241 Project (Summer 2017): Effect of Meditation on Blood Pressure

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Source code

Our entire project code and documents can be accessed from https://github.com/thongnbui/MIDS_241_project. This file is can be found at code/ProjectOhm.{Rmd,pdf}. Data file is data/meditation.csv

Abstract:

We examine the effects of meditation on blood pressure and pulse rates. In particular, using a within-subject experimental design, we compare the effects of a single fifteen-minute meditation session to a similar session of coloring graphic shapes. Subjects were randomly assigned to undergo either the meditation session first, followed by coloring, or the coloring session first, followed by meditation. In each case, a five-minute washout period was inserted between the sessions.

Generally, we find that both meditation and coloring have some lowering effect on blood pressure, while the difference in effect between the two treatments is inconclusive. The pulse results are inconclusive for both each treatment individually as well as comparatively. Details of our analysis will be further explored below.

Introduction:

Meditation has been used for thousands of years by religious practitioners for spiritual growth. In modern times, it is promoted as a means to reduce stress. Many scientific studies have shown its effectiveness in reducing anxiety and other negative states.

What is our question?

Our study seeks to take this a step further: is it meditation that decreases stress, or is it activites that accompany meditation that are effective? Can other calming activities work as well as meditation to reduce stress? We chose coloring as the activity that most closely resembles traditional meditation without the meditation part. Coloring is a quiet, focused activity, that is not verbal. We chose geometric shapes as a backdrop to avoid the focus on people or cultural associations. Similarly, in meditation there is a distancing of the connection to thoughts and people, and a focus on the abstract. By comparing similar activities, we can narrow our search to those activities that best reduce stress.

Why does it matter?

High blood pressure, left untreated, can harm a person's health for years before symptoms develop. Patients with high blood pressure may become disabled or suffer a fatal heart attack. About half of the people with high blood pressure who are left untreated die of heart disease, and another third die of stroke.
Our initial study may be limited to evaluating immediate blood pressure impacts, but even short term drops in blood pressure may potentially hold value in heart health and anxiety reduction.

Systolic vs Diastolic Blood Pressure vs Pulse

Our study uses portable wrist blood pressure monitors to measure three numbers: systolic and diastolic blood pressure, and pulse rates. Of these numbers the most important are systolic blood pressure (the first number given when reporting blood pressure), and pulse. Diastolic pressure is generally only used during an emergency such as a cardiac arrest. Pulse is more variable than systolic pressure, but both are indicators of stress levels.

Experiment

Overview

Our experiment observed thirty-two people both in groups and individually, in person and online. Subjects varied in age from under ten years to over eighty, and in years of meditation experience from zero to fifty. These volunteers were primarily drawn from researcher friends and family networks.

Our subjects were randomly divided into two groups: one group that listened to a fifteen-minute guided meditation (from https://www.appropriateresponse.com/teachings/) first and spent fifteen minutes coloring after, and another group that engaged in the coloring exercise first, followed by the guided meditation. Between each session, subjects were asked to get up and walk around for 5 minutes, to create a 'washout' period and avoid spillover effects.

Subjects were asked to measure their own blood pressure before and after each session, and the results were recorded either by the subject (during group sessions) or by the researcher (for individual sessions) after each measurement.

Considerations

Why within-subject design

The within-subject design gave the study two advantages: first, using the same person to represent both experimental and control conditions gives greater precision around treatment estimates, and second, we were able to use fewer volunteers for the same statistical power.

Within-subject designs have a few potential sources of bias: treatment assignment, anticipation, and persistence. We used an R function to assign subjects to either meditation-first or coloring-first groups. As new volunteers signed up, they were added to the next slot on a list which automatically assigned the pre-randomized group.

To avoid anticipation, subjects were not told what the sessions would entail until the sessions began. There may have been some guesswork, due to our pre-experiment questions that identified years of meditation experience, or to the packages that arrived in the mail that included colored pencils. However, the details were not known to the subjects in advance.

A washout of five minutes was used to combat persistence. While it might have been better to take a longer period of time to 'reset' our subjects' blood pressures, we tried to keep this time short in consideration of the overall time our volunteers were giving to the study.

Why Coloring

Coloring is used quite often in medical experiments as a control activity. We used it because of its similarity to meditation - subjects are focused, seated, not interacting with other people, not required to engage in verbal processing, and silent. It was the closest activity we found that included many of the calming features of meditation, without actually being meditation.

Why a Guided Meditation

We chose an online guided meditation from www.appropriateresponse.com for the meditation sessions. There was a great deal of debate about this choice within the team: meditation styles include silent, guided, mantras, visualizations, music and more. In the end, it was decided that for beginners, a guided meditation would be less arduous. Mantra meditations might be distracting, especially in group settings. In a music meditation, separating out whether it was the music or the meditation that created the effects would be impossible. And visualization meditations might take too long to explain, and have their own set of confounding factors (who gives the instructions, if they would be remembered, etc.).

Guided meditations themselves come with an array of variation. The meditation we chose was deemed to have the least potentially negative reaction, as it avoids spiritual and esoteric language. However, some of the more experienced meditators who were accustomed to a different mediation style reported that they found the guided meditation distracting.

Challenges

BP measurement device precision

While we were pleased to find affordable mobile blood pressure monitors, wrist monitors are not the best measuring devices for precision. Each person required some basic instructions in the use of the monitors - in most cases this was the first time they used a device of this kind, which may have increased the likelihood of measurement error. In one case we were forced to remove the measured results, as they were deemed an error by a medical professional.

Subject inexperience

Experienced meditators often aim for 30 to 60 minutes in a given session. However, this length of time might be uncomfortable for inexperienced meditators, so we limited the sessions to 15 minutes. An interesting follow-up study might test the results of a longer meditation, using only subjects with meditation experience.

Subject participation

The original study design called for subjects to test the long-term results of meditation. For practicality and to avoid non-compliance or attrition, the design was altered to measure the results of a single meditation. A follow up study might take advantage of subjects on a meditation retreat to look for longer term effects, although the generalizability of such findings would certainly be called into question.

Data:

```r
library(data.table)
library(sandwich)
library(lmtest)
library(stargazer)
library(RColorBrewer)
library(cobalt)
library(car)
library(rlm)
require(foreign)
require(MASS)
```

Data Exploration

Read in and clean up the data

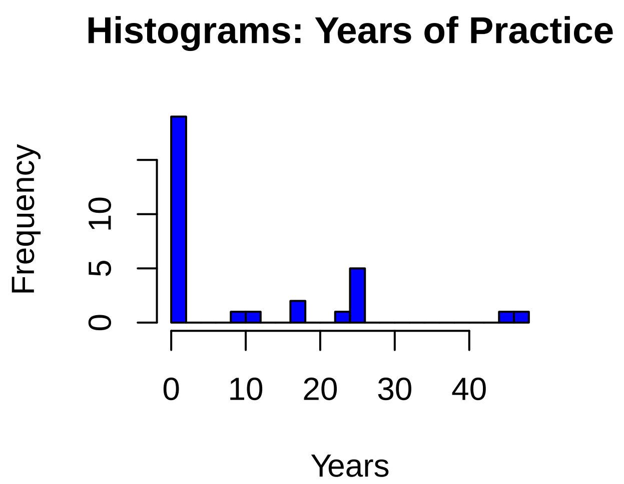
```
d <- fread("../data/meditation.csv")
# Should be 32 subjects
cat("Number of rows:", nrow(d), "\n")
```

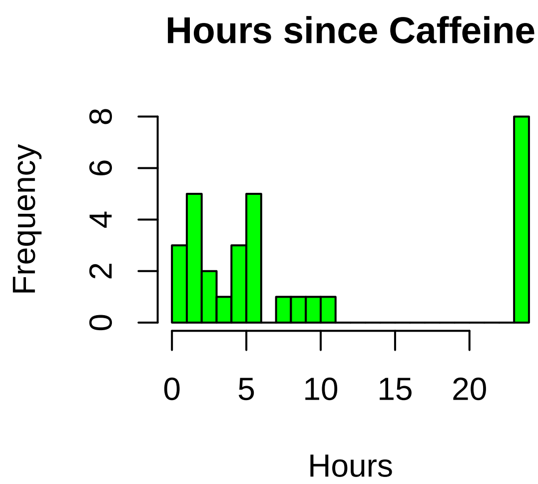
```
## Number of rows: 32
```

```
#str(d)
d <- data.table(d)

# ******Clean up the data*****
# 1. We are remove ID = 13 because this person's BP number is likely machine error
# 2. Reverse group number: 1 should be meditation first aka "med-first",
#    0 is coloring 1st aka "color-first"
# 3. convert string categories to numeric

d2 <- d[ID != 13 , ID, .(Group = ifelse(Group == 0, 1, 0), #Exclude 13th person & reverse groups
            Recruited_By,   caffeinated_drinks, Age_Group,     Gender,
            Religion,       Years_practice,     hours_since_last_caffeinated_drink,
            previous_strenuous_activity,        Before_Meditation_how_relaxed,
            Post_Med_focus, Enjoy_Coloring,
            in_person = ifelse(Online_in_person == 'I', 1, 0),
            pre_existing_BP = Pre_existing_blood_pressure,
            b4_all_sys = ifelse(Group == 0, B4_Med_BP_Sys, B4_color_BP_Sys),
            b4_all_pulse = ifelse(Group == 0, B4_Med_BP_PUL, B4_color_BP_Pul),
            B4_Med_BP_Sys, B4_Med_BP_PUL,
            After_Med_BP_Sys, After_Med_BP_PUL,
            B4_color_BP_Sys, B4_color_BP_Pul,
            After_color_BP_Sys, After_color_BP_Pul) ]

#summary(d2)
```

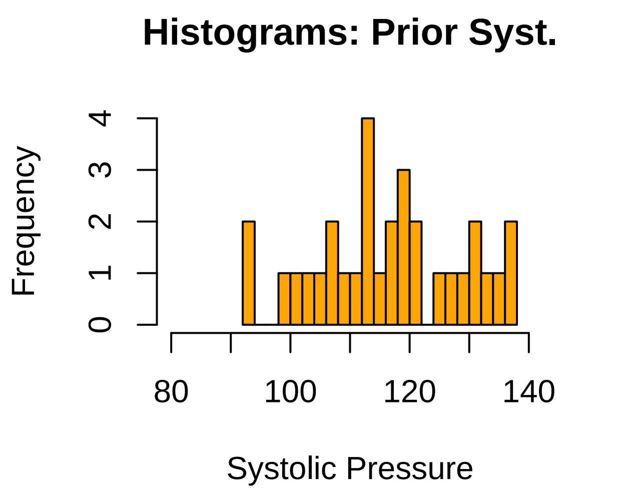
Chart the data

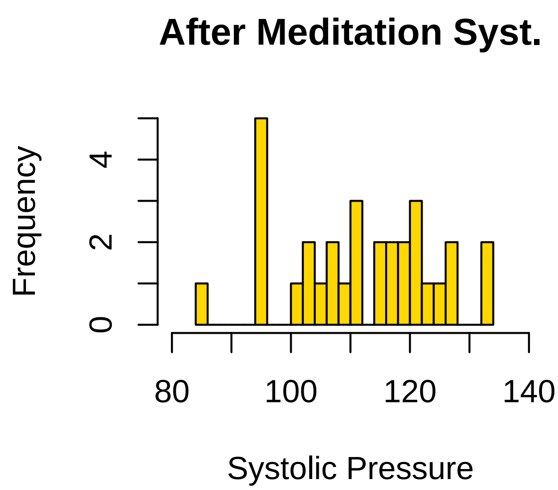
```
par(mfrow=c(1,2))
hist(d2$Years_practice, breaks = 30,col="blue",
     main = "Histograms: Years of Practice", xlab = "Years")
hist(d2$hours_since_last_caffeinated_drink, breaks = 30, col="green",
     main = "Hours since Caffeine", xlab = "Hours")
```



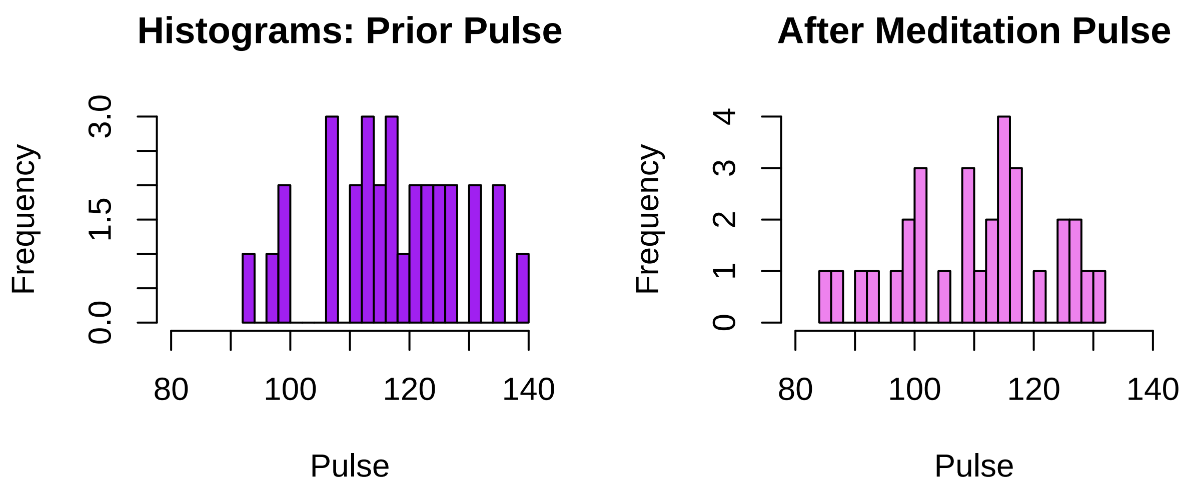



```r
hist(d2$B4_Med_BP_Sys, breaks = 30, xlim=c(80,140), col="orange",
     main = "Histograms: Prior Syst.", xlab = "Systolic Pressure")
hist(d2$After_Med_BP_Sys, breaks = 30, xlim=c(80,140),col="gold",
     main = "After Meditation Syst.", xlab = "Systolic Pressure")
```

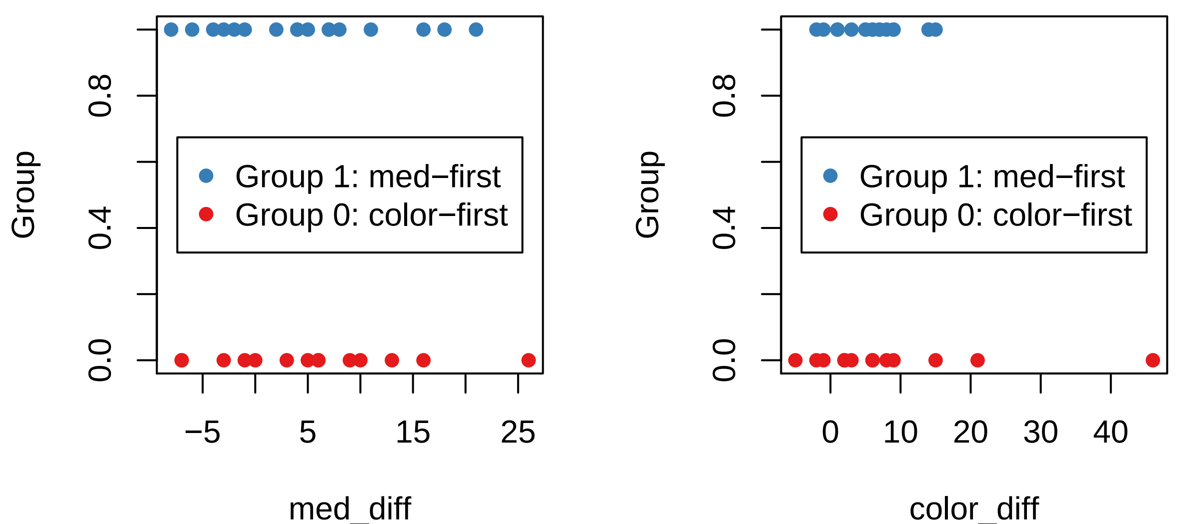





```r
hist(d2$B4_color_BP_Sys, breaks = 30, xlim=c(80,140), col="purple",
     main = "Histograms: Prior Pulse", xlab = "Pulse")
hist(d2$After_color_BP_Sys, breaks = 30, xlim=c(80,140), col="violet",
     main = "After Meditation Pulse", xlab = "Pulse")
```

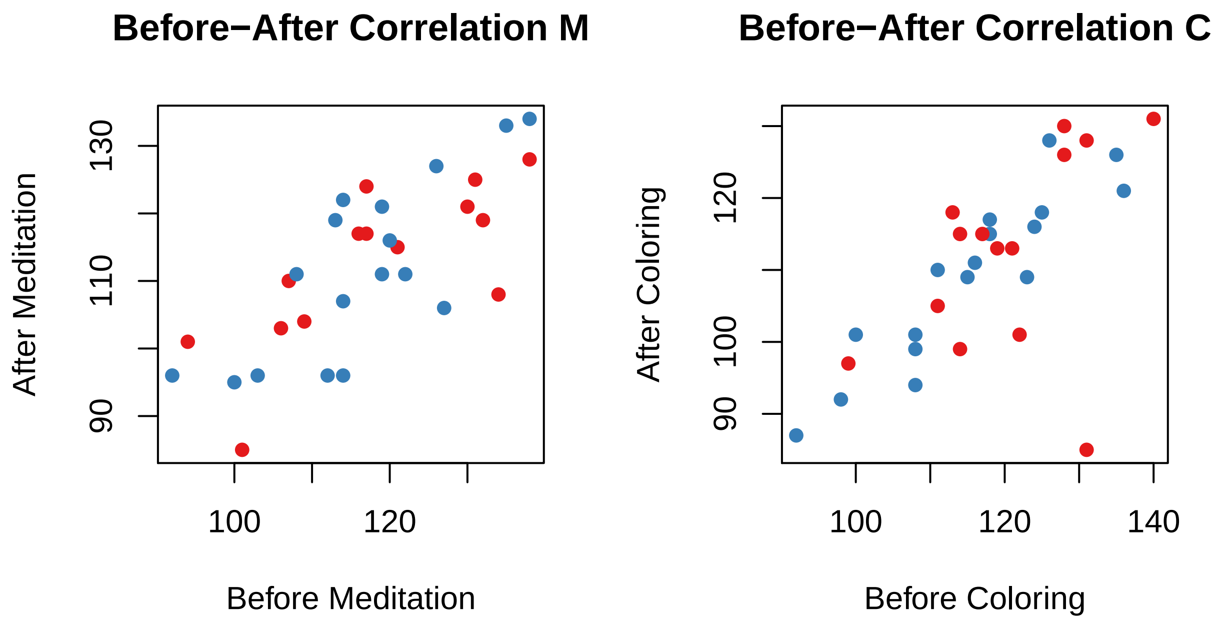



```
cols<-brewer.pal(n=3,name="Set1")
cols_t1<-cols[d2$Group+1] # red for group 0, blue for 1
med_diff <-  d2$B4_Med_BP_Sys - d2$After_Med_BP_Sys
color_diff <-   d2$B4_color_BP_Sys - d2$After_color_BP_Sys
par(mfrow =c(1,2))
plot(d2$Group ~ med_diff , col=cols_t1, pch=16, ylab="Group")
legend("center",legend=c("Group 1: med-first", "Group 0: color-first"),
       col=cols_t1, pch=16)
plot(d2$Group ~ color_diff , col=cols_t1, pch=16, ylab="Group")
legend("center",legend=c("Group 1: med-first", "Group 0: color-first"),
       col=cols_t1, pch=16)
```




```
# Plot b4 vs after meditation for 2 groups
plot(After_Med_BP_Sys ~ B4_Med_BP_Sys, data=d2 , col=cols_t1, pch=16,
     xlab = "Before Meditation", ylab="After Meditation", main="Before-After Correlation M")
legend(x=98,y=200, legend=c("Group 1: med-first", "Group 0: color-first"),
       col=cols_t1, pch=16, xpd=TRUE)

# Plot b4 vs after coloring for 2 groups
plot(After_color_BP_Sys ~ B4_color_BP_Sys, data=d2 , col=cols_t1, pch=16,
     xlab = "Before Coloring",ylab="After Coloring", main = "Before-After Correlation C")
legend(x=100,y=175, legend=c("Group 1: med-first", "Group 0: color-first"),
```

```
        col=cols_t1, pch=16, xpd=TRUE)
```



Covariate Balance Check

Matching was performed using the Matching package (Sekhon, 2011), and covariate balance was assessed using cobalt (Greifer, 2017), both in R 3.3.0 (R Core Team, 2016).

When using bal.tab() with continuous treatments, the balance statistic presented is the (weighted) Pearson correlation between each covariate and treatment.

```
covs <- subset(d2, select =
                 -c(Group, After_Med_BP_Sys, After_Med_BP_PUL,
                    After_color_BP_Sys, After_color_BP_Pul))

d2$p.score <- glm(f.build("Group", covs), data = d2,
                  family = "binomial")$fitted.values
d2$att.weights <- with(d2, Group + (1-Group)*p.score/(1-p.score))

bal.tab(covs, treat = d2$Group, weights = d2$att.weights,
         method = "weighting", estimand="ATE")
```

```
## Balance Measures:
##                                                 Type Diff.Adj
## Recruited_By_Erika                            Binary  -0.0756
## Recruited_By_Post                             Binary   0.0210
## Recruited_By_Thong                            Binary   0.0546
## caffeinated_drinks                           Contin.   0.6112
## Age_Group_10.19                               Binary   0.0462
## Age_Group_30.39                               Binary  -0.0252
## Age_Group_40.49                               Binary  -0.2059
## Age_Group_5.9                                 Binary  -0.0126
## Age_Group_50.59                               Binary   0.0210
## Age_Group_60.69                               Binary   0.0588
## Age_Group_80.90                               Binary   0.1176
```

```
## Gender_F                                         Binary   0.0546
## Religion_Agnostic                                Binary   0.0588
## Religion_Buddhist                                Binary   0.3277
## Religion_Christian                               Binary   0.0084
## Religion_Hindu                                   Binary   0.1176
## Religion_None                                    Binary  -0.4412
## Religion_Spiritual                               Binary  -0.0714
## Years_practice                                  Contin.   0.4922
## hours_since_last_caffeinated_drink              Contin.  -0.2369
## previous_strenuous_activity_Maybe..walking.      Binary  -0.1429
## previous_strenuous_activity_No                   Binary   0.1933
## previous_strenuous_activity_Yes                  Binary  -0.0504
## Before_Meditation_how_relaxed_a.little.tense     Binary   0.2899
## Post_Med_focus                                  Contin.   0.2817
## Enjoy_Coloring                                  Contin.   0.0808
## in_person                                        Binary  -0.3739
## pre_existing_BP_Avg                              Binary  -0.0924
## pre_existing_BP_High                             Binary   0.1050
## pre_existing_BP_Low                              Binary  -0.0126
## b4_all_sys                                      Contin.  -0.3884
## b4_all_pulse                                    Contin.   0.0461
## B4_Med_BP_Sys                                   Contin.  -0.1443
## B4_Med_BP_PUL                                   Contin.   0.2676
## B4_color_BP_Sys                                 Contin.  -0.4565
## B4_color_BP_Pul                                 Contin.  -0.0612
## ID                                              Contin.  -0.1397
##
## Effective sample sizes:
##            Control Treated
## Unadjusted      14      17
## Adjusted        14      17
```

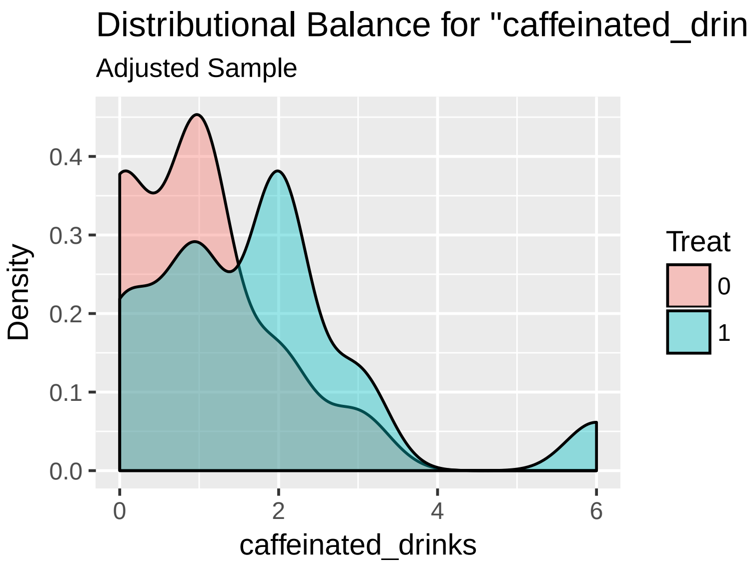
Covariate Balance Concerns

Of the covariates analyzed, the following stand out as unbalanced: caffeinated drinks, religion, and years of practice. The Med-First group is more likely to have participants who drink caffeine, are Buddhist and have more meditation experience, while the Color-First group is more likely to include subjects that do not identify with a particular religion.

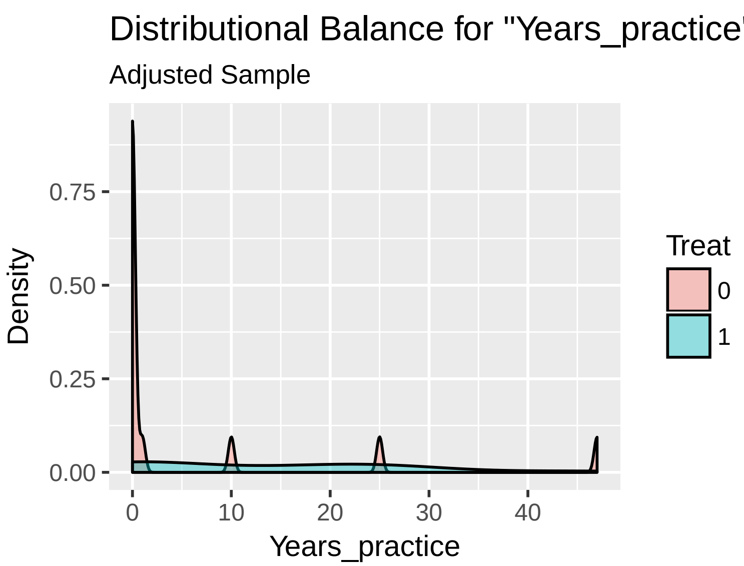
The difference in prior blood pressure and pulse measures is perhaps even more concerning. Systolic blood pressure measures before coloring for color-first participants tended to be consistently lower than for those starting out with meditation.

In each case, it will be important to include these variables when running regressions, to account for any possible bias.

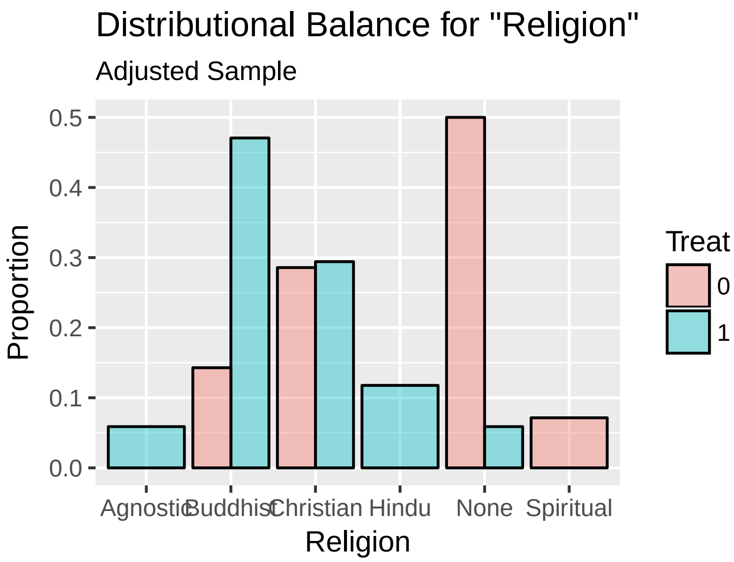
```r
bal.plot(covs, treat = d2$Group, weights = d2$att.weights, method = "weighting",
         estimand = "ATT", var.name = "caffeinated_drinks")
```



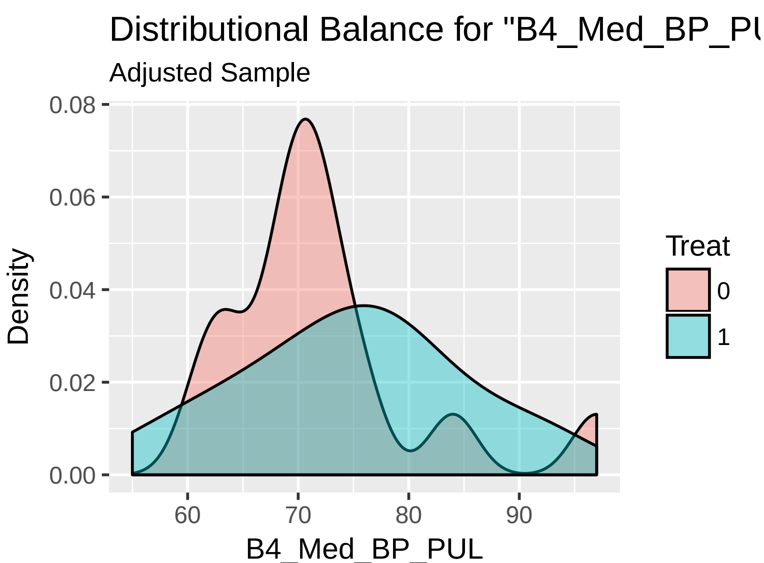

```r
bal.plot(covs, treat = d2$Group, weights = d2$att.weights, method = "weighting",
         estimand = "ATT", var.name = "Years_practice")
```



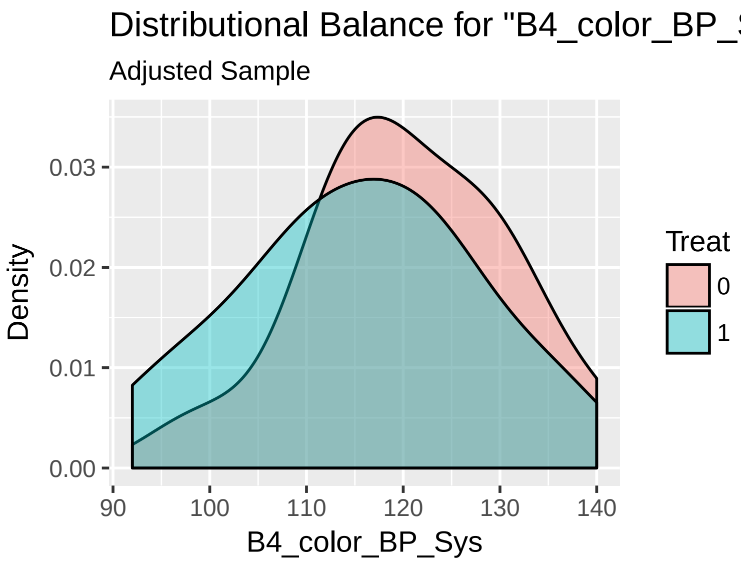

```r
bal.plot(covs, treat = d2$Group, weights = d2$att.weights, method = "weighting",
         estimand = "ATT", var.name = "Religion")
```




```
bal.plot(covs, treat = d2$Group, weights = d2$att.weights, method = "weighting",
         estimand = "ATT", var.name = "B4_Med_BP_PUL")
```




```
bal.plot(covs, treat = d2$Group, weights = d2$att.weights, method = "weighting",
         estimand = "ATT", var.name = "B4_color_BP_Sys")
```



Feature creation and selection

```r
#create bins for meditation experience
d2 <- transform(d2, experience=cut(Years_practice,
            breaks=c(-1,1, 10, 25, 50), labels= c(0,10, 25, 50)))
d2 <- transform(d2, exp_bin=cut(Years_practice,
            breaks=c(-1,0, 50),  labels= c(0,1)))
d2 <- transform(d2, pre_med_sys=cut(B4_Med_BP_Sys,
            breaks = c(50, 100, 125, 150), labels = c("low", "med", "high")))
d2 <- transform(d2, pre_col_sys=cut(B4_color_BP_Sys,
            breaks = c(50, 100, 125, 150), labels = c("low", "med", "high")))
d2 <- transform(d2, pre_med_pul=cut(B4_Med_BP_PUL,
            breaks = c(50, 70, 90, 110),  labels = c("low", "med", "high")))
d2 <- transform(d2, pre_col_pul=cut(B4_color_BP_Pul,
            breaks = c(50, 70, 90, 110), labels = c("low", "med", "high")))

age_str = "c('5-9', '10-19') = '< 20'; '30-39' = '30s';"
age_str = paste(age_str , "'40-49'= '40s'; c('50-59', '60-69', '80-90') = '50+'")
d2$age = recode(d2$Age_Group, age_str)

d2$prev_act = recode(d2$previous_strenuous_activity, "'No' = 'no'; else='yes'")

#create fields to capture the difference before and after each session
#for clarity, we subtract the number we expect to be smaller (after)
#from the larger (before), to keep the numbers positive
#Sysolic
d2$med_sys_diff = d2$B4_Med_BP_Sys - d2$After_Med_BP_Sys
cat("Average Meditation Effect on Systolic Blood Pressure:", mean(d2$med_sys_diff), "\n")
```

```
## Average Meditation Effect on Systolic Blood Pressure: 5
```

```r
d2$col_sys_diff = d2$B4_color_BP_Sys - d2$After_color_BP_Sys
cat("Average Coloring Effect on Systolic Blood Pressure:", round(mean(d2$col_sys_diff),2), "\n")
```

```
## Average Coloring Effect on Systolic Blood Pressure: 7.06
```

```
#Pulse
d2$med_pul_diff = d2$B4_Med_BP_PUL - d2$After_Med_BP_PUL
cat("Average Meditation Effect on Pulse Rate:",round(mean(d2$med_pul_diff),2), "\n")
```

```
## Average Meditation Effect on Pulse Rate: -0.52
```

```
d2$col_pul_diff = d2$B4_color_BP_Pul - d2$After_color_BP_Pul
cat("Average Coloring Effect on Pulse Rate:",round(mean(d2$col_pul_diff),2), "\n")
```

```
## Average Coloring Effect on Pulse Rate: 1.35
```

```
# The Coloring ATE is higher than Meditation, so subtract meditation results from coloring
# Create difference in differences measures between meditation and coloring
cat("\nAverage Difference on Systolic Blood Pressure between Coloring and Meditation Effects:",
    round(mean(d2$col_sys_diff - d2$med_sys_diff), 2), "\n")
```

```
##
## Average Difference on Systolic Blood Pressure between Coloring and Meditation Effects: 2.06
```

```
cat("\nAverage Difference on Pulse Rate between Coloring and Meditation Effects:",
    round(mean(d2$col_pul_diff - d2$med_pul_diff), 2))
```

```
##
## Average Difference on Pulse Rate between Coloring and Meditation Effects: 1.87
```

Correlations and Complications

```
cat("Are Recruiter, Age and Experience correlated?\n\n")
```

```
## Are Recruiter, Age and Experience correlated?
```

```
cat("Recruiter by Subject Age Group\n")
```

```
## Recruiter by Subject Age Group
```

```
table(d2$Recruited_By, d2$age)
```

```
##
##          < 20 30s 40s 50+
##   Erika     0   3   4   5
##   Post      5   1   0   1
##   Thong     0   0   8   4
```

```
cat("\nExperience by Subject Age Group\n")
```

```
##
## Experience by Subject Age Group
```

```
table(d2$experience, d2$age)
```

```
##
##       < 20 30s 40s 50+
##   0      5   2   7   4
##   10     0   1   1   0
##   25     0   1   4   4
##   50     0   0   0   2
```

```
cat("\nATE between meditation vs color by Group. Did we leave enough time for a washout?\n\n")
```

```
##
```

```
## ATE between meditation vs color by Group. Did we leave enough time for a washout?
```

```
ate_group_1_diff = mean(d2$col_sys_diff[d$Group==TRUE], na.rm=TRUE) -
   mean(d2$med_sys_diff[d2$Group==TRUE], na.rm=TRUE)
cat("   Med-first Group Systolic Difference:", round(ate_group_1_diff, 2), "\n")
```

```
##    Med-first Group Systolic Difference: 0.35
```

```
ate_group_0_diff = mean(d2$col_sys_diff[d$Group==FALSE], na.rm=TRUE) -
   mean(d2$med_sys_diff[d2$Group==FALSE], na.rm=TRUE)
cat("   Color-first Group Systolic Difference:", round(ate_group_0_diff, 2), "\n")
```

```
##    Color-first Group Systolic Difference: 3.34
```

```
ate_group_1_diff = mean(d2$col_pul_diff[d$Group==TRUE], na.rm=TRUE) -
   mean(d2$med_pul_diff[d2$Group==TRUE], na.rm=TRUE)
cat("   Med-first Group Pulse Difference:", round(ate_group_1_diff, 2), "\n")
```

```
##    Med-first Group Pulse Difference: 1.57
```

```
ate_group_0_diff = mean(d2$col_pul_diff[d$Group==FALSE], na.rm=TRUE) -
   mean(d2$med_pul_diff[d2$Group==FALSE], na.rm=TRUE)
cat("   Color-first Group Pulse Difference:", round(ate_group_0_diff, 2), "\n")
```

```
##    Color-first Group Pulse Difference: 2.97
```

OVerall, since we are doing within-subject design and we are facing general limitations in this initial study with a small sample size, we consider the generalizability of the model to be a somewhat secondary concern, which can only be more adequately addressed in an expanded study with a much larger sample size.

Model 1: Looking at the effect of each treatment

Predict outcome blood pressure based on when each measurement is being taken.

1. From the original data table, each row:

person_id	b4_all_bp	b4_med_bp	after_med_bp	b4_color_bp	after_color_bp
1	121	121	111	120	110

is convert into 5 rows like this:

person_id	bp	b4_all	b4_med	after_med	b4_color	after_color
1	121	1	0	0	0	0
1	121	0	1	0	0	0
1	111	0	0	1	0	0
1	120	0	0	0	1	0
1	110	0	0	0	0	1

then build the model `bp ~ 1 + b4_all + after_med + after_color + person_id`

```
d2.bp = melt(d2, id.vars = c("ID", "Group"), measure.vars = c("b4_all_sys", "B4_Med_BP_Sys", "After_Med
#d2.bp$b4_all <- ifelse(d2.bp$bp_type == "b4_all_sys", 1, 0)
d2.bp$b4_med <- ifelse(d2.bp$bp_type == "B4_Med_BP_Sys", 1, 0)
d2.bp$after_med <- ifelse(d2.bp$bp_type == "After_Med_BP_Sys", 1, 0)
```

```r
d2.bp$b4_color <- ifelse(d2.bp$bp_type == "B4_color_BP_Sys", 1, 0)
d2.bp$after_color <- ifelse(d2.bp$bp_type == "After_color_BP_Sys", 1, 0)
#summary(d2.bp)
```

Now, we build the same data table for pulse data

```r
d2.pulse = melt(d2, id.vars = c("ID", "Group"), measure.vars = c("b4_all_pulse", "B4_Med_BP_PUL", "Afte
#d2.pulse$b4_all <- ifelse(d2.pulse$pulse_type == "b4_all_pulse", 1, 0)
d2.pulse$b4_med <- ifelse(d2.pulse$pulse_type == "B4_Med_BP_PUL", 1, 0)
d2.pulse$after_med <- ifelse(d2.pulse$pulse_type == "After_Med_BP_PUL", 1, 0)
d2.pulse$b4_color <- ifelse(d2.pulse$pulse_type == "B4_color_BP_Pul", 1, 0)
d2.pulse$after_color <- ifelse(d2.pulse$pulse_type == "After_color_BP_Pul", 1, 0)
#summary(d2.pulse)
```

2. Now we are building the simple models

```r
# Non-Robust Linear Model
m1 <- lm(bp ~ 1 + b4_med + b4_color + after_color + after_med + ID, data=d2.bp)
m2 <- lm(pulse ~ 1 + b4_med + b4_color + after_color + after_med + ID, data=d2.pulse)

# Robust Linear Model
# rob_m1 <- rlm(bp ~ 1 + b4_med + b4_color + after_color + after_med + ID, data=d2.bp)
# rob_m2 <- rlm(pulse ~ 1 + b4_med + b4_color + after_color + after_med + ID, data=d2.pulse)

#coeftest(m1, vcovHC(m1))
#stargazer(m1, m2, rob_m1, rob_m2, type="text")
stargazer(m1, m2, type="text")
```

```
##
## ============================================================
##                                    Dependent variable:
##                                ----------------------------
##                                      bp           pulse
##                                     (1)            (2)
## ------------------------------------------------------------
## b4_med                             -1.129        -0.968
##                                   (3.036)        (2.555)
##
## b4_color                           -0.484        -0.645
##                                   (3.036)        (2.555)
##
## after_color                       -7.548**       -2.000
##                                   (3.036)        (2.555)
##
## after_med                         -6.129**       -0.452
##                                   (3.036)        (2.555)
##
## ID                                -0.212**      -0.220**
##                                   (0.103)        (0.086)
##
## Constant                         121.715***     78.197***
##                                   (2.741)        (2.307)
##
## ------------------------------------------------------------
## Observations                        155            155
```

```
## R2                                   0.091          0.046
## Adjusted R2                          0.061          0.014
## Residual Std. Error (df = 149)      11.953         10.059
## F Statistic (df = 5; 149)           2.993**         1.432
## ==============================================================
## Note:                              *p<0.1; **p<0.05; ***p<0.01
```

Notes:

The robust linear models showed only a small difference from the basic lm's–dropping the bp_drop after meditation to * ('1 star') significance. Other manipulations of outliers also made limited impact in overall conclusions–in both regression & other calculations. Adding group did not create significant change. Adding group plus interactions with treatment & group began to take signficance out of the model. When evaluating Group 0 & Group 1 separately, signficance of the change in blood pressure dropped to '1 star' essentially.

Here is part of the 'by-group' code

```
bp1 <- d2.bp[d2.bp$Group==1]
bp0 <- d2.bp[d2.bp$Group==0]
pulse1 <- d2.pulse[d2.pulse$Group==1]
pulse0 <- d2.pulse[d2.pulse$Group==0]
```

```
m1a <- lm(bp ~ b4_med + b4_color + after_color + after_med + ID, data=bp1)
m1b <- lm(bp ~ b4_med + b4_color + after_color + after_med + ID, data=bp0)
m2a <- lm(pulse ~ b4_med + b4_color + after_color + after_med + ID, data=pulse1)
m2b <- lm(pulse ~ b4_med + b4_color + after_color + after_med + ID, data=pulse0)
#coeftest(m1, vcovHC(m1))
#stargazer(m1a, m1b, m2a, m2b, type="text")
```

Now Look at a regression that essentially predicts change in bp & pulse based on whether one colored or meditated

```
# Create table for looking at sys bp outcome alone
dm = d2

dm$BPM = dm$B4_Med_BP_Sys - dm$After_Med_BP_Sys
dm$BPC = dm$B4_color_BP_Sys - dm$After_color_BP_Sys

dm.bp = melt(dm, id.vars = c("ID", "Group"), measure.vars = c("BPM", "BPC"), variable.name = "bp_type",
dm.bp$M1_C0 <- ifelse(dm.bp$bp_type == "BPM", 1, 0)

#dm.bp
```

```
# Create table for looking at sys pulse outcome alone
dp = d2

dp$PUM = dp$B4_Med_BP_PUL - dp$After_Med_BP_PUL
dp$PUC = dp$B4_color_BP_Pul - dp$After_color_BP_Pul

dp.pu = melt(dp, id.vars = c("ID", "Group"), measure.vars = c("PUM", "PUC"), variable.name = "pulse_typ
dp.pu$M1_C0 <- ifelse(dp.pu$pulse_type == "PUM", 1, 0)
```

```
#dp.pu[dp.pu$pulse_type=="PUM"]
```

Model 2: Looking More Closely At The Difference In the Effects of the Treatments

Predict outcomes [drop in blood pressure and drop in pulse] based on whether the subject colors or meditates. The baseline coefficient will show the common or baseline effect of treatment (both included). The "M1C0" coefficient will show the effect of meditation 'on top of' coloring (positive–means more drop by meditation)

Interpreting the table below:

The "bp_drop" and "pulse_drop" in the tables are positive when the relevant number decreases after treatment. "M1_C0" is 1 when meditation is the treatement and 0 when coloring is the treatment. The related "M1_C0" coefficient is positive if meditation lowers bp or pulse more effectively; negative if coloring lowers the number more effectively.

```
# Create simple model predicting changes in bp and pulse based on treatment (coloring or meditation)
# m1 <- lm(bp_drop ~ M1_C0, data=dm.bp)
# m2 <- lm(pulse_drop ~ M1_C0, data=dp.pu)
m1 <- rlm(bp_drop ~ M1_C0, data=dm.bp)
m2 <- rlm(pulse_drop ~ M1_C0, data=dp.pu)

#coeftest(m1, vcovHC(m1))
stargazer(m1, m2,type="text")
```

```
##
## ===========================================================
##                                  Dependent variable:
##                              ----------------------------
##                                 bp_drop      pulse_drop
##                                   (1)            (2)
## -----------------------------------------------------------
## M1_C0                           -1.605        -0.812
##                                (1.956)        (1.366)
##
## Constant                       5.949***        0.938
##                                (1.383)        (0.966)
##
## -----------------------------------------------------------
## Observations                      62            62
## Residual Std. Error (df = 60)   7.120          5.744
## ===========================================================
## Note:                          *p<0.1; **p<0.05; ***p<0.01
```

```
# Now add group & cross-effect of group & treatment as covariates
m1 <- lm(bp_drop ~ Group + M1_C0 + Group*M1_C0, data=dm.bp)
m2 <- lm(pulse_drop ~ Group + M1_C0 + Group*M1_C0, data=dp.pu)

#coeftest(m1, vcovHC(m1))
#stargazer(m1, m2,type="text")
```

Clarification of above results:

These models confirm a similar effect of coloring and meditation as the earlier models do. The RLM handles outliers more appropriately. The RLM estimate of effect on blood pressure is slightly lower than the LM estimate, and the pulse effect shows to be insignificant in this last RLM model–and only '1 star' significant in the previous RLM model.

The initial results (in printed table above) show that there is no significant difference between the effect of meditation and coloring (see M1_CO variable). However, when adding the group covariates with a basic lm, we see a '1 star' significance indicating that coloring may potentially lower pulse more effectively. The M1_C0 pulse_drop significance goes away for this last model when we utilize the robust model, with or without Group and/or related interaction effects.

Results Summary,

Both the coloring treatment and the meditation treatment on average lowered the blood pressure and pulse of our subjects. This effect appears to be significant for systolic blood pressure. Using the last robust model, particularly the constant which reflects the baseline effect across coloring and meditation together, this corresponds to a drop in blood pressure between approximately 3 and 9 points (based on 95% Confidence Interval). The individual 95% CI's of the two treatments overlap in the earlier models, with the coloring effect interval shifted about 1 or 2 points higher than that of meditation.

Pulse appears to be a little more erratic, as you can see in the related CI's, leading to the overall conclusion that we cannot confirm with confidence that meditation or coloring lower pulse. In addition, even though coloring had a larger impact on average pulse_drop and bp_drop than meditation, these differences also do not appear to be signficant.

At the end of the day, while we cannot make strong claims related to the impace of coloring and meditation on pulse, the results do build confidence in the ability of meditation and coloring to lower systollic blood pressure. No such confidence can be claimed for the superiority of meditation over coloring or vice versa.

Issues/Concerns

- One of the most difficult experiment decisions is what particular form of meditation to choose from and how long the meditation should be. We decided to go with 15-minute guided meditation from https://www.appropriateresponse.com/teachings/ so our analysis and conclusion can only be based on this particular setup. If we were to move from a 'class experiment' to a 'full experiment', we would definitely need to consider more carefully various forms and lengths of meditation, as well as how we may need to implement further blocking and clustering, across much larger treatment and control populations.
- The subjects consist of our friends and relatives. This sample is not randomized from the general population therefore doesn't represent the population's distribution hence no generalization can be drawn from our experiment even if we find causal effect from it.
- The wash-out period of 5 minutes may not be sufficient to remove the treatment of the first exercise on the second one.
- The on-line person with ID=13 seems to have unreliable blood pressure measurements which indicates a potential precision issue with the blood pressure device. It can also be an issue with how the experiment was conducted on-line.
- Some tests were conducted 'one-on-one', and some were conducted in groups which can lead to bias.
- It was our first experiment so there maybe mistakes or inconsistencies along the way that we are not aware of.

Based on these facts, we believe more future work needs to be done to refine our experiment design to provide more complete controls and more advanced methods across a larger population, in order to more clearly identify any causal effects of meditation on blood pressure.

Future Research

Our current project suffers from time constraints in setting up and conducting the experiment, financial limitations in acquiring the appropriate measurement devices, and difficulty in finding enough people to participate. Future research would need to address and overcome all of these challenges.

Five of the top improvements we would want to make are:

- Random selection from general population with larger size.
- Better blood pressure device and measurement.
- Longer periods and various forms of meditation.
- To address the insufficient washout period, either increase the time allocated to washout, or utilize 2 separate groups or time periods.
- Possibly implement more advanced blocking on covariates like experience and age to account for variance between groups.

Appendix – Some of our additional code and exploratory efforts

Additional T-tests

Check the significance of each treatment

```
t.test(d2$B4_Med_BP_Sys, d2$After_Med_BP_Sys, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$B4_Med_BP_Sys and d2$After_Med_BP_Sys
## t = 3.2391, df = 30, p-value = 0.002927
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  1.847486 8.152514
## sample estimates:
## mean of the differences
##                       5
```

```
t.test(d2$B4_Med_BP_PUL, d2$After_Med_BP_PUL, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$B4_Med_BP_PUL and d2$After_Med_BP_PUL
## t = -0.45594, df = 30, p-value = 0.6517
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -2.827999  1.795740
## sample estimates:
## mean of the differences
##               -0.516129
```

```r
t.test(d2$B4_color_BP_Sys, d2$After_color_BP_Sys, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$B4_color_BP_Sys and d2$After_color_BP_Sys
## t = 4.2399, df = 30, p-value = 0.0001967
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##   3.661692 10.467340
## sample estimates:
## mean of the differences
##                7.064516
```

```r
t.test(d2$B4_color_BP_Pul, d2$After_color_BP_Pul, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$B4_color_BP_Pul and d2$After_color_BP_Pul
## t = 1.1472, df = 30, p-value = 0.2604
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.057056  3.766734
## sample estimates:
## mean of the differences
##                1.354839
```

Check the significance of the difference-in-differences

```r
t.test(d2$col_sys_diff, d2$med_sys_diff, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$col_sys_diff and d2$med_sys_diff
## t = 0.96873, df = 30, p-value = 0.3404
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -2.287871  6.416903
## sample estimates:
## mean of the differences
##                2.064516
```

```r
t.test(d2$col_pul_diff, d2$med_pul_diff, paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  d2$col_pul_diff and d2$med_pul_diff
## t = 1.1152, df = 30, p-value = 0.2736
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.555244  5.297180
```

```
## sample estimates:
## mean of the differences
##                1.870968
```

Here is some of the original analysis which led to over-fitting.

Meditation Effects:

```r
#Systolic Blood Pressure
med_sys_exp_ols = lm(med_sys_diff ~ Group + pre_med_sys + experience + Gender +
               Religion +  caffeinated_drinks + in_person +
               prev_act + Before_Meditation_how_relaxed + Post_Med_focus , data=d2)

med_sys_age_ols = lm(med_sys_diff ~ Group + pre_med_sys + age + Gender +
               Religion + caffeinated_drinks + in_person +
               prev_act + Before_Meditation_how_relaxed + Post_Med_focus , data=d2)

#Pulse
med_pul_exp_ols = lm(med_pul_diff ~ Group + pre_med_pul + experience + Gender +
               Religion + caffeinated_drinks + in_person +
               prev_act + Before_Meditation_how_relaxed + Post_Med_focus , data=d2)

med_pul_age_ols = lm(med_pul_diff ~ Group + pre_med_pul + age + Gender +
               Religion + caffeinated_drinks + in_person +
               prev_act + Before_Meditation_how_relaxed + Post_Med_focus , data=d2)
```

Color Effects:

```r
col_sys_exp_ols = lm(col_sys_diff ~ Group + pre_col_sys + experience +
               Religion + caffeinated_drinks + in_person +
               prev_act  + Enjoy_Coloring , data=d2)

col_sys_age_ols = lm(col_sys_diff ~ Group + pre_col_sys + age +
               Religion + caffeinated_drinks + in_person +
               prev_act  + Enjoy_Coloring , data=d2)

#Pulse
col_pul_exp_ols = lm(col_pul_diff ~ Group + pre_col_pul + experience +
               Religion + caffeinated_drinks + in_person +
               prev_act + Enjoy_Coloring  , data=d2)

col_pul_age_ols = lm(col_pul_diff ~ Group + pre_col_pul + age +
               Religion + caffeinated_drinks + in_person +
               prev_act   + Enjoy_Coloring , data=d2)
```

Compare the Meditation and Color effects linear models, separately

```r
#compare meditation models
#cat("Meditation Model Comparison\n")
#stargazer(med_sys_exp_ols, med_sys_age_ols, med_pul_exp_ols, med_pul_age_ols, type = "text")
#compare coloring models
#cat("\n\nColor Model Comparison\n")
#stargazer(col_sys_exp_ols, col_sys_age_ols, col_pul_exp_ols, col_pul_age_ols, type = "text")
```

Difference-in-differences Estimate

Create some Diff variables

```
d2$col_med_sys_diff = d2$col_sys_diff - d2$med_sys_diff
d2$col_med_pul_diff = d2$col_pul_diff - d2$med_pul_diff
d2$pre_sys_diff= d2$B4_color_BP_Sys - d2$B4_Med_BP_Sys
d2$pre_pul_diff= d2$B4_color_BP_Pul - d2$B4_Med_BP_PUL
#cat("Difference in differences on systolic blood pressure:", mean(d2$col_med_sys_diff))
#cat("\nDifference in differences on pulse rate:", mean(d2$col_med_pul_diff), "\n")
```

Linear Regression model with difference-in-difference Estimate

```
cat("\nDifference in Differences Model Comparison:\n")
```

```
##
## Difference in Differences Model Comparison:
```

```
dd_sys_ols1 = lm(col_med_sys_diff~ Group + pre_sys_diff + experience + Gender +
                   Religion +  caffeinated_drinks + in_person +
                   prev_act + Before_Meditation_how_relaxed + Post_Med_focus, data = d2)
dd_sys_ols2 = lm(col_med_sys_diff~ Group + pre_sys_diff + age + Gender +
                   Religion +  caffeinated_drinks + in_person +
                   prev_act + Before_Meditation_how_relaxed + Post_Med_focus, data = d2)

dd_pul_ols1 = lm(col_med_pul_diff~ Group + pre_pul_diff + experience + Gender +
                   Religion +  caffeinated_drinks + in_person +
                   prev_act + Before_Meditation_how_relaxed + Post_Med_focus, data = d2)
dd_pul_ols2 = lm(col_med_pul_diff~ Group + pre_pul_diff + age + Gender +
                   Religion +  caffeinated_drinks + in_person +
                   prev_act + Before_Meditation_how_relaxed + Post_Med_focus, data = d2)

#stargazer(dd_sys_ols1, dd_sys_ols2, dd_pul_ols1, dd_pul_ols2,type = "text")
```