

Homework 7

Psych 5068

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Workspace

Packages

Data

```
source("https://raw.githubusercontent.com/emoriebeck/homeworks/master/table_fun.R")
data_url <- "https://raw.githubusercontent.com/emoriebeck/homeworks/master/homework7/daily_diary(4).csv"
dat      <- data_url %>% read.csv %>% tbl_df %>% select(-X)
```

Question 1

1. Begin by creating lagged variables for self-esteem (rse lag 1), the reported average positive events (posmn lag 1), and the reported average negative events (negmn lag 1). You may find functions that can help you do this or you may decide to do this with your own code. Either way, you will need to do this carefully because the reports by participants do not always reflect consecutive days. That is, a person might provide data on the following days: 1, 2, 3, 6, 8, 9, 10, 12, 13, and 14. Lagged variables would only be available for days 2, 3, 9, 10, 13, and 14. Those are the only days when there was also a measure available on the immediately preceding day. So, we will lose some data in the process of creating lagged variables but that will insure that the meaning of the lagged variable is consistent.

```
dat <- dat %>%
  mutate(cesd_z = as.numeric(scale(cesd))) %>%
  full_join(crossing(id = unique(dat$id), day = seq(1, max(dat$id)))) %>%
  arrange(id, day) %>%
  group_by(id) %>%
  mutate_at(vars(rse, posmn, negmn), funs(lag_1 = lag(., n = 1)))
```

Question 2

First, let's see how persistent self-esteem is for all of the participants.

Level 1:

$$rse_{ti} = \pi_{0i} + \pi_{1i}rse_lag_1_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

```
fit2 <- lmer(rse ~ 1 + rse_lag_1 + (rse_lag_1 | id), data = dat)
tab2 <- table_fun(fit2)
```

```
options(knitr.kable.NA = '')
tab2 %>% select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
        col.names = c("", c("b", "CI"))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1, 2) %>%
  group_rows("Fit", 5, 6) %>%
  group_rows("Random", 3, 4) %>%
  add_header_above(c(" " = 1, "Model Q2" = 2))
```

	Model Q2	
	b	CI
Fixed		
Intercept	3.56	[3.37, 3.76]
rse_lag_1	0.34	[0.31, 0.38]
Random		
τ_{00}	0.77	[0.52, 1.87]
τ_{11}	0.01	[0.00, 0.05]
R_m^2	0.15	
R_c^2	0.48	

Part A

What is the value of the fixed effect for rse lag 1? Is it significant?

The fixed effect for rse_lag_1 is significant, 0.34, 95% CI [0.31, 0.38].

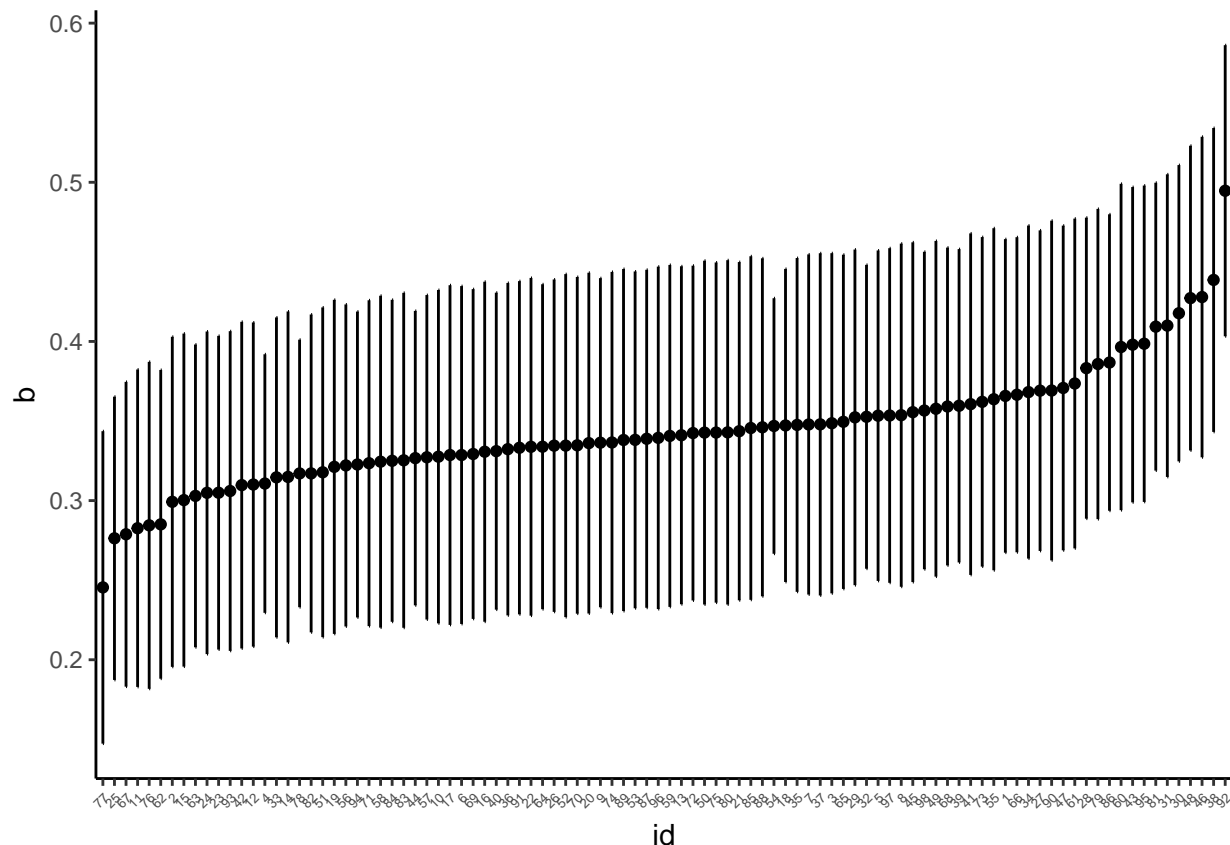
Part B

Provide a caterpillar plot showing the individual estimated coefficients for rse lag 1. The individual coefficients can be obtained using the `coef()` function for the fit object. Each individual coefficient has a standard error that can be obtained with the `se.coef()` function, a helper function from the `arm` package. Is persistence in self-esteem a common occurrence? What makes you say so?

```
coefs2 <- cbind(coef(fit2)[["id"]], arm::se.coef(fit2)[["id"]]) %>% data.frame %>%
  setNames(c("Intercept.b", "rse_lag_1.b", "Intercept.se", "rse_lag_1.se")) %>%
  mutate(id = rownames(.)) %>%
  tbl_df %>%
  gather(key = term, value = value, -id) %>%
  separate(term, c("term", "tmp"), sep = "[.]") %>%
  spread(key = tmp, value = value) %>%
  filter(term == "rse_lag_1")

orders <- coefs2 %>% arrange(b)

coefs2 %>% mutate(id = factor(id, levels = orders$id)) %>%
  ggplot(aes(x = id, y = b)) +
  geom_point() +
  geom_errorbar(aes(ymin = b - se, ymax = b + se), width = 0) +
  # geom_hline(aes(yintercept = fixef(fit3)["posmm_lag_1"]), color = "red", size = 1) +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = rel(.6)))
```



```
perc_above <- coefs2 %>% mutate(lower = b - 1.96*se, sign = sign(lower)) %>%
  group_by(sign) %>% summarize(n = n()) %>% ungroup() %>% mutate(n = n/sum(n))
```

Yes, across, the entire, sample, the lagged effect is positive. In other words, self-esteem at time t (the lagged variable) is associated with higher self-esteem at time $t + 1$.

Question 3

Now let's see how persistent positive events are for all of the participants.

Level 1:

$$posmn_{ti} = \pi_{0i} + \pi_{1i}posmn_lag_1_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

```
fit3 <- lmer(posmn ~ 1 + posmn_lag_1 + (posmn_lag_1 | id), data = dat)
tab3 <- table_fun(fit3)

options(knitr.kable.NA = '')
tab3 %>% select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
        col.names = c("", c("b", "CI"))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1, 2) %>%
  group_rows("Fit", 5, 6) %>%
```

```
group_rows("Random", 3, 4) %>%
add_header_above(c(" " = 1, "Model Q2" = 2))
```

	Model Q2	
	b	CI
Fixed		
Intercept	0.89	[0.82, 0.92]
posmn_lag_1	0.25	[0.24, 0.32]
Random		
τ_{00}	0.13	[0.08, 0.16]
τ_{11}	0.03	[0.00, 0.05]
R_m^2	0.08	
R_c^2	0.50	

Part A

Is there significant persistence for positive events? How would you interpret this effect? Speculate about why it might occur.

The fixed effect for posmn_lag_1 is significant, 0.25, 95% CI [0.24, 0.32]. In other words, positive events at time $t + 1$ (the lagged variable) predicts positive events at the previous time point. This may occur because of environmental or psychological carryover effects, which we often term selection effects. Someone who experiences positive events may live in an environment where positive events are more likely. Moreover, someone who experiences positive events may select into future positive events in order to maintain positive affect.

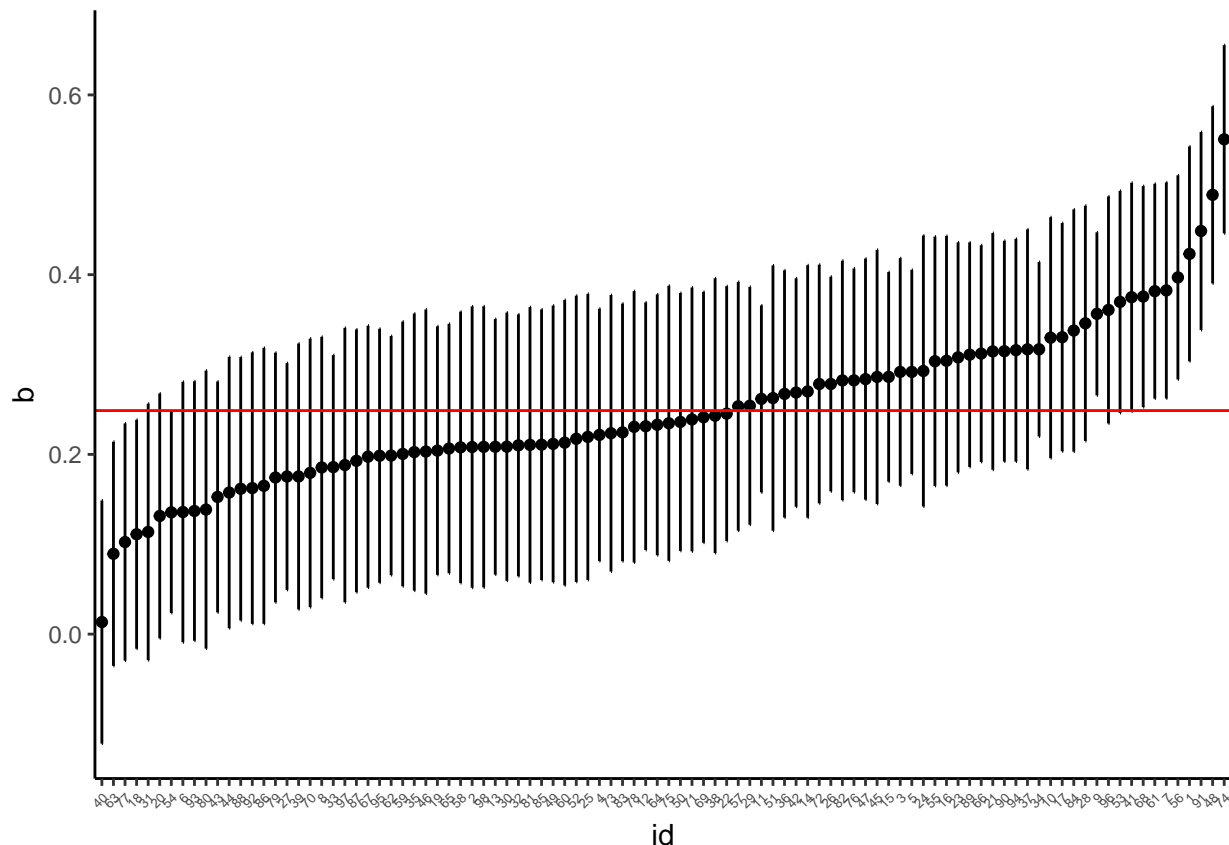
Part B

Provide a caterpillar plot of the individual estimated coefficients for posmn lag 1. Is this form of persistence common?

```
coefs3 <- cbind(coef(fit3)[["id"]], arm::se.coef(fit3)[["id"]]) %>% data.frame %>%
  setNames(c("Intercept.b", "posmn_lag_1.b", "Intercept.se", "posmn_lag_1.se")) %>%
  mutate(id = rownames(.)) %>%
  tbl_df %>%
  gather(key = term, value = value, -id) %>%
  separate(term, c("term", "tmp"), sep = "[.]") %>%
  spread(key = tmp, value = value) %>%
  filter(term == "posmn_lag_1")

orders <- coefs3 %>% arrange(b)

coefs3 %>% mutate(id = factor(id, levels = orders$id)) %>%
  ggplot(aes(x = id, y = b)) +
  geom_point() +
  geom_errorbar(aes(ymin = b - se, ymax = b + se), width = 0) +
  geom_hline(aes(yintercept = fixef(fit3)[["posmn_lag_1"]], color = "red") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = rel(.6)))
```



```
perc_above <- coefs3 %>% mutate(lower = b - 1.96*se, sign = sign(lower)) %>%
  group_by(sign) %>% summarize(n = n()) %>% ungroup() %>% mutate(n = n/sum(n))
```

Yes, this persistence is somewhat common but not greatly reliable. The lower bound of the confidence intervals on individual level slopes exceeds zero for 38% of people.

Question 4

Finally, let's see how persistent negative events are for all of the participants.

Level 1:

$$rse_{ti} = \pi_{0i} + \pi_{1i}rse_lag_1_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

```
fit4 <- lmer(negmn ~ 1 + negmn_lag_1 + (negmn_lag_1 | id), data = dat)
tab4 <- table_fun(fit4)

options(knitr.kable.NA = '')
tab4 %>% select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
        col.names = c("", c("b", "CI"))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1,2) %>%
  group_rows("Fit", 5, 6) %>%
```

```
group_rows("Random", 3, 4) %>%
add_header_above(c(" " = 1, "Model Q4" = 2))
```

	Model Q4	
	b	CI
Fixed		
Intercept	0.36	[0.33, 0.40]
negmn_lag_1	0.32	[0.31, 0.36]
Random		
τ_{00}	0.05	[0.03, 0.07]
τ_{11}	0.03	[0.00, 0.05]
R_m^2	0.13	
R_c^2	0.45	

Part A

Is there significant persistence for negative events?

The fixed effect for negmn_lag_1 is significant, , 95% CI .

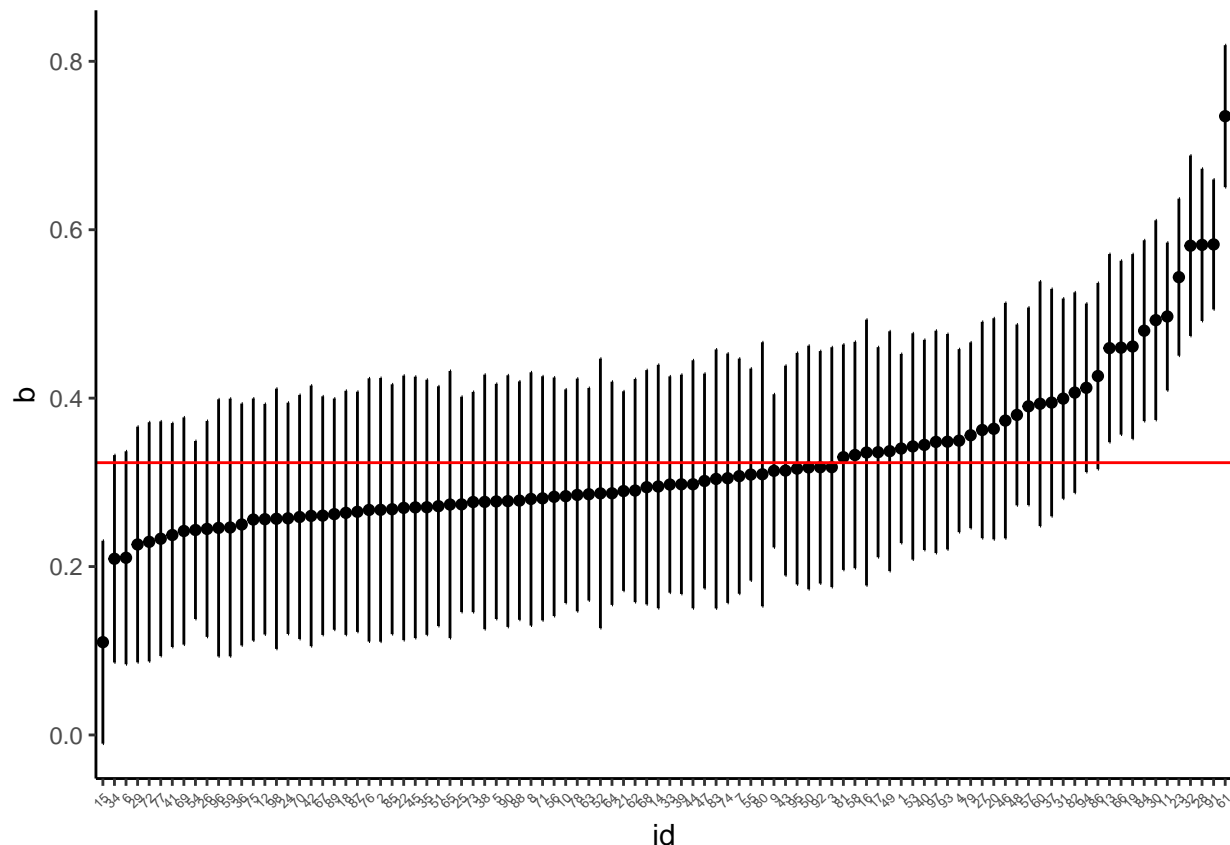
Part B

Provide a caterpillar plot of the individual estimated coefficients for negmn lag 1 and comment on how common this form of persistence is among participants.

```
coefs4 <- cbind(coef(fit4)[["id"]], arm::se.coef(fit4)[["id"]]) %>% data.frame %>%
  setNames(c("Intercept.b", "negmn_lag_1.b", "Intercept.se", "negmn_lag_1.se")) %>%
  mutate(id = rownames(.)) %>%
  tbl_df %>%
  gather(key = term, value = value, -id) %>%
  separate(term, c("term", "tmp"), sep = "[.]") %>%
  spread(key = tmp, value = value) %>%
  filter(term == "negmn_lag_1")

orders <- coefs4 %>% arrange(b)

coefs4 %>% mutate(id = factor(id, levels = orders$id)) %>%
  ggplot(aes(x = id, y = b)) +
  geom_point() +
  geom_errorbar(aes(ymin = b - se, ymax = b + se), width = 0) +
  geom_hline(aes(yintercept = fixef(fit4)["negmn_lag_1"]), color = "red") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = rel(.6)))
```



```
perc_above <- coefs4 %>% mutate(lower = b - 1.96*se, sign = sign(lower)) %>%
  group_by(sign) %>% summarize(n = n()) %>% ungroup() %>% mutate(n = n/sum(n))
```

Yes, this persistence is common. The lower bound of the confidence intervals on individual level slopes exceeds zero for 64% of people.

Question 5

Now fit a model with self-esteem as the outcome and with lagged self-esteem, current positive events, and current negative events as predictors:

Level 1:

$$rse_{ti} = \pi_{0i} + \pi_{1i}rse_lag_1_{ti} + \pi_{2i}posmn_{ti} + \pi_{3i}negmn_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

$$\pi_{2i} = \beta_{20} + r_{2i}$$

$$\pi_{3i} = \beta_{30} + r_{3i}$$

```
fit5 <- lmer(rse ~ rse_lag_1 + posmn + negmn +
  (rse_lag_1 + posmn + negmn | id), data = dat)

tab5 <- table_fun(fit5)

options(knitr.kable.NA = '')
tab5 %>% select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
```



```
col.names = c("", c("b", "CI")) %>%
kable_styling(full_width = F) %>%
group_rows("Fixed", 1, 4) %>%
group_rows("Fit", 9, 10) %>%
group_rows("Random", 5, 8) %>%
add_header_above(c(" " = 1, "Model Q5" = 2))
```

	Model Q5	
	b	CI
Fixed		
Intercept	3.81	[3.37, 3.95]
rse_lag_1	0.30	[0.25, 0.39]
posmn	0.39	[0.33, 0.52]
negmn	-0.81	[-0.93, -0.72]
Random		
τ_{00}	1.16	[0.51, 2.32]
τ_{11}	0.02	[0.01, 0.05]
τ_{22}	0.12	[0.06, 0.19]
τ_{33}	0.07	[0.02, 0.19]
R_m^2	0.40	
R_c^2	0.63	

Part A

This model provides a different way of examining the impact of current events on self-esteem. By partialling the previous day's self-esteem, how would the influence of current events be interpreted in this model?

By partialling out the previous day's self-esteem, we are able to look at the unique of current negative and positive emotion on the self-esteem.

Part B

Fit the model and comment on the magnitude and interpretation of the coefficients for positive and negative events.

There is a negative effect of current negative events on self-esteem ($b = -0.81$; 95% CI [-0.93, -0.72]). The current day's negative events predict lower self esteem.

There is a positive effect of current positive events on self-esteem ($b = 0.39$; 95% CI [0.33, 0.52]). The current day's positive predict higher self esteem.

Question 6

Fit a full lagged model.

Level 1:

$$rse_{ti} = \pi_{0i} + \pi_{1i}rse_lag_1_{ti} + \pi_{2i}posmn_{ti} + \pi_{3i}negmn_{ti} + \pi_{4i}posmn_lag_1_{ti} + \pi_{5i}negmn_lag_1_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

$$\begin{aligned}\pi_{2i} &= \beta_{20} + r_{2i} \\ \pi_{3i} &= \beta_{30} + r_{3i} \\ \pi_{4i} &= \beta_{40} + r_{4i} \\ \pi_{5i} &= \beta_{50} + r_{5i}\end{aligned}$$

```
fit6 <- lmer(rse ~ rse_lag_1 + posmn + negmn + posmn_lag_1 + negmn_lag_1 +
  (posmn + negmn + rse_lag_1 + posmn_lag_1 + negmn_lag_1 | id), data = dat)

tab6 <- table_fun(fit6)

options(knitr.kable.NA = '')
tab6 %>% select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
    col.names = c("", c("b", "CI"))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1, 6) %>%
  group_rows("Fit", 13, 14) %>%
  group_rows("Random", 7, 12) %>%
  add_header_above(c(" " = 1, "Model Q6" = 2))
```

	Model Q6	
	b	CI
Fixed		
Intercept	3.60	[3.22, 3.72]
rse_lag_1	0.35	[0.33, 0.39]
posmn	0.42	[0.33, 0.48]
negmn	-0.83	[-0.96, -0.73]
posmn_lag_1	-0.08	[-0.20, -0.00]
negmn_lag_1	0.05	[-0.03, 0.20]
Random		
τ_{00}	1.35	[0.68, 2.92]
τ_{11}	0.14	[0.08, 0.21]
τ_{22}	0.09	[0.04, 0.36]
τ_{33}	0.04	[0.02, 0.09]
τ_{44}	0.11	[0.06, 0.16]
τ_{55}	0.05	[0.01, 0.16]
R_m^2	0.43	
R_c^2	0.67	

Part A

With current positive events controlled, is there any residual effect of the previous day's positive events on self-esteem? There is no effect of residual positive events on self-esteem ($b = -0.08$; 95% CI [-0.20, -0.00]). The previous day's positive events do not predict self esteem.

Part B

With current negative events controlled, is there any residual effect of the previous day's negative events on self-esteem?

There is no effect of residual negative events on self-esteem ($b = 0.05$; 95% CI 0.05). The previous day's negative events do not predict self esteem.

Question 7

Lastly, take the model from the previous problem and add the standardized CES-D depression measure (you will need to create this) as a predictor in each Level 2 equation:

Level 1:

$$rse_{ti} = \pi_{0i} + \pi_{1i}rse_lag_1_{ti} + \pi_{2i}posmn_{ti} + \pi_{3i}negmn_{ti} + \pi_{4i}posmn_lag_1_{ti} + \pi_{5i}negmn_lag_1_{ti} + \epsilon_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + \beta_{01}cesd_z_i + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}cesd_z_i + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}cesd_z_i + r_{2i}$$

$$\pi_{3i} = \beta_{30} + \beta_{31}cesd_z_i + r_{3i}$$

$$\pi_{4i} = \beta_{40} + \beta_{41}cesd_z_i + r_{4i}$$

$$\pi_{5i} = \beta_{50} + \beta_{51}cesd_z_i + r_{5i}$$

```
c12 <- lmerControl(optimizer = "optimx",
                  optCtrl=list(method="nlopt",maxiter=1e9))
dat <- dat %>% group_by(id) %>%
  mutate(cesd_z = ifelse(is.na(cesd_z) == T, max(cesd_z, na.rm = T), cesd_z))
fit7 <- lmer(rse ~ rse_lag_1*cesd_z + posmn*cesd_z + negmn*cesd_z +
            posmn_lag_1*cesd_z + negmn_lag_1*cesd_z +
            (posmn + negmn + rse_lag_1 + posmn_lag_1 + negmn_lag_1 | id), data = dat, control = c12)
tab7 <- table_fun(fit7)
```

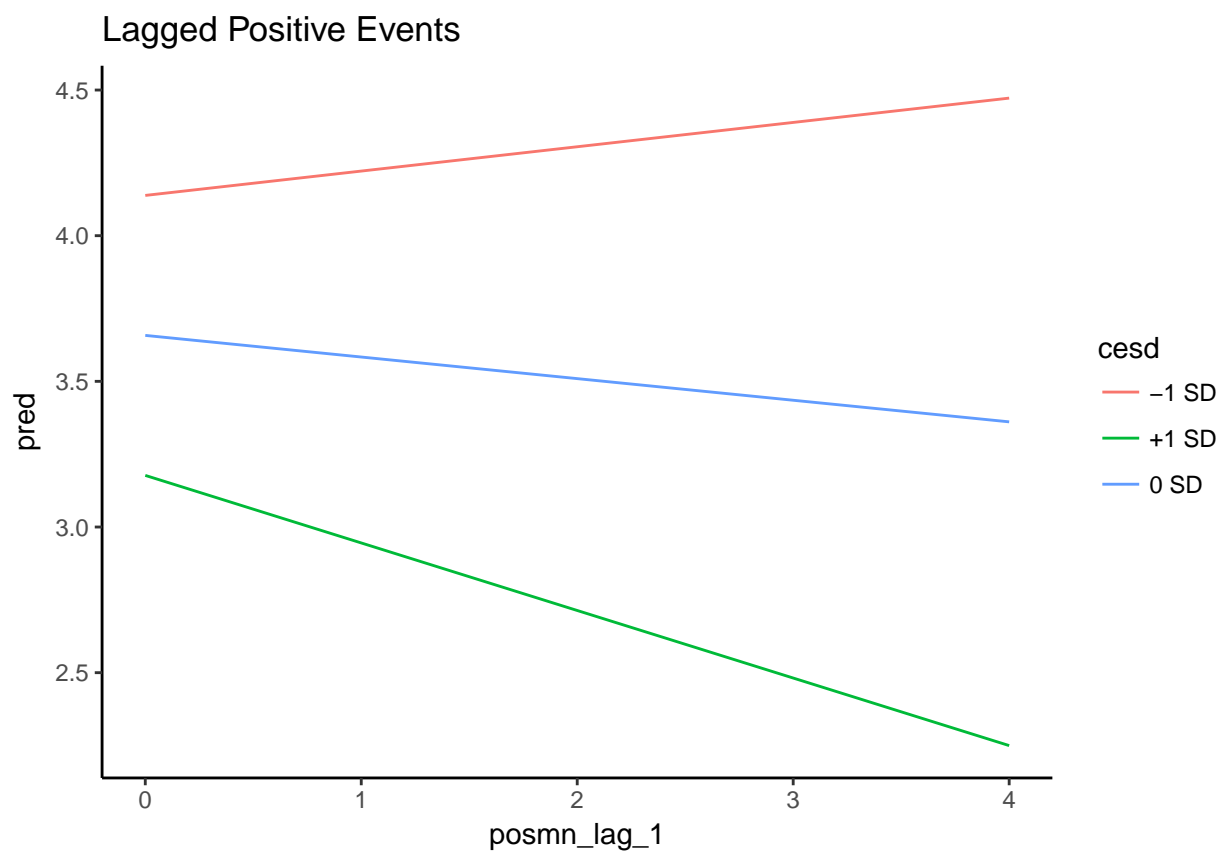
```
tab7 %>%
  select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
        col.names = c("", rep(c("b", "CI"), times = 1))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1,12) %>%
  group_rows("Fit", 19, 20) %>%
  group_rows("Random", 13, 18) %>%
  add_header_above(c(" " = 1, "Full" = 2))
```

	Full	
	b	CI
Fixed		
Intercept	3.66	[3.55, 3.90]
rse_lag_1	0.33	[0.29, 0.33]
cesd_z	-0.48	[-0.72, -0.39]
posmn	0.42	[0.29, 0.54]
negmn	-0.81	[-0.94, -0.77]
posmn_lag_1	-0.07	[-0.20, -0.03]
negmn_lag_1	0.05	[-0.03, 0.13]
rse_lag_1:cesd_z	0.04	[0.01, 0.08]
cesd_z:posmn	0.19	[0.14, 0.30]
cesd_z:negmn	-0.00	[-0.10, 0.11]
cesd_z:posmn_lag_1	-0.16	[-0.30, -0.00]
cesd_z:negmn_lag_1	0.07	[-0.02, 0.24]
Random		
τ_{00}	0.78	[0.29, 1.89]
τ_{11}	0.12	[0.08, 0.19]
τ_{22}	0.11	[0.05, 0.40]
τ_{33}	0.03	[0.01, 0.07]
τ_{44}	0.10	[0.06, 0.17]
τ_{55}	0.09	[0.02, 0.28]
R_m^2	0.50	
R_c^2	0.69	

There are two moderating effects of depression score: 1 SD change in depression is associated with a -0.16 * current posmn increase (95 % CI [-0.30, -0.00]) in self-esteem. In other words, current positive events are especially beneficial for those who are more depressed.

In addition, a 1SD change in depression is associated with a -0.16 * posmn_lag_1 increase (95 % CI [-0.30, -0.00]). In other words, past positive events only benefit the self-esteem of those who are less depressed than average.

```
crossing(
  cesd_z = c(-1,0,1),
  posmn = 0,
  negmn = 0,
  posmn_lag_1 = seq(min(dat$posmn_lag_1, na.rm = T), max(dat$posmn_lag_1, na.rm = T),1),
  negmn_lag_1 = 0,
  rse_lag_1 = 0
) %>%
mutate(pred = predict(fit7, newdata = ., re.form = NA),
       cesd = mapvalues(cesd_z, c(-1, 0, 1), c("-1 SD", "0 SD", "+1 SD"))) %>%
ggplot(aes(x = posmn_lag_1, y = pred, color = cesd)) +
labs(title = "Lagged Positive Events") +
  geom_line() +
  theme_classic()
```



```
crossing(
  cesd_z = c(-1,0,1),
  posmn = seq(min(dat$posmn, na.rm = T), max(dat$posmn, na.rm = T),1),
  negmn = 0,
  posmn_lag_1 = 0,
  negmn_lag_1 = 0,
  rse_lag_1 = 0
) %>%
mutate(pred = predict(fit7, newdata = ., re.form = NA),
       cesd = mapvalues(cesd_z, c(-1, 0, 1), c("-1 SD", "0 SD", "+1 SD"))) %>%
ggplot(aes(x = posmn, y = pred, color = cesd)) +
labs(title = "Lagged Positive Events") +
  geom_line() +
  theme_classic()
```

