# PAIRS ESM Networks

# Emorie D Beck

# June 5, 2017

## Contents

1	Workspace 2			
	1.1 Packages	2		
2	Prepare Data			
	2.1 Clean Data	2		
	2.2 Missing Data Handling	4		
	2.3 Screen Participants	5		
	2.4 Response Order			
	2.5 Outcomes Data	6		
3	Question 0: Do Traits Predict Outcomes?			
4	Question1: Does State Personality Predict Outcomes			
	4.1 Idiographic Predictive Networks	8		
	4.2 Split Half Networks (Reliability Check)			
	4.3 Regressions			
5	Question 2: Does centrality relate to outcomes?			
	5.1 Run Centrality Analyses	13		
	5.2 Regressions			
6	Question 3: Does density predict outcomes	16		
	6.1 Regressions	16		

## 1 Workspace

#### 1.1 Packages

```
library(lavaan)
library(qgraph)
library(igraph)
library(glasso)
library(GPArotation)
library(mlVAR)
library(graphicalVAR)
library(knitr)
library(gridExtra)
library(Rmisc)
library(psych)
library(rlist)
library(stargazer)
library(magrittr)
library(data.table)
library(tidyverse)
library(Matrix)
library(pander)
library(RColorBrewer)
library(broom)
meanSD_r2z2r <- function(x) {</pre>
  z <- fisherz(x)
  z[is.infinite(z)] <- NA
  x_{bar} \leftarrow mean(z, na.rm = T)
  x_sd \leftarrow sd(z, na.rm = T)
  r_bar <- fisherz2r(x_bar)
  r_sd <- fisherz2r(x_sd)
  return(c(r_bar, r_sd))
```

# 2 Prepare Data

The data include three waves of experience sampling method data from the Personality and Intimate Relationship Study. Data were previously cleaned to remove data points that did not meet inclusion criteria. ##Load Data

```
wave1_all <- tbl_df(read.csv("~/Box Sync/network/PAIRS/Wave 1/esm_w1_RENAMED.csv"))
wave4_all <- tbl_df(read.csv("~/Box Sync/network/PAIRS/Wave 4/esm_w4_RENAMED_all.csv"))
wave7_all <- tbl_df(read.csv("~/Box Sync/network/PAIRS/Wave 7/esm_w7_RENAMED_all.csv"))</pre>
```

#### 2.1 Clean Data

Because the data sets include data that are not being used in this study, we extract the relevant columns (Subject ID, frequency, hour block, day of study, measurement point, and personality items) from the original data frames. Next, we rename the columns for later ease of use and visualization. Finally, because of the small sample size for waves 4 and 7, we merge those data sets.

```
#Getting necessary columns
#Keeping subject ID and all esm.BFI items
w1 <- dplyr::select(wave1_all, esm.IDnum.w1, esm.PR001.w1, esm.PR003.w1,
                     esm.PR004.w1, esm.PR005.w1, dplyr::matches("BFI"),
                     -dplyr::contains(".1."), esm.BH02.w1)
w4 <- dplyr::select(wave4_all, esm.IDnum.w4, esm.PR001.w4, esm.PR003.w4,
                     esm.PR004.w4, esm.PR005.w4, matches("BFI"), esm.BH02.w4)
w7 <- dplyr::select(wave7_all, esm.IDnum.w7, esm.PR001.w7, esm.PR003.w7,
                     esm.PR004.w7, esm.PR005.w7, matches("BFI"), esm.BH02.w7)
w7 <- w7[,!(colnames(w7) %in% c("esm.BFI20.w7", "esm.BFI12.w7"))]
# column names for w1
varnames <- c("SID", "freq", "hourBlock", "day", "beepvar",</pre>
              "A_rude", "E_quiet", "C_lazy",
              "N_relaxed", "N_depressed", "E_outgoing",
              "A_kind", "C_reliable", "N_worried", "studied")
# column names for w4 and w7
varnames_w47 <- c("SID", "freq", "hourBlock", "day", "beepvar",</pre>
              "E_outgoing", "E_quiet",
               "C lazy", "C reliable",
              "N_worried", "N_relaxed",
              "N_depressed", "A_rude",
              "A_kind", "studied")
# short column names (for plots)
varnames2 <- c("rude", "quiet", "lazy",</pre>
              "relaxed", "depressed", "outgoing",
              "kind", "reliable", "worried")
# rename columns
colnames(w1) <- varnames</pre>
colnames(w4) <- varnames_w47</pre>
colnames(w7) <- varnames_w47</pre>
# change subject IDs to factor
w1$SID <- factor(w1$SID)</pre>
w4$SID <- factor(w4$SID)
w7$SID <- factor(w7$SID)
# reorder w4 and w7 columns to match w1
w4 <- w4[,c(varnames,setdiff(names(w4), varnames))]</pre>
w7 <- w7[,c(varnames,setdiff(names(w7), varnames))]
# create wave variable before combining data sets.
w4$Wave <- "4"
w7$Wave <- "7"
# merge wave 4 and 7 data sets
w2 \leftarrow merge(w4, w7, all = T)
```

Variable	New Name	Description
esm.IDnum.w1	SID	numeric variable; identification number
esm.BFI37.w1	$A_{rude}$	agreeablness, negative; "During the last hour, how
		rude were you?" Likert scale from 1 to $5$ ; $1 = Not$
DEIO4 4	<b>.</b>	a lot, $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI21.w1	$E_{quiet}$	extraversion, negative; "During the last hour, how
		quiet were you?" Likert scale from 1 to 5; $1 = \text{Not}$ a lot, $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI23.w1	$C_{lazy}$	conscientiousness, negative; "During the last hour,
CSIII.DI 120.W1	$\bigcirc$ _ $\square$ a $_{J}$	how lazy were you?" Likert scale from 1 to 5; 1 =
		Not a lot, $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI09.w1	$N_{relaxed}$	neuroticism, positive; "During the last hour, how
		relaxed were you?" Likert scale from 1 to $5; 1 =$
		Not a lot, $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI04.w1	$N_{depressed}$	neuroticism, positive; "During the last hour, did
		you feel 'depressed, blue'?" Likert scale from 1 to
esm.BFI36.w1	E outgoing	5; $1 = Not a lot$ , $3 = Somewhat$ , $5 = Very$ extraversion, positive; "During the last hour, how
esiii.Dr 130.w1	E_outgoing	'outgoing, sociable' were you?" Likert scale from 1
		to 5; $1 = \text{Not a lot}$ , $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI32.w1	A kind	agreeablness, positive; "During the last hour, how
	_	'considerate, kind' were you?" Likert scale from 1
		to 5; $1 = \text{Not a lot}$ , $3 = \text{Somewhat}$ , $5 = \text{Very}$
esm.BFI13.w1	$C_{reliable}$	conscientiousness, positive; "During the last hour,
		how reliable were you?" Likert scale from 1 to 5; 1
DDI10 1	NT . 1	= Not a lot, 3 = Somewhat, 5 = Very
esm.BFI19.w1	N_worried	neuroticism, positive; "During the last hour, how
		worried were you?" Likert scale from 1 to 5; $1 = $ Not a lot, $3 = $ Somewhat, $5 = $ Very
		riot a lot, 3 — somewhat, 5 — very

### 2.2 Missing Data Handling

Participants in the study only answered Agreeableness items if they indicated they were interacting with another person during the hour block previous to responding. To retain those measurement points for use in models later, we fill in gaps using within-person means of Agreeabless items.

```
for (i in unique(w1$SID)){
    mean_A_rude <- mean(w1$A_rude[w1$SID == i], na.rm = T)
    w1$A_rude[is.na(w1$A_rude) & w1$SID == i] <- mean_A_rude
    mean_A_kind <- mean(w1$A_kind[w1$SID == i], na.rm = T)
    w1$A_kind[is.na(w1$A_kind) & w1$SID == i] <- mean_A_kind
}

for (i in unique(w2$SID)){
    mean_A_rude <- mean(w2$A_rude[w2$SID == i], na.rm = T)
    w2$A_rude[is.na(w2$A_rude) & w2$SID == i] <- mean_A_rude
    mean_A_kind <- mean(w2$A_kind[w2$SID == i], na.rm = T)
    w2$A_kind[is.na(w2$A_kind] & w2$SID == i] <- mean_A_kind
}</pre>
```

### 2.3 Screen Participants

To be able to construct individual networks for participants, we ideally need approximately 50 measurement points. However, for current purposes, we will keep all participants who have at least 10 responses, lest we eliminate a large portion of our subjects.

```
# retain cases where all personality data are retained
w1_com <- w1[complete.cases(w1[,c(6:14)]),]
w2_com <- w2[complete.cases(w2[,c(6:14)]),]

# for waves 4 and 7, create a variable that combines wave and day of study
w2_com$waveDay <- paste(w2_com$Wave, w2_com$day, sep = ".")

# reorder data sets by SID, day, and block
w1_com <- w1_com[order(w1_com$SID, w1_com$day, w1_com$hourBlock),]
w2_com <- w2_com[order(w2_com$SID, w2_com$waveDay, w2_com$hourBlock),]</pre>
```

#### 2.4 Response Order

Because of the way the mlVAR() handles measurement points, we create a new variable that numbers participants included responses, which we will use for the final model.

```
w1_com <- tbl_df(w1_com) %>%
  mutate(studied = as.numeric(studied)) %>%
  group_by(SID) %>%
  arrange(day, hourBlock) %>%
  mutate(beepvar3 = seq(1, n(), 1)) \%
  group_by(SID) %>%
  mutate_each_(funs(comp = mean), vars = colnames(w1_com)[6:14]) %>%
  ungroup()
w2 com \leftarrow tbl df(w2 com) \%
  mutate(studied = as.numeric(studied)) %>%
  group_by(SID) %>%
  arrange(waveDay, hourBlock) %>%
  mutate(beepvar3 = seq(1, n(), 1)) %>%
  group_by(SID) %>%
  mutate_each_(funs(comp = mean), vars = colnames(w2_com)[6:14]) %>%
  ungroup()
# Make numeric subject IDs for each df because mlVAR won't run for factors #
w1_com$SID2 <- as.numeric(w1_com$SID)</pre>
w2_com$SID2 <- as.numeric(w2_com$SID)</pre>
w1_test <- w1_com %>%
  select(SID, SID2, beepvar3, A_rude:N_worried, studied) %>%
  group_by(SID) %>%
 mutate_each(funs(sd = sd(., na.rm = TRUE)), A_rude:N_worried) %>%
  mutate(count = n(), wave = "1") %>%
  filter(count > 10)
w2_test <- w2_com %>%
  select(SID, SID2, beepvar3, A_rude:N_worried, studied) %>%
  group_by(SID) %>%
```

```
mutate_each(funs(sd = sd(., na.rm = TRUE)), A_rude:N_worried) %>%
  mutate(count = n(), wave = "2") %>%
  filter(count > 10)
for(i in 1:9){
  for(k in 1:dim(w1_test)[1]){
    if(w1_test[k, i + 13] == 0){
      w1 \text{ test[k, i + 3]} \leftarrow
        jitter(as.numeric(w1_test[k, i + 3]), amount = runif(1, 0, .05))
    }
 }
}
for(i in 1:9){
 for(k in 1:dim(w2_test)[1]){
    if(w2_{test}[k, i + 13] == 0){
      w2_{test[k, i + 3]} \leftarrow
        jitter(as.numeric(w2_test[k, i + 3]), amount = runif(1, 0, .05))
    }
 }
}
keys <-c(-1,-1,-1,-1,1,1,1,1,1)
w1_composites <- w1_test %>%
  select(SID, beepvar3, A_rude:N_worried) %>%
  mutate_each(funs(reverse.code(-1,.,mini = 1, maxi = 5)), A_rude:N_relaxed) %%
  gather(key = item, value = rating, A_rude:N_worried) %>%
  separate(item, c("trait", "item")) %>%
  group_by(SID, trait) %>%
  summarize(composite = mean(rating, na.rm = T)) %>%
  mutate(trait = mapvalues(trait, unique(trait), paste("ESM", c("Agreeableness", "Conscientiousness", "
         wave = "1") %>%
  spread(key = trait, value = composite)
```

#### 2.5 Outcomes Data

#### 2.5.1 Read in, Clean, and Create Composites for Outcomes Data

```
# read outcome variables from wave 1 #
target.ratings.initial.v1 <~ read.csv("-/Box Sync/network/PAIRS/Wave 1/target_w1_RENAMED.csv")
target.ratings.initial.v4 <~ read.csv("-/Box Sync/network/PAIRS/Wave 4/home_w4_RENAMED.csv")

# get column names of target subjects #
names.v1 <~ colnames(target.ratings.initial.v1)
names.v4 <~ colnames(target.ratings.initial.v4)

# replace subject ID variable to match centrality data #
names.w1[2] <~ "SID"; colnames(target.ratings.initial.v1) <~ names.v1
names.w4[2] <~ "SID"; colnames(target.ratings.initial.v4) <~ names.w4
target.ratings.initial.v1$\wave <~ "1"
target.ratings.initial.v4\wave <~ "2"

short.names <~ c("SID", "wave", "life_sat", "GPA")

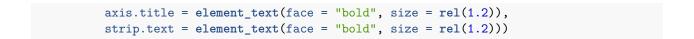
target.ratings.v1 <~ target.ratings.initial.v1 \%\%
select(SID, wave, ts.NQ34.v1, ts.AQQ03.v1, ts.BQ13.v1) \%\%
select(SID, wave, ts.NQ34.v4, ts.AQQ03.v4) \%\%</pre>
```

```
target.ratings <- tbl_df(target.ratings.w1) %>%
full_join(target.ratings.w4) %>%
mutate(SID = as.character(SID))
```

You#Question 1: Networks and the Prediction of Momentary Behaviors

## 3 Question 0: Do Traits Predict Outcomes?

```
tidy_mod_fun <- function(model){</pre>
  tidy(model) %>%
   bind_cols(tbl_df(confint(model, method = "boot")))
}
trait_fits <- w1_composites %>%
  left_join(select(target.ratings, SID, wave, GPA, procrastinate, life_sat)) %>%
  ungroup() %>%
  gather(key = outcome, value = value, GPA:life_sat) %>%
  gather(key = trait, value = value2, ESM_Agreeableness:ESM_Neuroticism) %>%
  group_by(wave, outcome, trait) %>%
  nest() %>%
  mutate(model = map(data, possibly(~lm(value ~ value2, data = .), NA_real_)),
         tidy = map(model, possibly(tidy_mod_fun, NA_real_)))
trait.dat <- trait_fits %>%
  filter(!is.na(model) & wave == "1" & outcome != "procrastinate" ) %>%
  unnest(tidy, .drop = T) %>%
  filter(term != "(Intercept)") %>%
  mutate(trait = mapvalues(trait, unique(trait),
                c("Extraversion", "Agreeableness", "Conscientiousness", "Neuroticism")),
         outcome = recode(outcome, `life_sat` = "Life\nSatisfaction"),
         outcome = factor(outcome, levels = rev(unique(outcome)))) %>%
  filter(trait %in% c("Conscientiousness", "Neuroticism"))
trait.dat %>%
  ggplot(aes(x = outcome, y = estimate)) +
    scale_color_manual(values = c("blue", "seagreen3")) +
    geom_errorbar(data = filter(trait.dat, outcome == "GPA"), width = .2,
                  aes(ymin = ^2.5 \% *5, ymax = ^97.5 \% *5), position = "dodge") +
    geom_errorbar(data = filter(trait.dat, outcome == "Life\nSatisfaction"),
                  aes(ymin = `2.5 %`, ymax = `97.5 %`), width = .2, position = "dodge") +
    geom_hline(yintercept = 0) +
    geom_point(data = filter(trait.dat, outcome == "GPA"),
               aes(y = estimate*5, color = outcome), size = 6) +
  geom_point(data = filter(trait.dat, outcome == "Life\nSatisfaction"),
             aes(y = estimate, color = outcome), size = 6) +
    scale_y_continuous(limits = c(-5,5), breaks = seq(-5,5,2),
                     sec.axis = sec_axis(~./5, name = "Estimated GPA Coefficient")) +
   labs(y = "Estimated Life Satisfaction Coefficient", x = NULL) +
    coord flip() +
   facet_grid(trait~.) +
    theme_classic() +
   theme(legend.position = "none",
          axis.text = element_text(face = "bold", size = rel(1.2)),
```



-0.5

**Estimated GPA Coefficient** 

0.0

0.5

1.0



# 4 Question1: Does State Personality Predict Outcomes

## 4.1 Idiographic Predictive Networks

-1.0

#### 4.1.1 Extract Results and Save Into Data Frames

```
kappa_mat_fun <- function(fit){fit$PCC}
 kappa_long_fun <- function(fit){
     PCC <- fit$PCC
    PCC <- PCC[order(colnames(PCC))]
PCC <- PCC[order(rownames(PCC)),]
PCC[lower.tri(PCC, diag = T)] <- NA
    mutate(sign = ifelse(value < 0, -1, 1)) %>% unite(var, Var1, Var2, sep = ".", remove = F
 {\tt gVAR\_fit} \; \leftarrow \; {\tt gVAR\_fit} \; \%{\gt}\%
    VAR_fit <- gVAR_fit %>%
#filter(!is.na(gVAR_fit)) %>%
mutate(beta0 = map2(gVAR_fit(), SID, possibly(beta_fun, NA_real_)),
    beta1 = map2(gVAR_fit(), SID, possibly(beta_fun, NA_real_)),
    kappa_mat0 = map(gVAR_fit(), possibly(kappa_mat_fun, NA_real_)),
    kappa_mat1 = map(gVAR_fit(), possibly(kappa_mat_fun, NA_real_)),
    kappa0 = map(gVAR_fit(), possibly(kappa_long_fun, NA_real_)),
    kappa1 = map(gVAR_fit(), possibly(kappa_long_fun, NA_real_)))
beta_long0 <- gVAR_fit %>% filter(!is.na(beta0)) %>% unnest(beta0)
beta_long1 <- gVAR_fit %>% filter(!is.na(beta1)) %>% unnest(beta1)
kappa_long0 <- gV&R_fit %>% filter(!is.na(kappa0)) %>% unnest(kappa0)
kappa_long1 <- gV&R_fit %>% filter(!is.na(kappa1)) %>% unnest(kappa1)
beta_long0\fit <- "personality"
kappa_long0\fit <- "personality"
beta_long1\fit <- "studied"
 kappa_long1$fit <- "studied"
 #get variable names from models
 varnames_fit0 <- row.names(gVAR_fit$gVAR_fit0[[1]]$beta)
varnames_fit! <- row.names(gVAR_fit%gVAR_fit![[1]]$beta)
# extract PCC information
PCC_fit0 <- gVAR_fit%sppa_mat0; names(PCC_fit0) <- gVAR_fit%SID
PCC_fit1 <- gVAR_fit%sppa_mat1; names(PCC_fit1) <- gVAR_fit%SID
```

#### 4.1.2 Plots

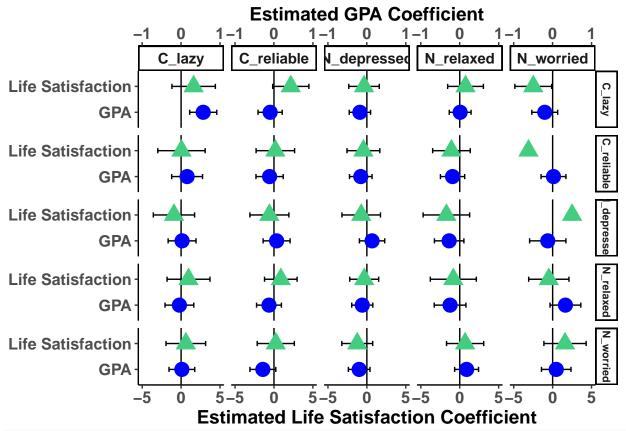
## 4.2 Split Half Networks (Reliability Check)

To test the reliability of the networks, we split each person's responses in half and calculate a network of eah and then compare the two using profile correlations.

### 4.3 Regressions

#### 4.3.1 Temporal

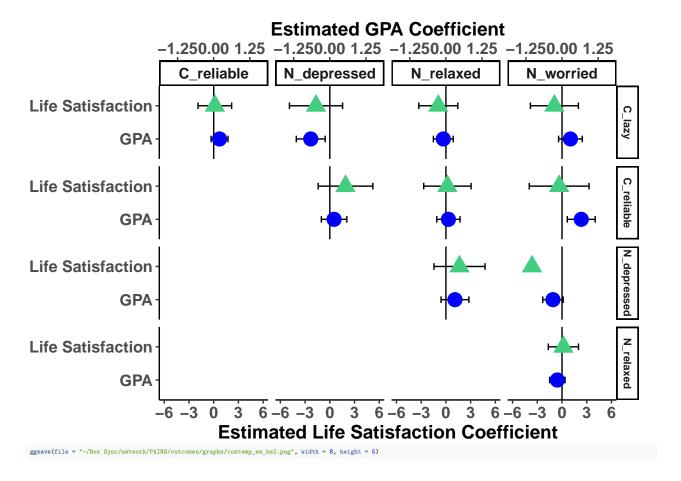
```
beta <- tbl_df(beta_long0) %>%
full_join(beta_long1) %>%
left_join(select(target.ratings, SID, wave,
        GPA, procrastinate, life_sat)) %>% left_join(w1_composites) %>% filter(!is.na(value))
PDC_model <- function(df) {
    mod0 <- lm(value2 - ESM_Neuroticism, data = df)
    mod1 <- lm(value2 - value, data = df)
    modC <- lm(value2 - value + ESM_Conscientiousness, data = df)
    modN <- lm(value2 - value + ESM_Neuroticism, data = df)
    modT <- lm(value2 - value + ESM_Neuroticism, data = df)
    modT <- lm(value2 - value + ESM_Neuroticism, data = df)</pre>
                results <- list(mod0, mod1, modC, modN, modT)
                return(results)
PDC_tidy <- function(mod_list){
    tidy_mod0 <- tidy(mod_list[1]]) %>% mutate(covar = "Nonly") %>%
    bind_cols(tbl_df(confint(mod_list[1]]), method = "boot")))
    tidy_mod1 <- tidy(mod_list[2]]) %>% mutate(covar = "%") %>%
    bind_cols(tbl_df(confint(mod_list[2]], method = "boot")))
    tidy_mod2 <- tidy(mod_list[3]) %>% mutate(covar = "C") %>%
    bind_cols(tbl_df(confint(mod_list[[3]], method = "boot")))
    tidy_mod8 <- tidy(mod_list[43]) %>% mutate(covar = "Noot"))>
    tidy_mod1 <- tidy(mod_list[43]) %>% mutate(covar = "Noot"))>
    tidy_mod7 <- tidy(mod_list[63]) %>% mutate(covar = "C+N") %>%
    bind_cols(tbl_df(confint(mod_list[[43]], method = "boot")))
    tidy_mod3 <- tidy_mod1 d1 %>%
       bind_cois(tol_df(con;int)
tidy_mods <- tidy_mod1 %>%
full_join(tidy_mod0) %>%
full_join(tidy_modN) %>%
full_join(tidy_modT) %>%
full_join(tidy_mod0)
        return(tidy_mods)
 PDC_fits <- beta_long %>% group_by(outcome, wave, fit, var) %>% nest() %>% nest() %>% mutate(model = map(data, possibly(PDC_model, NA_real_)),
                                tidy = map(model, possibly(PDC_tidy, NA_real_)))
  PDC.dat <- PDC fits %>%
         filter(!is.na(tidy)) %>% unnest(tidy) %>%
          filter(fit == "studied" & term == "value" & covar == "EW" & outcome != "procrastinate") %>%
       filter(fit == "studied" & term == "value" & covar == DN & OULLOME : separate(var, into = c(from", ito"), sep = [[.]") %\footnote{\text{wt}} unite(outcome = recode(outcome, life_sat = "life_Satisfaction")) %\footnote{\text{wt}} unite(comb, outcome, wave, sep = ": ", remove = F) %\footnote{\text{wt}} unite(comb = factor(comb, levels = rev(unique(comb))),
                                 outcome = factor(outcome, levels = rev(unique(outcome))))
       DC.dat %>% ggplot(aes(x = outcome, y = estimate)) + geom_errorbar(data = filter(PDC.dat, outcome == "GPA"), width = .2, aes(ymin = '2.5 %'*5, ymax = '97.5 %'*5), position = "dodge") + geom_errorbar(data = filter(PDC.dat, outcome != "GPA"), aes(ymin = '2.5 %', ymax = '97.5 %'), position = "dodge", width = .2) + geom_phine(data = filter(PDC.dat, outcome != "GPA"), aes(y = estimate * 5, color = outcome, shape = outcome), size = 5) + geom_point(data = filter(PDC.dat, outcome != "GPA"), aes(color = outcome, shape = outcome), size = 5) + scale_color_manual(values = c("blue", "seagreen3")) + scale_y_continuous(limits = c(-5,5), breaks = seq(-5,5,5), sec.axis = sec_axis(-./5, name = "Estimated GPA Coefficient", breaks = seq(-1,1,1)) + $scale_color_manual(values = c("red", "blue", "green")) + labs(y = "Estimated Life Satisfaction Coefficient", x = NULL) + coord_flip() +
                coord_flip() +
facet_grid(from~to) +
                theme classic() +
               theme_classic() +
theme(legend, position = "none",
    axis.text = element_text(face = "bold", size = rel(1.1)),
    axis.title = element_text(face = "bold", size = rel(1.3)),
    strip.text.x = element_text(face = "bold", size = rel(1.3)),
    strip.text.y = element_text(face = "bold", size = rel(1.9)))
```



ggsave(file = "-/Box Sync/network/PAIRS/outcomes/graphs/temp\_ew\_bs2.png", width = 8, height = 5)

#### 4.3.2 Contemporaneous

```
| POC - No. Actions | Decomposition | Decompos
```



## 5 Question 2: Does centrality relate to outcomes?

#### 5.1 Run Centrality Analyses

#### 5.1.1 Idiographic

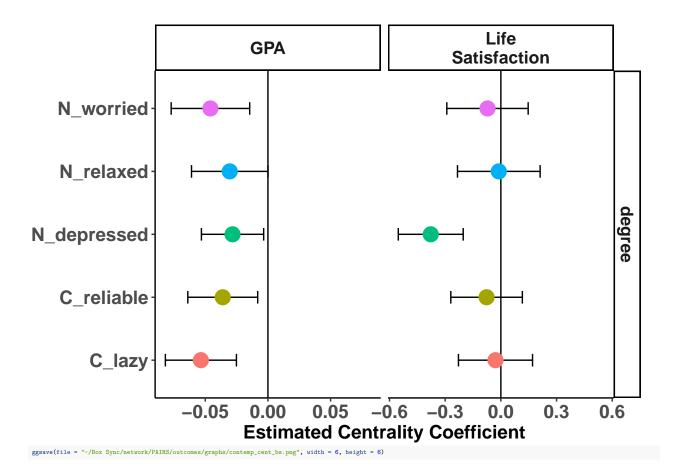
```
}
  return(df)
gVAR_fit <- gVAR_fit %>%
    mutate(beta_centrality0 = map2(beta0, gVAR_fit0, possibly(~centralityList(.x,
              # let's reshape and merge the results within models centrality_fit0_PDC_long <- gVAR_fit %>% filter('is.na(beta_centrality0)) %>% unnest (beta_centrality0, .drop = 17 %>% mutate(fit = "personality", type = "Temporal")
centrality_fiti_PDC_long <- gVAR_fit %>%
  filter(!is.na(beta_centrality1)) %>%
  unnest(beta_centrality1, drop = T) %>%
  mutate(fit = "studied", type = "Temporal")
centrality_fitO_PCC_long <- gVAR_fit %>% filter(!is.na(kappa_centrality0)) %>% unnest(kappa_centrality0, .drop = T) %>% mutate(fit = "personality", type = "Conte
                                                                         mporaneous")
centrality_fit1_PCC_long <- gVAR_fit %>%
  filter(lis.na(kappa_centrality1)) %/%
unnest(kappa_centrality1, .drop = T) %/%
mutate(fit = "studied", type = "Contemporaneous")
# let's reshape and merge the results across models centrality <- centrality_fit0_PDC_long %>% full_join(centrality_fit1_PDC_long) %>%
  full_join(centrality_fitt_PCC_long) %>%
full_join(centrality_fitt_PCC_long) %>%
gather(key = measure, value = value, Betweenness:OutStrength,
Strength, InDegree, OutDegree, degree) %>%
  Strength, inbegree, UutDegree, degree filter(lis.na(value)) %>% group by(fit, wave, type, SID, measure) %>% mutate(z = as.numeric(scale(value))) %>% ungroup()
# all the centrality ratings with rankings + outcomes centrality5 <- centrality %>% left_join(target.ratings) %>%
   left_join(w1_composites) %>%
filter(!is.na(fit)) %>%
mutate()
subsw1 <- (gVAR_fit %>% filter(!is.na(gVAR_fit0) & !is.na(beta_centrality0) &
    !is.na(kappa_centrality0) & wave == "1"))$SID
centrality_plot_fun <- function(sub, Type){
   print(sub)
centrality %>%
      trainty $\rangle \chi_{\text{titer}} (use == "i" & fit == "personality" & SID == sub & type == Type & grepl("egree", measure) == T) %>% ggplot(aes(x = var, y = z, group = measure)) + geom_point() + geom_point() + geom_point() +
          facet_grid(.~measure) +
          theme bw() +
          library(animation)
#set up function to loop through the draw.a.plot() function #
# temporal network centrality #
loop.animate <- function() {
       lapply(subsw1[1:50], function(i) {
    print(centrality_plot_fun(i, "Temporal"))
}
saveGIF(loop.animate(), interval = .5, movie.name="PDC_centrality.gif", ani.width = 400, ani.height = 350,
    imgdir = "-/Box Sync/network/PAIRS/Brown Bag 3.31/")
loop.animate <- function() {
    lapply(subsw1[1:50], function(i) {</pre>
      print(centrality_plot_fun(i, "Contemporaneous"))
})
saveGIF(loop.animate(), interval = .5, movie.name="PCC_centrality.gif", ani.width = 275, ani.height = 350,
             imgdir = "~/Box Sync/network/PAIRS/Brown Bag 3.31/")
```

#### 5.2 Regressions

#### 5.2.1 Centrality Indices

```
contraity, model < function(df)(
mod) < ln(value) = SEM, Neuroticin, data = df)
mod) < in(value) = value + SEM, Conscientionumese, data = df)
mod) < in(value) = value + SEM, Conscientionumese, data = df)
mod) < in(value) = value + SEM, Conscientionumese, data = df)
mod) < in(value) = value + SEM, Conscientionumese, task = df)
mod) < in(value) = value + SEM, Conscientionumese, task = df)
results < lins(insdo), modi, modi, modi, modi)
results < lins(insdo), modi, modi, modi)

contraity, long <- contraity > DX
sales(CDD, measure, value, z. GPA, procramationt, 11fe_mat,
gather(toy = outcome, value = value), GPA; interpretations > DX
mates(Cong, Trait = ifsise(grapi(CC, "val) = T, "v", "b))) DX
filter(Edge, Trait = ifsise(grapi(CC, "val) = T, "v", "b))) DX
filter(Edge, Trait = ifsise(grapi(CC, "val) = T, "v", "b))) DX
filter(Edge, Trait = ifsise(grapi(CC, "val) = T, "v", "b))) DX
filter(Edge, Trait = vertical outcomese) DX
mates(Cong, "prait = vertical outcomese = vertical value)
mates(cong, type = ifsise(cong task, "vertical value)) DX
mates(Cong, value) = ifsise(cong task, "vertical value)
mates(cong, value) = ifsise(cong task, value) DX
mates(DX
mates(DX
mates(Cong, value), value = value)
filter(Is.na.(node)) DX
filter(Is.na.(node)) DX
mates(Cong, value) = ifsise(spise(value)) DX
filter(Is.na.(node)) DX
mates(cong, value) = ifsise(spise(value)) DX
mates(cong, value) = ifsise(spise(value)) = ifsise(spise(
```



# 6 Question 3: Does density predict outcomes

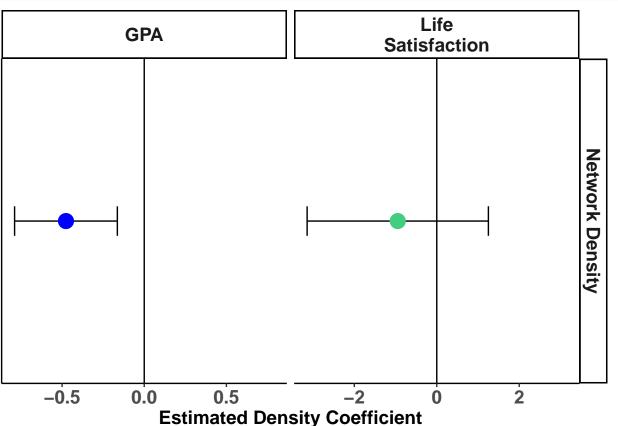
## 6.1 Regressions

```
mod_density <- function(data){lm(value - density , data = data)}

tidy_density <- function(model){
    tidy(model) %>%
        bind_cols(tbl_df(confint(model, method = "boot")))
}

density_fits <- density %>%
    left_join(target.ratings) %>%
    left_join(varget.ratings) %>%
    left_join(varget.ratings) %>%
    select(SID, vave, density, type, fit, GPA, procrastinate, life_sat, ESM_Neuroticism, ESM_Conscientiousness) %>%
    gather(key = outcome, value = value, GPA:life_sat) %>%
    group_by(type, wave, fit, outcome) %>%
    nest() %>%
    nest() %>%
    uutate(model = map(data, possibly(mod_density, NA_real_)),
        tidy = map(model, possibly(tidy_density, NA_real_)))
```

```
density_fits.df <- density_fits %\footnote{Titler(lis.na(tidy)) %\footnote{Titler(lis.na(
```



ggsave(file = "~/Box Sync/network/PAIRS/outcomes/graphs/contemp\_density\_bs.png", width = 5, height = 5)