 | 0.141 | -0.430 | 0.407 | 3 | BMIB(0)-BA(0) | |
| 14 | 0.229 | 0.181 | -0.311 | 1.192 | 3 | BA(1)-BA(0) | |
| 15 | 0.398 | 0.159 | -0.160 | 1.327 | 3 | BMI(1)-BA(0) | |
| 16 | 0.408 | 0.230 | -0.325 | 1.940 | 3 | BMIB(1)-BA(0) | |
| 17 | 0.025 | 0.136 | -0.337 | 0.583 | 3 | BA(2)-BA(0) | |
| 18 | 0.240 | 0.174 | -0.288 | 1.162 | 3 | BMI(2)-BA(0) | |
| 19 | -0.143 | 0.368 | -0.736 | 1.782 | 3 | BMIB(2)-BA(0) | |
| 20 | 0.183 | 0.133 | -0.226 | 0.809 | 3 | BA(3)-BA(0) | |
| 21 | 0.327 | 0.164 | -0.214 | 1.242 | 3 | BMI(3)-BA(0) | |
| 22 | 0.419 | 0.241 | -0.344 | 2.067 | 3 | BMIB(3)-BA(0) | |
| 23 | 0.049 | 0.129 | -0.305 | 0.585 | 6 | BMI(0)-BA(0) | |
| 24 | -0.162 | 0.149 | -0.480 | 0.350 | 6 | BMIB(0)-BA(0) | |
| 25 | 0.229 | 0.181 | -0.311 | 1.192 | 6 | BA(1)-BA(0) | |
| 26 | 0.513 | 0.166 | -0.109 | 1.569 | 6 | BMI(1)-BA(0) | |
| 27 | 0.318 | 0.231 | -0.370 | 1.757 | 6 | BMIB(1)-BA(0) | |
| 28 | 0.025 | 0.136 | -0.337 | 0.583 | 6 | BA(2)-BA(0) | |
| 29 | 0.342 | 0.180 | -0.246 | 1.389 | 6 | BMI(2)-BA(0) | |
| 30 | -0.199 | 0.370 | -0.755 | 1.619 | 6 | BMIB(2)-BA(0) | |
| 31 | 0.183 | 0.133 | -0.226 | 0.809 | 6 | BA(3)-BA(0) | |
| 32 | 0.436 | 0.171 | -0.168 | 1.479 | 6 | BMI(3)-BA(0) | |
| 33 | 0.327 | 0.245 | -0.393 | 1.903 | 6 | BMIB(3)-BA(0) | |

## 4.5 Efficacy of Treatments on Percent of Days of Heavy Drinking (PDH)

### 4.5.1 Effect of PTSD on Treatments for PDH

In the model analyzing the effect of PTSD on the treatments for PDH, the best model chosen had gender and number of prior injuries as covariates. In order to determine the moderation effect of PTSD on the treatments for PDH, a term involving the study groups' interactions with the binary PTSD variable was included. The model detected a significant negative interaction (z=-1.73) between PTSD and BMI for PDH at the 0.05 level.

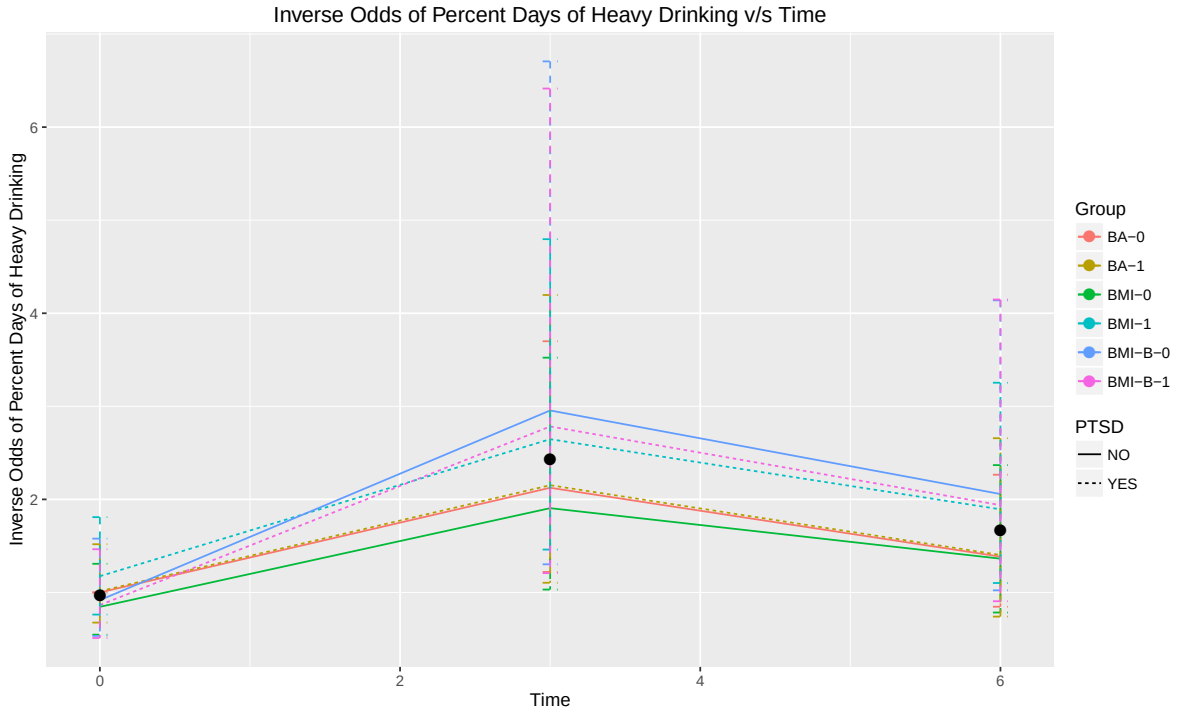


Figure 4.5: PDH Growth Curves for Levels of PTSD

Table 4.10: Differences in Inverse Odds of PDH for PTSD

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Study Group | Sig. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.845 | 0.146 | 0.546 | 1.308 | 0.546 | 1.310 | 0 | BMI-BA(0) | |
| 2 | 0.917 | 0.181 | 0.533 | 1.578 | 0.532 | 1.582 | 0 | BMIB-BA(0) | |
| 3 | 1.085 | 0.175 | 0.644 | 1.829 | 0.643 | 1.833 | 0 | BMIB-BMI(0) | |
| 4 | 1.159 | 0.147 | 0.748 | 1.797 | 0.746 | 1.800 | 0 | BMI-BA(1) | |
| 5 | 0.853 | 0.179 | 0.500 | 1.457 | 0.498 | 1.460 | 0 | BMIB-BA(1) | |
| 6 | 0.736 | 0.169 | 0.444 | 1.220 | 0.443 | 1.222 | 0 | BMIB-BMI(1) | |
| 7 | 0.897 | 0.251 | 0.424 | 1.898 | 0.423 | 1.904 | 3 | BMI-BA(0) | |
| 8 | 1.391 | 0.308 | 0.553 | 3.499 | 0.551 | 3.512 | 3 | BMIB-BA(0) | |
| 9 | 1.551 | 0.306 | 0.620 | 3.878 | 0.618 | 3.893 | 3 | BMIB-BMI(0) | |
| 10 | 1.230 | 0.239 | 0.602 | 2.513 | 0.600 | 2.520 | 3 | BMI-BA(1) | |
| 11 | 1.293 | 0.311 | 0.510 | 3.278 | 0.508 | 3.290 | 3 | BMIB-BA(1) | |
| 12 | 1.052 | 0.307 | 0.420 | 2.633 | 0.418 | 2.643 | 3 | BMIB-BMI(1) | |
| 13 | 0.984 | 0.214 | 0.519 | 1.867 | 0.517 | 1.872 | 6 | BMI-BA(0) | |
| 14 | 1.486 | 0.259 | 0.686 | 3.220 | 0.684 | 3.230 | 6 | BMIB-BA(0) | |
| 15 | 1.510 | 0.255 | 0.703 | 3.241 | 0.701 | 3.251 | 6 | BMIB-BMI(0) | |
| 16 | 1.350 | 0.212 | 0.715 | 2.548 | 0.713 | 2.555 | 6 | BMI-BA(1) | |
| 17 | 1.382 | 0.279 | 0.600 | 3.183 | 0.598 | 3.194 | 6 | BMIB-BA(1) | |
| 18 | 1.024 | 0.272 | 0.454 | 2.307 | 0.453 | 2.314 | 6 | BMIB-BMI(1) | |

No significant differences were found in table 4.10 between any of the treatments at any of the time-points.

Comparison of PDH values for the treatments to the control group (patients in the BA group at each time-point with no PTSD) in table 4.11 showed no significant odds of reducing PDH for any of the treatments at any of the time-points.

Table 4.11: Comparison of Inverse Odds of PDH to Control Group for PTSD

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | 0.845 | 0.146 | 0.546 | 1.308 | 0 | BMI(0)-BA(0) | |
| 2 | 0.917 | 0.181 | 0.533 | 1.578 | 0 | BMIB(0)-BA(0) | |
| 3 | 1.013 | 0.135 | 0.676 | 1.518 | 0 | BA(1)-BA(0) | |
| 4 | 1.174 | 0.144 | 0.762 | 1.809 | 0 | BMI(1)-BA(0) | |
| 5 | 0.864 | 0.176 | 0.510 | 1.464 | 0 | BMIB(1)-BA(0) | |
| 6 | 0.897 | 0.251 | 0.424 | 1.898 | 3 | BMI(0)-BA(0) | |
| 7 | 1.391 | 0.308 | 0.553 | 3.499 | 3 | BMIB(0)-BA(0) | |
| 8 | 1.013 | 0.135 | 0.676 | 1.518 | 3 | BA(1)-BA(0) | |
| 9 | 1.246 | 0.245 | 0.598 | 2.594 | 3 | BMI(1)-BA(0) | |
| 10 | 1.310 | 0.314 | 0.513 | 3.348 | 3 | BMIB(1)-BA(0) | |
| 11 | 0.984 | 0.214 | 0.519 | 1.867 | 6 | BMI(0)-BA(0) | |
| 12 | 1.486 | 0.259 | 0.686 | 3.220 | 6 | BMIB(0)-BA(0) | |
| 13 | 1.013 | 0.135 | 0.676 | 1.518 | 6 | BA(1)-BA(0) | |
| 14 | 1.367 | 0.211 | 0.727 | 2.572 | 6 | BMI(1)-BA(0) | |
| 15 | 1.400 | 0.277 | 0.611 | 3.204 | 6 | BMIB(1)-BA(0) | |

### 4.5.2 Effect of Suicidal Tendencies on Treatments for PDH

In the model analyzing the effect of reduced suicidal tendencies (levels 0,1,2,3) on the treatments for PDH, the best model was one predicted by gender, number of prior injuries and ethnicity. To determine the moderation effect of the suicidal tendencies on the treatments for PDH, a term involving the study groups' interactions with the four-level suicidal tendency variable was also included. The model showed a significant negative interaction between the BMI-B group and suicide level 2 (z=-3.32) at the 0.05 level.

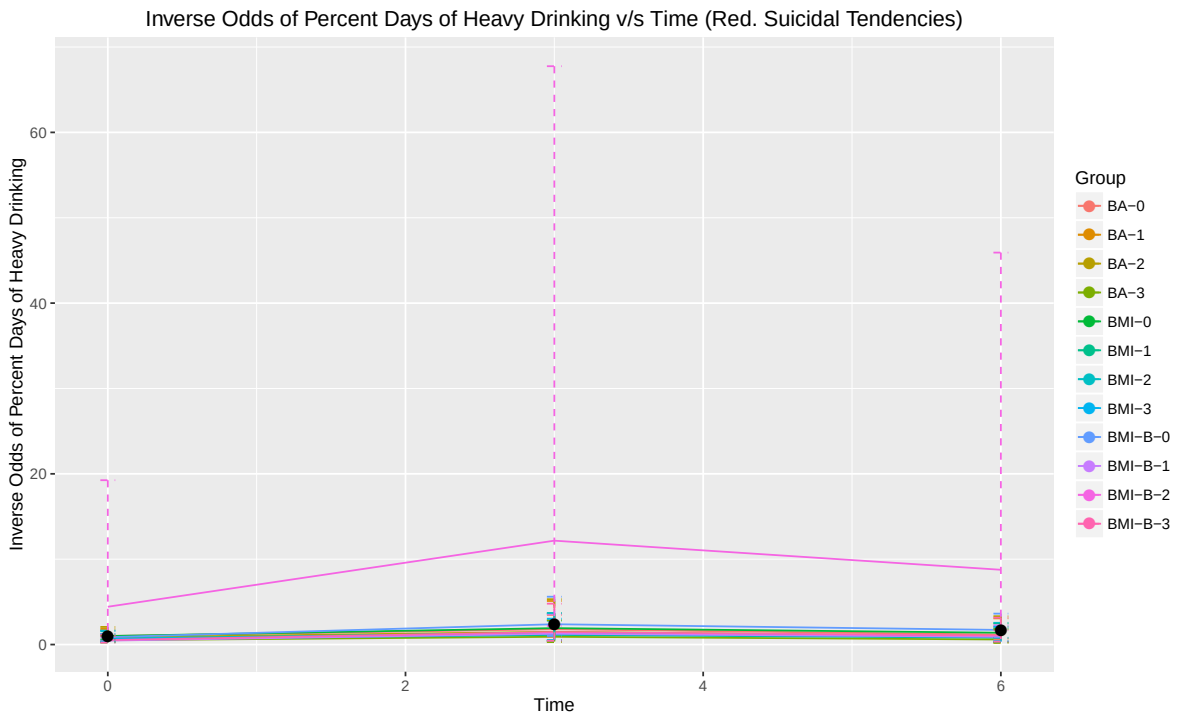


Figure 4.6: PDH Growth Curves for Levels of Suicidal Tendencies

In table 4.12 significant odds of reducing PDH were observed at baseline, 3 months and 6 months between BMI-B and BA, and BMI-B and BMI at suicide level 2 at the 0.05 significance level.

When comparing to the control group (patient in BA group at each time-point with no suicidal tendencies) in table 4.13, the odds of a patient in the BMI-B group at suicide level 1 reducing PDH significantly decreased at baseline. The odds of a patient reducing PDH in the BMI-B group at suicide level 2 increased significantly at all three time-points.

Table 4.12: Differences in Inverse Odds of PDH for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | HW-L | HW-U | Time | Study Group | Significant |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.001 | 0.160 | 0.600 | 1.671 | 0.598 | 1.675 | 0 | BMI-BA(0) | |
| 2 | 0.866 | 0.197 | 0.461 | 1.626 | 0.460 | 1.631 | 0 | BMIB-BA(0) | |
| 3 | 0.865 | 0.182 | 0.483 | 1.550 | 0.482 | 1.554 | 0 | BMIB-BMI(0) | |
| 4 | 0.810 | 0.306 | 0.304 | 2.159 | 0.303 | 2.169 | 0 | BMI-BA(1) | |
| 5 | 0.640 | 0.289 | 0.254 | 1.612 | 0.253 | 1.619 | 0 | BMIB-BA(1) | |
| 6 | 0.790 | 0.234 | 0.374 | 1.668 | 0.373 | 1.674 | 0 | BMIB-BMI(1) | |
| 7 | 0.851 | 0.332 | 0.294 | 2.461 | 0.293 | 2.473 | 0 | BMI-BA(2) | |
| 8 | 5.306 | 0.510 | 1.040 | 27.087 | 1.032 | 27.292 | 0 | BMIB-BA(2) | * |
| 9 | 6.235 | 0.490 | 1.300 | 29.897 | 1.291 | 30.115 | 0 | BMIB-BMI(2) | * |
| 10 | 1.256 | 0.246 | 0.572 | 2.756 | 0.570 | 2.766 | 0 | BMI-BA(3) | |
| 11 | 1.046 | 0.281 | 0.426 | 2.573 | 0.424 | 2.583 | 0 | BMIB-BA(3) | |
| 12 | 0.833 | 0.272 | 0.349 | 1.988 | 0.348 | 1.996 | 0 | BMIB-BMI(3) | |
| 13 | 1.073 | 0.222 | 0.528 | 2.182 | 0.526 | 2.189 | 3 | BMI-BA(0) | |
| 14 | 1.328 | 0.284 | 0.536 | 3.291 | 0.533 | 3.305 | 3 | BMIB-BA(0) | |
| 15 | 1.237 | 0.284 | 0.498 | 3.071 | 0.496 | 3.084 | 3 | BMIB-BMI(0) | |
| 16 | 0.869 | 0.435 | 0.216 | 3.487 | 0.215 | 3.510 | 3 | BMI-BA(1) | |
| 17 | 0.981 | 0.461 | 0.225 | 4.280 | 0.223 | 4.309 | 3 | BMIB-BA(1) | |
| 18 | 1.129 | 0.394 | 0.321 | 3.978 | 0.319 | 4.002 | 3 | BMIB-BMI(1) | |
| 19 | 0.912 | 0.433 | 0.229 | 3.639 | 0.227 | 3.663 | 3 | BMI-BA(2) | |
| 20 | 8.134 | 0.617 | 1.132 | 58.444 | 1.122 | 58.981 | 3 | BMIB-BA(2) | * |
| 21 | 8.915 | 0.593 | 1.341 | 59.271 | 1.329 | 59.794 | 3 | BMIB-BMI(2) | * |
| 22 | 1.346 | 0.370 | 0.412 | 4.401 | 0.410 | 4.425 | 3 | BMI-BA(3) | |
| 23 | 1.604 | 0.446 | 0.385 | 6.676 | 0.383 | 6.720 | 3 | BMIB-BA(3) | |
| 24 | 1.191 | 0.430 | 0.301 | 4.715 | 0.299 | 4.746 | 3 | BMIB-BMI(3) | |
| 25 | 1.182 | 0.190 | 0.644 | 2.170 | 0.642 | 2.176 | 6 | BMI-BA(0) | |
| 26 | 1.467 | 0.242 | 0.678 | 3.175 | 0.675 | 3.187 | 6 | BMIB-BA(0) | |
| 27 | 1.241 | 0.238 | 0.580 | 2.653 | 0.578 | 2.663 | 6 | BMIB-BMI(0) | |
| 28 | 0.957 | 0.402 | 0.265 | 3.455 | 0.264 | 3.475 | 6 | BMI-BA(1) | |
| 29 | 1.084 | 0.412 | 0.290 | 4.047 | 0.289 | 4.071 | 6 | BMIB-BA(1) | |
| 30 | 1.133 | 0.348 | 0.372 | 3.448 | 0.370 | 3.466 | 6 | BMIB-BMI(1) | |
| 31 | 1.005 | 0.414 | 0.268 | 3.771 | 0.266 | 3.794 | 6 | BMI-BA(2) | |
| 32 | 8.988 | 0.595 | 1.343 | 60.130 | 1.332 | 60.662 | 6 | BMIB-BA(2) | * |
| 33 | 8.942 | 0.569 | 1.451 | 55.123 | 1.439 | 55.589 | 6 | BMIB-BMI(2) | * |
| 34 | 1.483 | 0.348 | 0.487 | 4.514 | 0.485 | 4.537 | 6 | BMI-BA(3) | |
| 35 | 1.773 | 0.414 | 0.471 | 6.665 | 0.469 | 6.706 | 6 | BMIB-BA(3) | |
| 36 | 1.195 | 0.397 | 0.336 | 4.255 | 0.334 | 4.280 | 6 | BMIB-BMI(3) | |

Table 4.13: Comparison of Inverse Odds of PDH to Control Group for Reduced Suicidal Tendencies

| | Mu Hat | SE | L | U | Time | Group | Sig. |
|---|---|---|---|---|---|---|---|
| 1 | 1.001 | 0.160 | 0.600 | 1.671 | 0 | BMI(0)-BA(0) | |
| 2 | 0.866 | 0.197 | 0.461 | 1.626 | 0 | BMIB(0)-BA(0) | |
| 3 | 0.721 | 0.297 | 0.279 | 1.864 | 0 | BA(1)-BA(0) | |
| 4 | 0.585 | 0.219 | 0.291 | 1.176 | 0 | BMI(1)-BA(0) | |
| 5 | 0.462 | 0.196 | 0.247 | 0.864 | 0 | BMIB(1)-BA(0) | * |
| 6 | 0.835 | 0.284 | 0.337 | 2.067 | 0 | BA(2)-BA(0) | |
| 7 | 0.710 | 0.250 | 0.319 | 1.580 | 0 | BMI(2)-BA(0) | |
| 8 | 4.429 | 0.460 | 1.019 | 19.253 | 0 | BMIB(2)-BA(0) | * |
| 9 | 0.507 | 0.227 | 0.246 | 1.047 | 0 | BA(3)-BA(0) | |
| 10 | 0.637 | 0.214 | 0.322 | 1.262 | 0 | BMI(3)-BA(0) | |
| 11 | 0.531 | 0.247 | 0.241 | 1.171 | 0 | BMIB(3)-BA(0) | |
| 12 | 1.073 | 0.222 | 0.528 | 2.182 | 3 | BMI(0)-BA(0) | |
| 13 | 1.328 | 0.284 | 0.536 | 3.291 | 3 | BMIB(0)-BA(0) | |
| 14 | 0.721 | 0.297 | 0.279 | 1.864 | 3 | BA(1)-BA(0) | |
| 15 | 0.627 | 0.300 | 0.240 | 1.635 | 3 | BMI(1)-BA(0) | |
| 16 | 0.708 | 0.338 | 0.240 | 2.086 | 3 | BMIB(1)-BA(0) | |
| 17 | 0.835 | 0.284 | 0.337 | 2.067 | 3 | BA(2)-BA(0) | |
| 18 | 0.761 | 0.326 | 0.269 | 2.157 | 3 | BMI(2)-BA(0) | |
| 19 | 6.789 | 0.546 | 1.186 | 38.857 | 3 | BMIB(2)-BA(0) | * |
| 20 | 0.507 | 0.227 | 0.246 | 1.047 | 3 | BA(3)-BA(0) | |
| 21 | 0.683 | 0.298 | 0.264 | 1.771 | 3 | BMI(3)-BA(0) | |
| 22 | 0.814 | 0.384 | 0.239 | 2.775 | 3 | BMIB(3)-BA(0) | |
| 23 | 1.182 | 0.190 | 0.644 | 2.170 | 6 | BMI(0)-BA(0) | |
| 24 | 1.467 | 0.242 | 0.678 | 3.175 | 6 | BMIB(0)-BA(0) | |
| 25 | 0.721 | 0.297 | 0.279 | 1.864 | 6 | BA(1)-BA(0) | |
| 26 | 0.690 | 0.273 | 0.288 | 1.653 | 6 | BMI(1)-BA(0) | |
| 27 | 0.782 | 0.290 | 0.310 | 1.974 | 6 | BMIB(1)-BA(0) | |
| 28 | 0.835 | 0.284 | 0.337 | 2.067 | 6 | BA(2)-BA(0) | |
| 29 | 0.839 | 0.303 | 0.318 | 2.213 | 6 | BMI(2)-BA(0) | |
| 30 | 7.501 | 0.522 | 1.414 | 39.809 | 6 | BMIB(2)-BA(0) | * |
| 31 | 0.507 | 0.227 | 0.246 | 1.047 | 6 | BA(3)-BA(0) | |
| 32 | 0.753 | 0.274 | 0.313 | 1.809 | 6 | BMI(3)-BA(0) | |
| 33 | 0.900 | 0.348 | 0.296 | 2.738 | 6 | BMIB(3)-BA(0) | |

## 4.6 Alcohol Research Conclusions

Thus, it can be observed that mental health indicators such as injury-related PTSD and suicidal tendencies do have a moderating effect on the efficacy of particular brief interventions aimed at treating alcohol abuse.

PTSD negatively moderated the effect of BMI for MAXD and PDH, thereby implying that brief motivational interventions could have an improved effect on patients diagnosed with injury-related PTSD than on those who were not.

Suicide level 2 (patients who thought about committing suicide) negatively moderated the effect of the BMI-B treatment, thereby implying that brief motivational interventions followed by a booster session could have an improved effect on patients who contemplated suicide than on those with other suicidal tendencies.

# Chapter 5

# Concluding Remarks

## 5.1 Overall Results

In this thesis, Linear Mixed Modeling (LMM) methods were applied in the field of alcohol research, and various multiplicity-corrected sets of inferences enabled comparisons between treatments to be made while controlling the overall family-wise error rate to a specified amount. Also described in the thesis is how using the Hunter-Worsley method to generate more efficient simultaneous confidence bounds (SCBs) can help reduce the conservativeness associated with using the Bonferroni approach to generate SCBs.

In the alcohol research application part of this thesis, injury-related PTSD negatively moderated the effects of the brief motivational intervention (BMI) treatment for the drinking outcomes, the maximum number of drinks on a drinking occasion (MAXD) and the percent of days of heavy drinking (PDH). This result indicates that BMI works better at helping reduce a PTSD-diagnosed patient's maximum number of drinks consumed on a drinking occasion and their percent of days of heavy drinking than brief advice (BA) or BMI-B (BMI with a telephone booster sessions). A patient who ever thought about committing suicide's suicidal tendency level also negatively moderated the effect of BMI-B for PDH. The result indicates that BMI-B works better at helping reduce a patient's percent of days of heavy drinking when they are at the stage of contemplating suicide. Finally, the Hunter-Worsley SCB method did not present a significant advantage over the Bonferroni SCB method when using an exchangeable correlation structure in the Generalized Estimating Equations (GEEs) modeling the data.

In the Hunter-Worsley simulation part of this thesis, no significant difference was ob-

served in the empirical coverage rates between the Hunter-Worsley SCBs and the Bonferroni SCBs for both the LMM and the GEE methods employed at the lower correlation values of 0.0 and 0.5, but an advantage was observed for the Hunter-Worsley SCB at the higher correlation value of 0.9. Exchangeable correlation structures were used in both methodologies. Additionally, the GEE methodology was successful in reducing the conservativeness of both methods, by bringing the empirical coverage rates of both approaches much closer to the desired value of 95% than the LMM method.

## 5.2 Future Work

Further research in the development of efficient simultaneous confidence bounds could involve investigating the effects of the Hunter-Worsley SCBs on other assumed correlation structures. Since the Hunter-Worsley SCBs were not able to significantly reduce empirical error rates from those of the Bonferroni SCBs at lower correlation values in the simulations, investigating other correlation structures such as the unstructured or autoregressive ones could enable a difference to be observed.

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# Chapter 6

# Appendix

## 6.1 Model Results for ADW

### 6.1.1 Effect of PTSD on Treatments for ADW

Table 6.1: Model Coefficients for Effect of PTSD on Treatments for ADW

| Parameter | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 2.171 | 0.122 | 17.834 | 0.110 | 19.675 | * |
| BLATIN2 | -0.316 | 0.072 | -4.367 | 0.066 | -4.755 | * |
| BGENDERMale | 0.387 | 0.076 | 5.098 | 0.074 | 5.255 | * |
| timepoint3 | -1.223 | 0.132 | -9.273 | 0.128 | -9.537 | * |
| timepoint6 | -0.901 | 0.134 | -6.723 | 0.140 | -6.440 | * |
| C_STUDYGROUP2 | -0.049 | 0.141 | -0.348 | 0.130 | -0.377 | |
| C_STUDYGROUP3 | -0.001 | 0.168 | -0.006 | 0.159 | -0.006 | |
| PTSDYES | -0.026 | 0.110 | -0.235 | 0.112 | -0.232 | |
| timepoint3:C_STUDYGROUP2 | 0.042 | 0.175 | 0.241 | 0.169 | 0.251 | |
| timepoint6:C_STUDYGROUP2 | 0.075 | 0.178 | 0.421 | 0.182 | 0.410 | |
| timepoint3:C_STUDYGROUP3 | -0.251 | 0.210 | -1.192 | 0.201 | -1.247 | |
| timepoint6:C_STUDYGROUP3 | -0.234 | 0.213 | -1.100 | 0.220 | -1.065 | |
| C_STUDYGROUP2:PTSDYES | -0.205 | 0.147 | -1.389 | 0.149 | -1.374 | |
| C_STUDYGROUP3:PTSDYES | 0.067 | 0.175 | 0.381 | 0.175 | 0.381 | |

Table 6.2: Model Coefficients for Effect of PTSD on Treatments for ADW with No Interaction

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 2.207 | 0.114 | 19.431 | 0.103 | 21.414 | * |
| BLATIN2 | -0.322 | 0.072 | -4.452 | 0.066 | -4.856 | * |
| BGENDERMale | 0.387 | 0.076 | 5.094 | 0.074 | 5.240 | * |
| timepoint3 | -1.223 | 0.132 | -9.271 | 0.128 | -9.536 | * |
| timepoint6 | -0.901 | 0.134 | -6.721 | 0.140 | -6.438 | * |
| C_STUDYGROUP2 | -0.162 | 0.117 | -1.379 | 0.103 | -1.577 | |
| C_STUDYGROUP3 | 0.035 | 0.144 | 0.241 | 0.135 | 0.256 | |
| PTSDYES | -0.099 | 0.065 | -1.528 | 0.065 | -1.534 | |
| timepoint3:C_STUDYGROUP2 | 0.043 | 0.175 | 0.244 | 0.169 | 0.253 | |
| timepoint6:C_STUDYGROUP2 | 0.074 | 0.178 | 0.419 | 0.182 | 0.408 | |
| timepoint3:C_STUDYGROUP3 | -0.251 | 0.210 | -1.194 | 0.201 | -1.248 | |
| timepoint6:C_STUDYGROUP3 | -0.234 | 0.213 | -1.099 | 0.220 | -1.063 | |

### 6.1.2 Effect of Suicidal Tendencies on Treatments for ADW

Table 6.3: Model Coefficients for Effect of Suicidal Tendencies on Treatments for ADW

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 1.993 | 0.129 | 15.389 | 0.123 | 16.230 | * |
| BLATIN2 | -0.299 | 0.072 | -4.169 | 0.066 | -4.551 | * |
| BGENDERMale | 0.413 | 0.075 | 5.503 | 0.073 | 5.658 | * |
| timepoint3 | -1.093 | 0.146 | -7.485 | 0.146 | -7.484 | * |
| timepoint6 | -0.766 | 0.148 | -5.160 | 0.158 | -4.855 | * |
| C_STUDYGROUP2 | -0.213 | 0.145 | -1.470 | 0.132 | -1.618 | |
| C_STUDYGROUP3 | -0.087 | 0.182 | -0.479 | 0.171 | -0.510 | |
| SUIFINAL32 | 0.385 | 0.239 | 1.608 | 0.281 | 1.371 | |
| SUIFINAL33 | 0.017 | 0.260 | 0.064 | 0.211 | 0.079 | |
| SUIFINAL34 | 0.637 | 0.254 | 2.511 | 0.245 | 2.600 | * |
| timepoint3:C_STUDYGROUP2 | 0.078 | 0.192 | 0.408 | 0.188 | 0.417 | |
| timepoint6:C_STUDYGROUP2 | 0.105 | 0.195 | 0.536 | 0.201 | 0.521 | |
| timepoint3:C_STUDYGROUP3 | -0.136 | 0.235 | -0.579 | 0.226 | -0.603 | |
| timepoint6:C_STUDYGROUP3 | -0.138 | 0.237 | -0.585 | 0.242 | -0.572 | |
| C_STUDYGROUP2:SUIFINAL32 | 0.200 | 0.313 | 0.640 | 0.361 | 0.555 | |
| C_STUDYGROUP3:SUIFINAL32 | 0.374 | 0.350 | 1.069 | 0.387 | 0.967 | |
| C_STUDYGROUP2:SUIFINAL33 | 0.434 | 0.355 | 1.221 | 0.316 | 1.372 | |
| C_STUDYGROUP3:SUIFINAL33 | -0.307 | 0.478 | -0.642 | 0.382 | -0.802 | |
| C_STUDYGROUP2:SUIFINAL34 | -0.189 | 0.335 | -0.565 | 0.314 | -0.603 | |
| C_STUDYGROUP3:SUIFINAL34 | 0.296 | 0.413 | 0.716 | 0.360 | 0.822 | |

Table 6.4: Model Coefficients for Effect of Suicidal Tendencies on Treatments for ADW with No Interaction

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 1.947 | 0.116 | 16.727 | 0.109 | 17.896 | * |
| BLATIN2 | -0.297 | 0.072 | -4.147 | 0.066 | -4.514 | * |
| BGENDERMale | 0.420 | 0.075 | 5.610 | 0.073 | 5.742 | * |
| timepoint3 | -1.059 | 0.136 | -7.770 | 0.134 | -7.925 | * |
| timepoint6 | -0.730 | 0.139 | -5.273 | 0.146 | -5.018 | * |
| C_STUDYGROUP2 | -0.164 | 0.116 | -1.410 | 0.102 | -1.600 | |
| C_STUDYGROUP3 | -0.006 | 0.143 | -0.042 | 0.130 | -0.046 | |
| SUIFINAL32 | 0.572 | 0.132 | 4.328 | 0.148 | 3.864 | * |
| SUIFINAL33 | 0.166 | 0.162 | 1.023 | 0.149 | 1.116 | |
| SUIFINAL34 | 0.614 | 0.149 | 4.137 | 0.136 | 4.520 | * |
| timepoint3:C_STUDYGROUP2 | 0.035 | 0.173 | 0.202 | 0.168 | 0.209 | |
| timepoint6:C_STUDYGROUP2 | 0.059 | 0.176 | 0.336 | 0.182 | 0.326 | |
| timepoint3:C_STUDYGROUP3 | -0.209 | 0.209 | -1.001 | 0.197 | -1.060 | |
| timepoint6:C_STUDYGROUP3 | -0.210 | 0.211 | -0.991 | 0.216 | -0.970 | |

## 6.2 Model Results for MAXD

### 6.2.1 Effect of PTSD on Treatments for MAXD

Table 6.5: Model Coefficients for Effect of PTSD on Treatments for MAXD

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 2.161 | 0.109 | 19.746 | 0.093 | 23.200 | * |
| timepoint3 | -1.034 | 0.106 | -9.757 | 0.102 | -10.104 | * |
| timepoint6 | -0.873 | 0.108 | -8.105 | 0.108 | -8.067 | * |
| C_STUDYGROUP2 | 0.076 | 0.114 | 0.666 | 0.087 | 0.873 | |
| C_STUDYGROUP3 | 0.142 | 0.135 | 1.054 | 0.111 | 1.281 | |
| INJURY11 | -0.014 | 0.069 | -0.196 | 0.069 | -0.196 | |
| INJURY12 | 0.140 | 0.073 | 1.916 | 0.074 | 1.891 | * |
| INJURY13 | 0.303 | 0.097 | 3.141 | 0.091 | 3.341 | * |
| INJURY14 | 0.525 | 0.113 | 4.635 | 0.115 | 4.562 | * |
| BGENDERMale | 0.219 | 0.061 | 3.599 | 0.058 | 3.760 | * |
| PTSDYES | 0.024 | 0.089 | 0.271 | 0.091 | 0.267 | |
| timepoint3:C_STUDYGROUP2 | 0.023 | 0.141 | 0.161 | 0.133 | 0.170 | |
| timepoint6:C_STUDYGROUP2 | 0.105 | 0.143 | 0.736 | 0.142 | 0.742 | |
| timepoint3:C_STUDYGROUP3 | -0.157 | 0.169 | -0.927 | 0.164 | -0.955 | |
| timepoint6:C_STUDYGROUP3 | -0.211 | 0.171 | -1.235 | 0.171 | -1.235 | |
| C_STUDYGROUP2:PTSDYES | -0.215 | 0.119 | -1.808 | 0.117 | -1.837 | * |
| C_STUDYGROUP3:PTSDYES | -0.188 | 0.141 | -1.335 | 0.144 | -1.302 | |

### 6.2.2 Effect of Suicidal Tendencies on Treatments for MAXD

Table 6.6: Model Coefficients for Effect of Suicidal Tendencies on Treatments for MAXD

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | 2.121 | 0.114 | 18.642 | 0.094 | 22.545 | * |
| timepoint3 | -0.994 | 0.118 | -8.392 | 0.112 | -8.893 | * |
| timepoint6 | -0.830 | 0.120 | -6.893 | 0.118 | -7.022 | * |
| INJURY11 | -0.027 | 0.069 | -0.392 | 0.070 | -0.390 | |
| INJURY12 | 0.122 | 0.073 | 1.663 | 0.074 | 1.642 | |
| INJURY13 | 0.279 | 0.097 | 2.872 | 0.092 | 3.021 | * |
| INJURY14 | 0.500 | 0.114 | 4.392 | 0.116 | 4.319 | * |
| BGENDERMale | 0.243 | 0.061 | 3.997 | 0.058 | 4.177 | * |
| C_STUDYGROUP2 | -0.117 | 0.118 | -0.990 | 0.082 | -1.426 | |
| C_STUDYGROUP3 | -0.057 | 0.148 | -0.383 | 0.109 | -0.518 | |
| SUIFINAL32 | 0.206 | 0.194 | 1.061 | 0.181 | 1.139 | |
| SUIFINAL33 | 0.025 | 0.212 | 0.116 | 0.136 | 0.181 | |
| SUIFINAL34 | 0.168 | 0.206 | 0.816 | 0.133 | 1.268 | |
| timepoint3:C_STUDYGROUP2 | 0.086 | 0.156 | 0.554 | 0.142 | 0.606 | |
| timepoint6:C_STUDYGROUP2 | 0.165 | 0.158 | 1.044 | 0.151 | 1.091 | |
| timepoint3:C_STUDYGROUP3 | -0.053 | 0.190 | -0.279 | 0.178 | -0.298 | |
| timepoint6:C_STUDYGROUP3 | -0.120 | 0.192 | -0.625 | 0.184 | -0.652 | |
| C_STUDYGROUP2:SUIFINAL32 | 0.159 | 0.254 | 0.628 | 0.213 | 0.750 | |
| C_STUDYGROUP3:SUIFINAL32 | 0.246 | 0.284 | 0.867 | 0.255 | 0.965 | |
| C_STUDYGROUP2:SUIFINAL33 | 0.221 | 0.289 | 0.766 | 0.187 | 1.185 | |
| C_STUDYGROUP3:SUIFINAL33 | -0.069 | 0.389 | -0.179 | 0.367 | -0.189 | |
| C_STUDYGROUP2:SUIFINAL34 | 0.145 | 0.272 | 0.535 | 0.171 | 0.851 | |
| C_STUDYGROUP3:SUIFINAL34 | 0.291 | 0.335 | 0.870 | 0.235 | 1.237 | |

## 6.3 Model Results for PDH

### 6.3.1 Effect of PTSD on Treatments for PDH

Table 6.7: Model Coefficients for Effect of PTSD on Treatments for PDH

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | -1.960 | 0.150 | -13.086 | 0.163 | -12.040 | * |
| timepoint3 | -0.754 | 0.155 | -4.854 | 0.185 | -4.066 | * |
| timepoint6 | -0.325 | 0.139 | -2.334 | 0.165 | -1.978 | * |
| C_STUDYGROUP2 | 0.168 | 0.139 | 1.208 | 0.146 | 1.152 | |
| C_STUDYGROUP3 | 0.086 | 0.164 | 0.525 | 0.181 | 0.475 | |
| INJURY11 | 0.336 | 0.103 | 3.257 | 0.119 | 2.818 | * |
| INJURY12 | 0.458 | 0.107 | 4.296 | 0.122 | 3.762 | * |
| INJURY13 | 0.319 | 0.138 | 2.307 | 0.142 | 2.241 | * |
| INJURY14 | 0.360 | 0.156 | 2.317 | 0.164 | 2.196 | * |
| BGENDERMale | 0.170 | 0.089 | 1.916 | 0.102 | 1.670 | * |
| PTSDYES | -0.013 | 0.121 | -0.107 | 0.135 | -0.096 | |
| timepoint3:C_STUDYGROUP2 | -0.059 | 0.210 | -0.282 | 0.253 | -0.234 | |
| timepoint6:C_STUDYGROUP2 | -0.152 | 0.191 | -0.796 | 0.223 | -0.682 | |
| timepoint3:C_STUDYGROUP3 | -0.416 | 0.258 | -1.613 | 0.321 | -1.297 | |
| timepoint6:C_STUDYGROUP3 | -0.482 | 0.234 | -2.061 | 0.281 | -1.714 | * |
| C_STUDYGROUP2:PTSDYES | -0.316 | 0.163 | -1.932 | 0.182 | -1.730 | * |
| C_STUDYGROUP3:PTSDYES | 0.073 | 0.196 | 0.371 | 0.228 | 0.320 | |

### 6.3.2 Effect of Suicidal Tendencies on Treatments for PDH

Table 6.8: Model Coefficients for Effect of Suicidal Tendencies on Treatments for PDH

| | Estimate | Naive S.E. | Naive z | Robust S.E. | Robust z | Sig. |
|---|---|---|---|---|---|---|
| (Intercept) | -2.066 | 0.156 | -13.220 | 0.173 | -11.921 | * |
| timepoint3 | -0.584 | 0.169 | -3.460 | 0.206 | -2.827 | * |
| timepoint6 | -0.155 | 0.156 | -0.995 | 0.185 | -0.838 | |
| C_STUDYGROUP2 | -0.001 | 0.149 | -0.008 | 0.160 | -0.007 | |
| C_STUDYGROUP3 | 0.144 | 0.179 | 0.802 | 0.197 | 0.729 | |
| BLATIN2 | -0.420 | 0.088 | -4.784 | 0.093 | -4.490 | * |
| BGENDERMale | 0.242 | 0.087 | 2.772 | 0.103 | 2.360 | * |
| INJURY11 | 0.273 | 0.101 | 2.692 | 0.118 | 2.311 | * |
| INJURY12 | 0.418 | 0.105 | 3.999 | 0.121 | 3.453 | * |
| INJURY13 | 0.223 | 0.137 | 1.630 | 0.143 | 1.558 | |
| INJURY14 | 0.263 | 0.155 | 1.699 | 0.163 | 1.610 | |
| SUIFINAL32 | 0.327 | 0.225 | 1.454 | 0.297 | 1.100 | |
| SUIFINAL33 | 0.181 | 0.258 | 0.700 | 0.284 | 0.637 | |
| SUIFINAL34 | 0.678 | 0.212 | 3.203 | 0.227 | 2.993 | * |
| timepoint3:C_STUDYGROUP2 | -0.070 | 0.226 | -0.308 | 0.276 | -0.252 | |
| timepoint6:C_STUDYGROUP2 | -0.166 | 0.209 | -0.795 | 0.245 | -0.678 | |
| timepoint3:C_STUDYGROUP3 | -0.427 | 0.278 | -1.537 | 0.346 | -1.236 | |
| timepoint6:C_STUDYGROUP3 | -0.527 | 0.255 | -2.068 | 0.302 | -1.744 | * |
| C_STUDYGROUP2:SUIFINAL32 | 0.211 | 0.289 | 0.733 | 0.359 | 0.589 | |
| C_STUDYGROUP3:SUIFINAL32 | 0.303 | 0.312 | 0.971 | 0.356 | 0.850 | |
| C_STUDYGROUP2:SUIFINAL33 | 0.162 | 0.340 | 0.477 | 0.371 | 0.438 | |
| C_STUDYGROUP3:SUIFINAL33 | -1.813 | 0.784 | -2.311 | 0.547 | -3.316 | * |
| C_STUDYGROUP2:SUIFINAL34 | -0.227 | 0.286 | -0.794 | 0.294 | -0.771 | |
| C_STUDYGROUP3:SUIFINAL34 | -0.189 | 0.341 | -0.555 | 0.344 | -0.549 | |

# Curriculum Vitae

Emmanuel Joseph Sequeira was born on September 14, 1991, in Chennai, India. He spent a majority of his growing years in Abu Dhabi, the capital of the United Arab Emirates. After enrolling at the Metropolitan State University of Denver on June 7, 2010, he graduated a year ahead of his class on May 19, 2013, with a Bachelor of Science degree in Applied Mathematics, summa cum laude. While pursuing his bachelor's degree, he served as a tutor of Mathematics and Physics at the Student Academic Support Center (SASC) at his university, while also serving as a supplemental instructor (SI) for an introductory statistics course. For his efforts, he was recognized as being an outstanding graduate by the Department of Mathematical Sciences and Computer Science for the academic year 2012-2013.

Thereafter, he enrolled in Graduate School at The University of Texas at El Paso in the Fall of 2014 to pursue a Master of Science degree in Statistics. During the Master's degree, he served as a Teaching Assistant and a tutor at the Mathematics Resource Center for Students (MaRCS). He also served as the Statistics Research Assistant within the Latino Alcohol & Health Disparities (LAHDR) Center at UTEP. He has attended and presented his research results at both regional and national conferences across the United States and is awaiting the publishing of his results.

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