

ManyBabies 5: The Hunter and Ames Model of Infant Looking Preference

Supplementary Materials: Data Simulation and Power Analysis

ManyBabies Analysis Team

Contents

1	Data Simulation	3
2	Visualisation of Simulated Data	5
2.1	Familiarization:	5
2.2	Complexity:	6
2.3	Age:	7
2.4	Age*Familiarization:	8
2.5	Age*Complexity:	9
2.6	Familiarization*Complexity:	10
2.7	Variability by Lab	12
2.8	Variability by Item	13
3	Power Calculation with Full Data and Varying Intercepts and Varying Slopes	14
3.1	Effect Size = 0.5	14
3.2	Effect Size = 0.4	14
3.3	Effect Size = 0.3	14
3.3.1	Visualise Estimates for Fixed Effects:	15
3.3.2	Visualise Estimates for Random Effects:	16
3.4	Effect Size = 0.2	17
3.5	Effect Size = 0.1	17
4	Power Calculation with Full Data and Varying Intercepts	18
4.1	Effect Size = 0.5	18
4.2	Effect Size = 0.4	18
4.3	Effect Size = 0.3	18
4.3.1	Visualise Estimates for Fixed Effects:	19
4.3.2	Visualise Estimates for Random Effects:	20
4.4	Effect Size = 0.2	21
4.5	Effect Size = 0.1	21

5 Power Calculation with 20 pct. Missing Data and Varying Intercepts and Varying Slopes	22
5.1 Effect Size = 0.5	22
5.2 Effect Size = 0.4	22
5.3 Effect Size = 0.3	23
5.3.1 Visualise Estimates for Fixed Effects:	23
5.3.2 Visualise Estimates for Random Effects:	24
5.4 Effect Size = 0.2	25
5.5 Effect Size = 0.1	25
6 Power Calculation with 50 pct. Missing Data and Varying Intercepts and Varying Slopes	26
6.1 Effect Size = 0.5	26
6.2 Effect Size = 0.4	26
6.3 Effect Size = 0.3	27
6.3.1 Visualise Estimates for Fixed Effects:	27
6.3.2 Visualise Estimates for Random Effects:	28
6.4 Effect Size = 0.2	29
6.5 Effect Size = 0.1	29
7 Overview of Power Simulation Results	30
7.1 Summary Statistics for Power Calculation with Full Data and Varying Intercepts and Varying Slopes:	30
7.2 Summary Statistics for Power Calculation with Full Data and Varying Intercepts:	30
7.3 Summary Statistics for Power Calculation with 20 pct. Missing Data and Varying Intercepts and Varying Slopes: . . .	30
7.4 Summary Statistics for Power Calculation with 50 pct. Missing Data and Varying Intercepts and Varying Slopes: . . .	31

1 Data Simulation

```
my_sim_data <- function(  
  n_subj      = 1280,    # number of subjects  
  n_simple   = 12,     # number of complex stimuli  
  n_complex = 12,     # number of complex stimuli  
  n_small_fam = 8,    #small familiarization time  
  n_medium_fam = 8,   #medium familiarization time  
  n_high_fam = 8,     #high familiarization time  
  n_lab       = 40,  
  
  beta_0      = 0,      # intercept; i.e., the grand mean  
  beta_c      = 0.3,    # main effect for complexity  
  beta_f      = 0.3,    # main effect for familiarization time  
  beta_a      = 0.3,    # main effect for age  
  
  beta_ca     = 0.3,  
  beta_af     = 0.3,  
  beta_cf     = 0.3,  
  
  beta_cfa    = 0.3,   #main effect for interaction between complexity and familiarization.  
  
  subject_0   = 0.2,   # by-subject random intercept sd  
  
  subject_c   = 0.2,   # by-subject slope complexity sd  
  subject_f   = 0.2,   # by-subject slope familiarization sd  
  subject_a   = 0.2,   # by-subject slope age sd  
  
  subject_ca  = 0.2,  # by-subject slope for interaction between age and complexity sd  
  subject_af  = 0.2,  # by-subject slope for interaction between age and familiarization sd  
  subject_cf  = 0.2,  # by-subject slope complexity*familiarization sd  
  
  subject_cfa = 0.2,  # by-subject slope for interaction between age, complexity and familiarization sd  
  
  subj_rho    = .2,    # correlations between by-subject random effects  
  
  lab_0       = 0.2,   # by-lab random intercept sd  
  
  lab_c       = 0.2,   # by-lab slope complexity sd  
  lab_f       = 0.2,   # by-lab slope familiarization sd  
  lab_a       = 0.2,   # by-lab slope age sd  
  
  lab_ca     = 0.2,   # by-lab slope for interaction between age and complexity sd  
  lab_af     = 0.2,   # by-lab slope for interaction between age and familiarization sd  
  lab_cf     = 0.2,   # by-lab random slope complexity*familiarization sd  
  
  lab_cfa    = 0.2,   # by-lab slope for interaction between age, complexity and familiarization sd  
  
  lab_rho    = 0.2,   # correlations between by-lab random effects  
  
  item_0      = 0.2,   # by-item random intercept sd  
  
  item_c      = 0.2,   # by-item slope complexity sd  
  item_f      = 0.2,   # by-item slope familiarization sd  
  item_a      = 0.2,   # by-item slope age sd  
  
  item_ca    = 0.2,   # by-item slope for interaction between age and complexity sd  
  item_af    = 0.2,   # by-item slope for interaction between age and familiarization sd  
  item_cf    = 0.2,   # by-item random slope complexity*familiarization sd  
  
  item_cfa   = 0.2,   # by-item slope for interaction between age, complexity and familiarization sd
```

```

item_rho = 0.2, # correlations between by-item random effects

sigma = 0.3 # residual (error) sd
) { # residual (standard deviation)

# simulate a sample of items
items <- data.frame(
  item_id = seq_len(n_simple + n_complex),
  category = rep(c("simple", "complex"), c(n_simple, n_complex)),
  X_c = rep(c(-0.5, 0.5), c(n_simple, n_complex)),
  familiarization = rep(c("short", "medium", "long"), (n_simple + n_complex)/3),
  X_f = rep(c(-0.5, 0, 0.5), (n_simple + n_complex)/3),
  faux::rnorm_multi(
    n = n_simple + n_complex, mu = 0, sd = c(item_0,
                                                item_c,
                                                item_f,
                                                item_a,
                                                item_ca,
                                                item_af,
                                                item_cf,
                                                item_cfa), r = item_rho,
    varnames = c("I_0", "I_c", "I_f", "I_a",
                "I_ca", "I_af", "I_cf",
                "I_cfa")))
  )

# simulate a sample of subjects
subjects <-
  faux::rnorm_multi(
    n = n_subj, mu = 0, sd = c(subject_0,
                                subject_c,
                                subject_f,
                                subject_a,
                                subject_ca,
                                subject_af,
                                subject_cf,
                                subject_cfa), r = subj_rho,
    varnames = c("S_0", "S_c", "S_f", "S_a",
                "S_ca", "S_af", "S_cf",
                "S_cfa"))
  ) %>%
  mutate(subj_id = faux::make_id(nrow(.), "S")) %>%
  mutate(X_a = runif(n_subj, min = -0.5, max = 0.5))
#add subject age measure, sample from distribution from -0.5 to 0.5. #subjects$subj_id <- 1:n_subj

labs <- faux::rnorm_multi(
  n = n_lab, mu = 0, sd = c(lab_0, lab_c, lab_f, lab_a,
                            lab_ca, lab_af, lab_cf,
                            lab_cfa), r = lab_rho,
  varnames = c("L_0", "L_c", "L_f", "L_a",
              "L_ca", "L_af", "L_cf",
              "L_cfa"))
  ) %>%
  mutate(lab_id = faux::make_id(nrow(.), "L"))

#create lab and subj nesting structure
#Number of subjects must be a multiple of number of labs
lab_multiplier = n_subj/n_lab
lab_subj_dict <- data.frame(
  subj_id = subjects$subj_id,
  lab_id = rep(labs$lab_id, lab_multiplier)
)

```

```

)
# cross subject and item IDs
temp <- crossing(subjects, items) %>%
  left_join(lab_subj_dict, by = "subj_id") %>%
  left_join(labs, by = "lab_id")

temp %>%
  mutate(
    B_0 = beta_0 + S_0 + L_0 + I_0,
    B_c = beta_c + S_c + L_c + I_c,
    B_f = beta_f + S_f + L_f + I_f,
    B_a = beta_a + S_a + L_a + I_a,
    B_ca = beta_ca + S_ca + L_ca + I_ca,
    B_af = beta_af + S_af + L_af + I_af,
    B_cf = beta_cf + S_cf + L_cf + I_cf,
    B_cfa = beta_cfa + S_cfa + L_cfa + I_cfa,
    e_si = rnorm(nrow(temp), mean = 0, sd = sigma),
    DV = B_0 +
      (B_a * X_a) + (B_c * X_c) + (B_f * X_f) +
      (B_cf * X_c * X_f) + (B_af * X_a * X_f) + (B_ca * X_c * X_a) +
      (B_cfa * X_c * X_f * X_a) + e_si
  )
}

dat_sim <- my_sim_data()

```

2 Visualisation of Simulated Data

2.1 Familiarization:

```

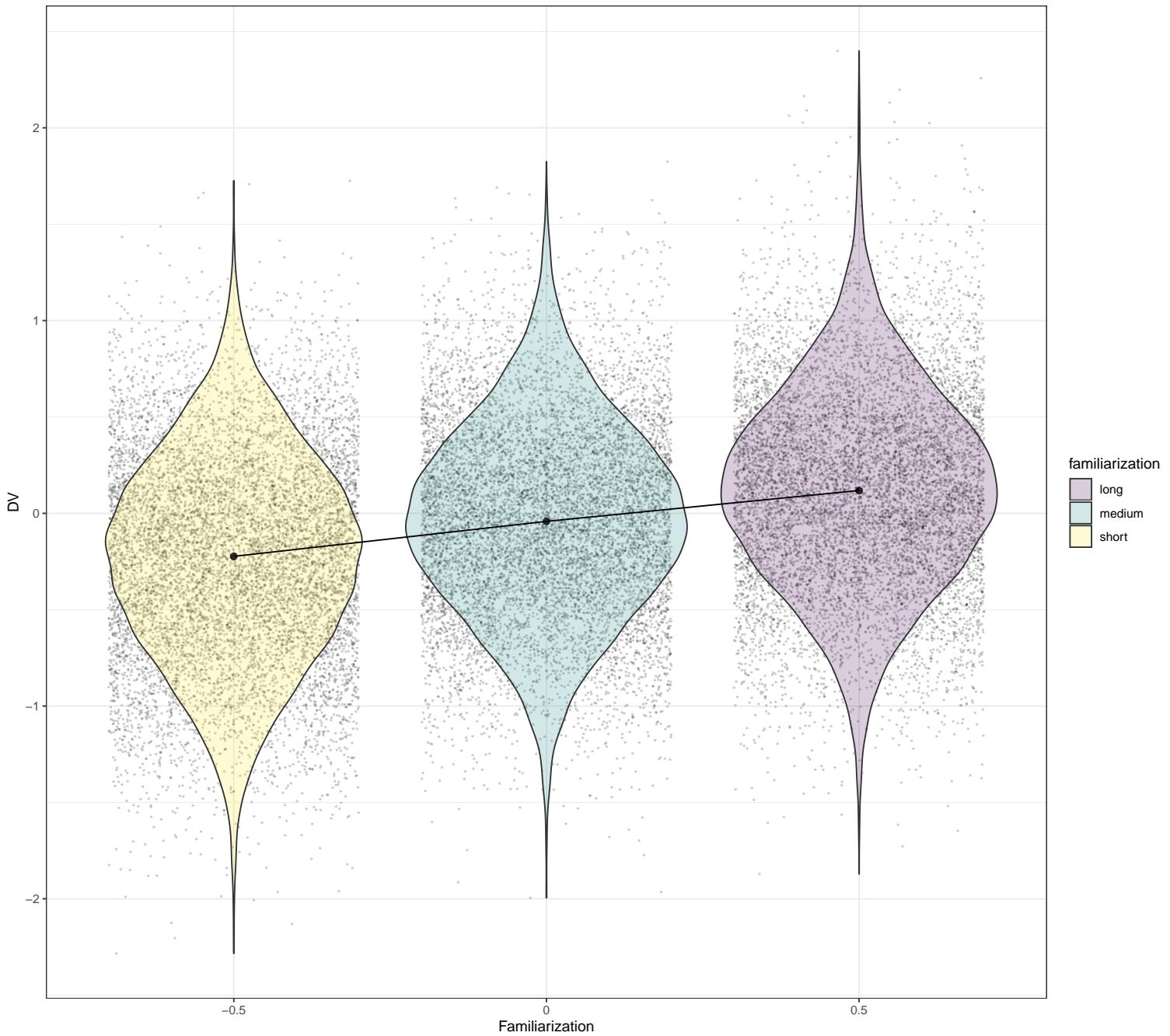
dat_sim_plot_familiarization <- dat_sim %>%
  group_by(X_f) %>%
  dplyr::summarise(med_DV = median(DV))

plot_familiarization <- dat_sim %>%
  mutate(X_f = as.factor(X_f)) %>%
  ggplot() + geom_point(aes(y = DV, x = X_f), position = "jitter",
  alpha = 0.2, size = 0.2) + geom_violin(aes(y = DV, x = X_f,
  fill = familiarization), alpha = 0.2) + geom_line(aes(y = med_DV,
  x = as.factor(X_f), group = 1), data = dat_sim_plot_familiarization) +
  geom_point(aes(y = med_DV, x = as.factor(X_f)), alpha = 0.8,
  size = 2, data = dat_sim_plot_familiarization) + scale_fill_manual(values = viridis(n = 3)) +
  ggtitle("Familiarization") + xlab("Familiarization") + theme_bw()

plot_familiarization <- plot_familiarization + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
plot_familiarization

```

Familiarization



2.2 Complexity:

```
dat_sim_plot_complexity <- dat_sim %>%
  group_by(X_c) %>%
  dplyr::summarise(med_DV = median(DV))

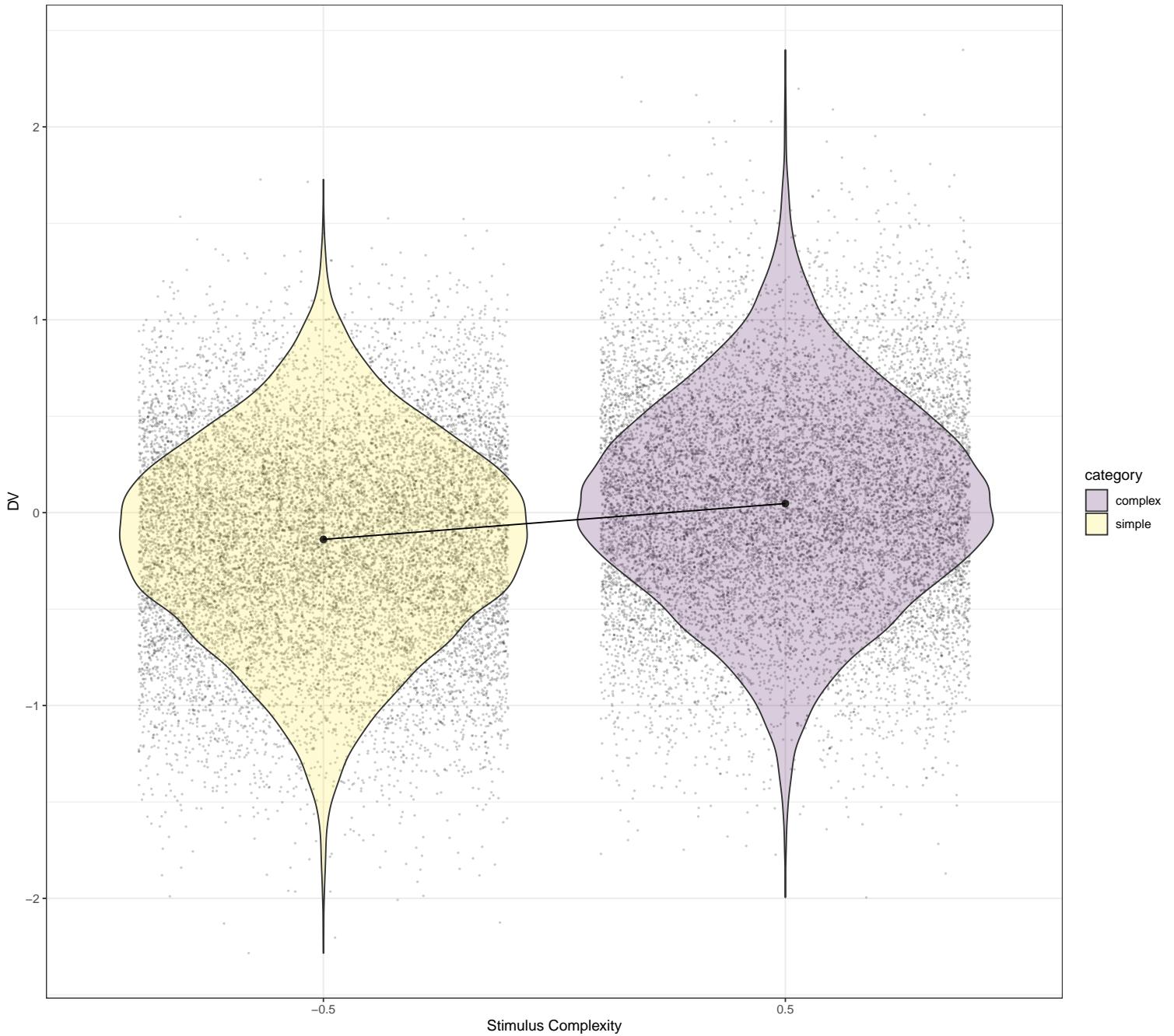
plot_complexity <- dat_sim %>%
  mutate(X_c = as.factor(X_c)) %>%
  ggplot() + geom_point(aes(y = DV, x = X_c), position = "jitter",
  alpha = 0.2, size = 0.2) + geom_violin(aes(y = DV, x = X_c,
  fill = category), alpha = 0.2) + geom_line(aes(y = med_DV,
  x = as.factor(X_c), group = 1), data = dat_sim_plot_complexity) +
  geom_point(aes(y = med_DV, x = as.factor(X_c)), alpha = 0.8,
  size = 2, data = dat_sim_plot_complexity) + scale_fill_manual(values = viridis(n = 2)) +
  ggtitle("Stimulus Complexity") + xlab("Stimulus Complexity") +
  theme_bw()
```

```

plot_complexity <- plot_complexity + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
plot_complexity

```

Stimulus Complexity



2.3 Age:

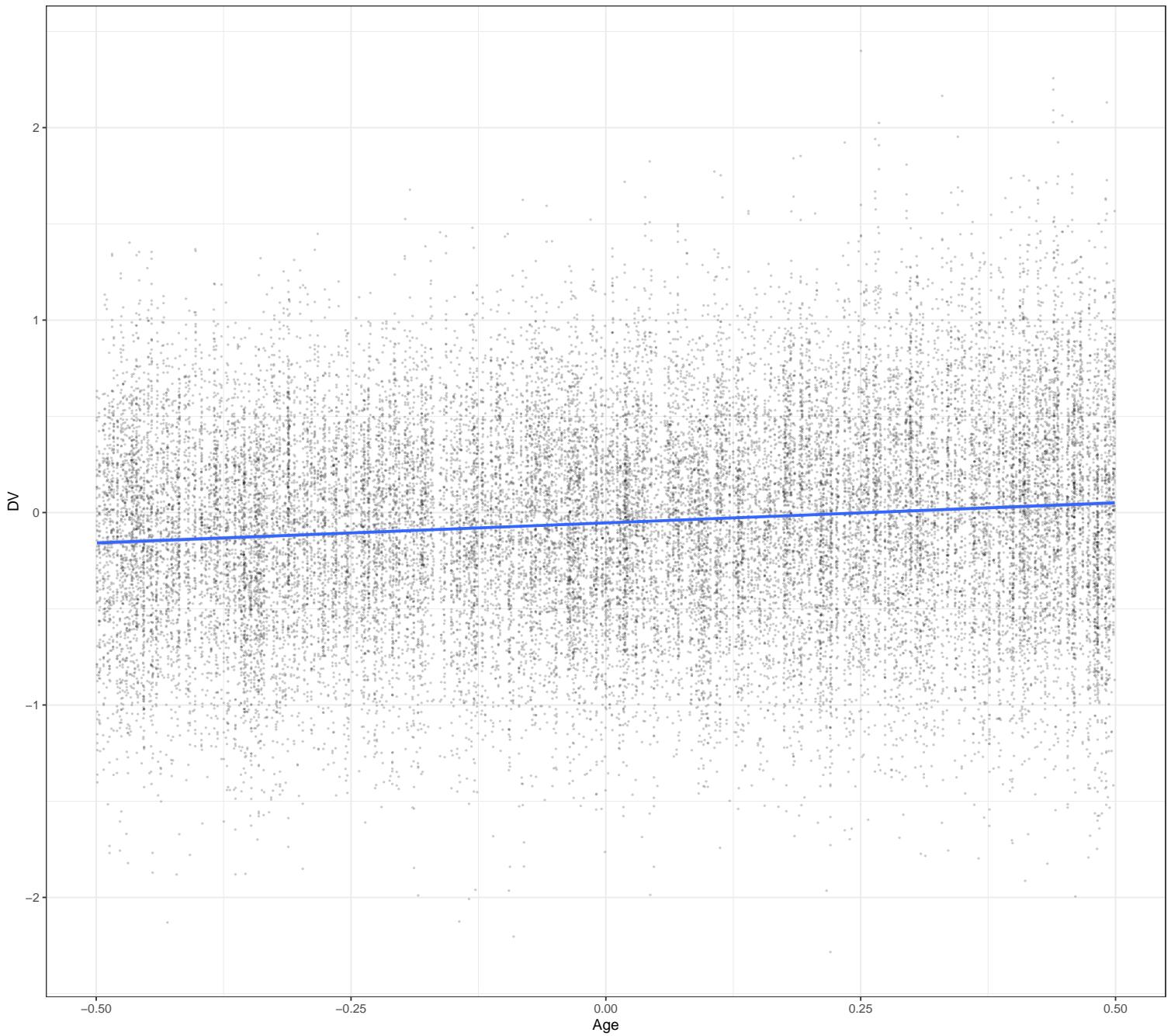
```

plot_age <- dat_sim %>%
  ggplot() + geom_point(aes(y = DV, x = X_a), position = "jitter",
    alpha = 0.2, size = 0.2) + geom_smooth(method = "lm", se = TRUE,
    formula = y ~ x, aes(y = DV, x = X_a)) + ggtitle("Age") +
    xlab("Age") + theme_bw()

plot_age <- plot_age + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
plot_age

```

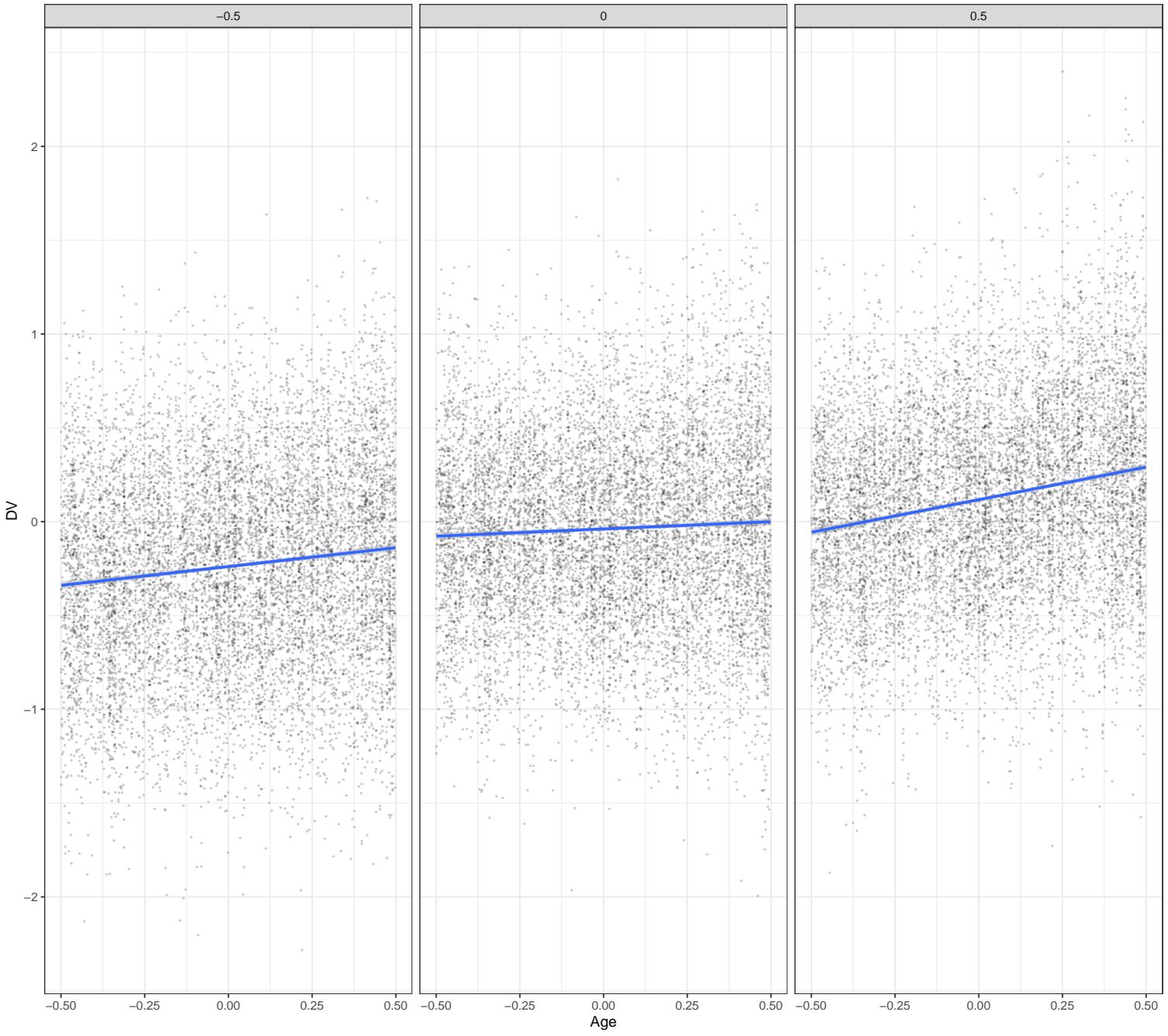
Age



2.4 Age*Familiarization:

```
plot_age_familiarization <- dat_sim %>%
  ggplot() + geom_point(aes(y = DV, x = X_a), position = "jitter",
    alpha = 0.2, size = 0.2) + geom_smooth(method = "lm", formula = y ~
    x, se = TRUE, aes(y = DV, x = X_a)) + facet_wrap(~X_f) +
  ggtitle("Age x Familiarization Interaction") + xlab("Age") +
  theme_bw()
plot_age_familiarization <- plot_age_familiarization + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
plot_age_familiarization
```

Age x Familiarization Interaction



2.5 Age*Complexity:

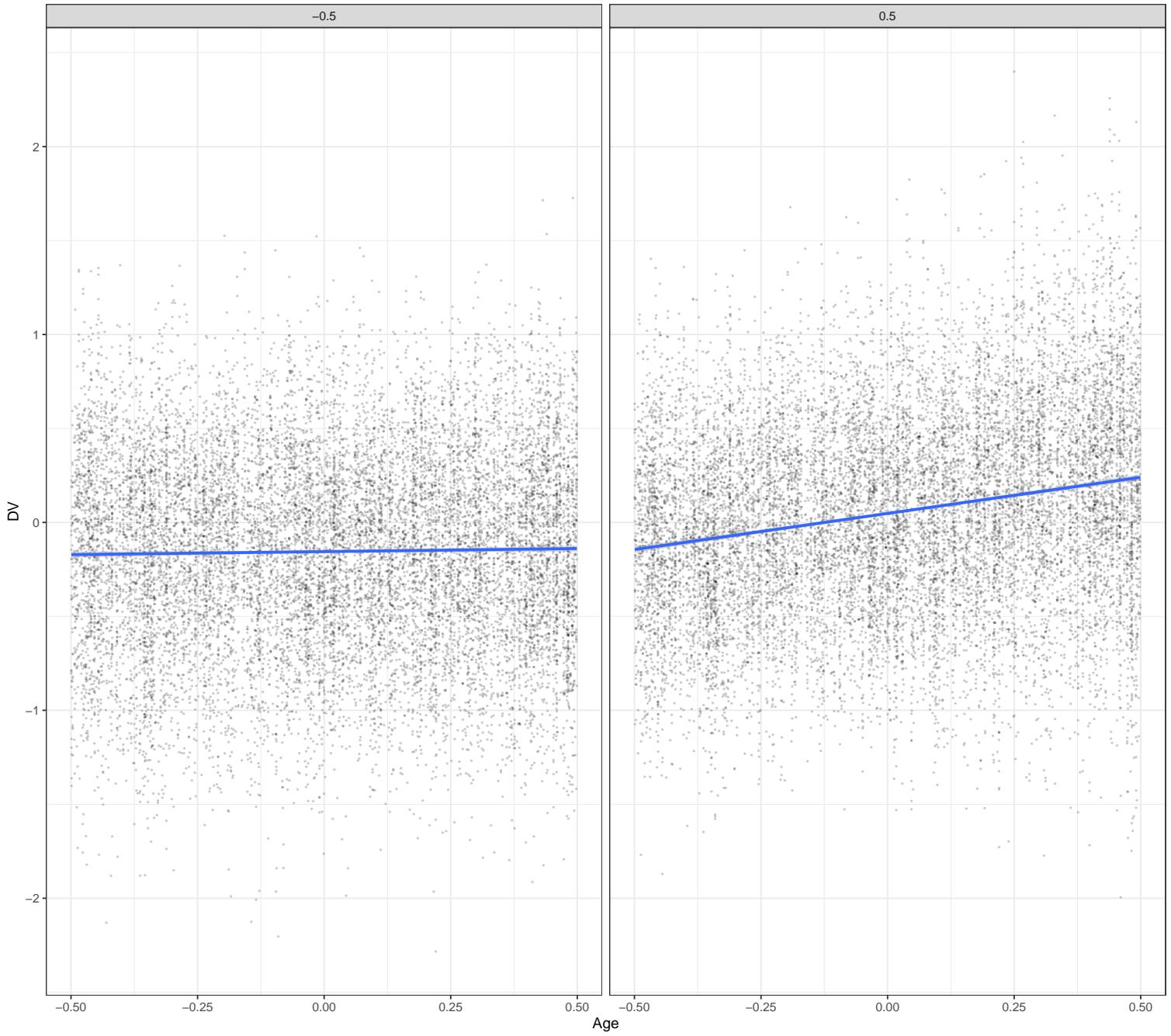
```

plot_age_complexity <- dat_sim %>%
  ggplot() + geom_point(aes(y = DV, x = X_a), position = "jitter",
                        alpha = 0.2, size = 0.2) + geom_smooth(method = "lm", formula = y ~
  x, se = TRUE, aes(y = DV, x = X_a)) + facet_wrap(~X_c) +
  ggtitle("Age x Complexity Interaction") + xlab("Age") + theme_bw()

plot_age_complexity <- plot_age_complexity + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
plot_age_complexity

```

Age x Complexity Interaction



2.6 Familiarization*Complexity:

```
dat_f_c_interaction <- dat_sim %>%
  mutate(X_c = as.factor(X_c)) %>%
  mutate(X_f = as.factor(X_f)) %>%
  group_by(X_f, X_c) %>%
  dplyr::summarise(med_DV = median(DV))
```

```
## `summarise()` has grouped output by 'X_f'. You can override using the `.`groups` argument.
```

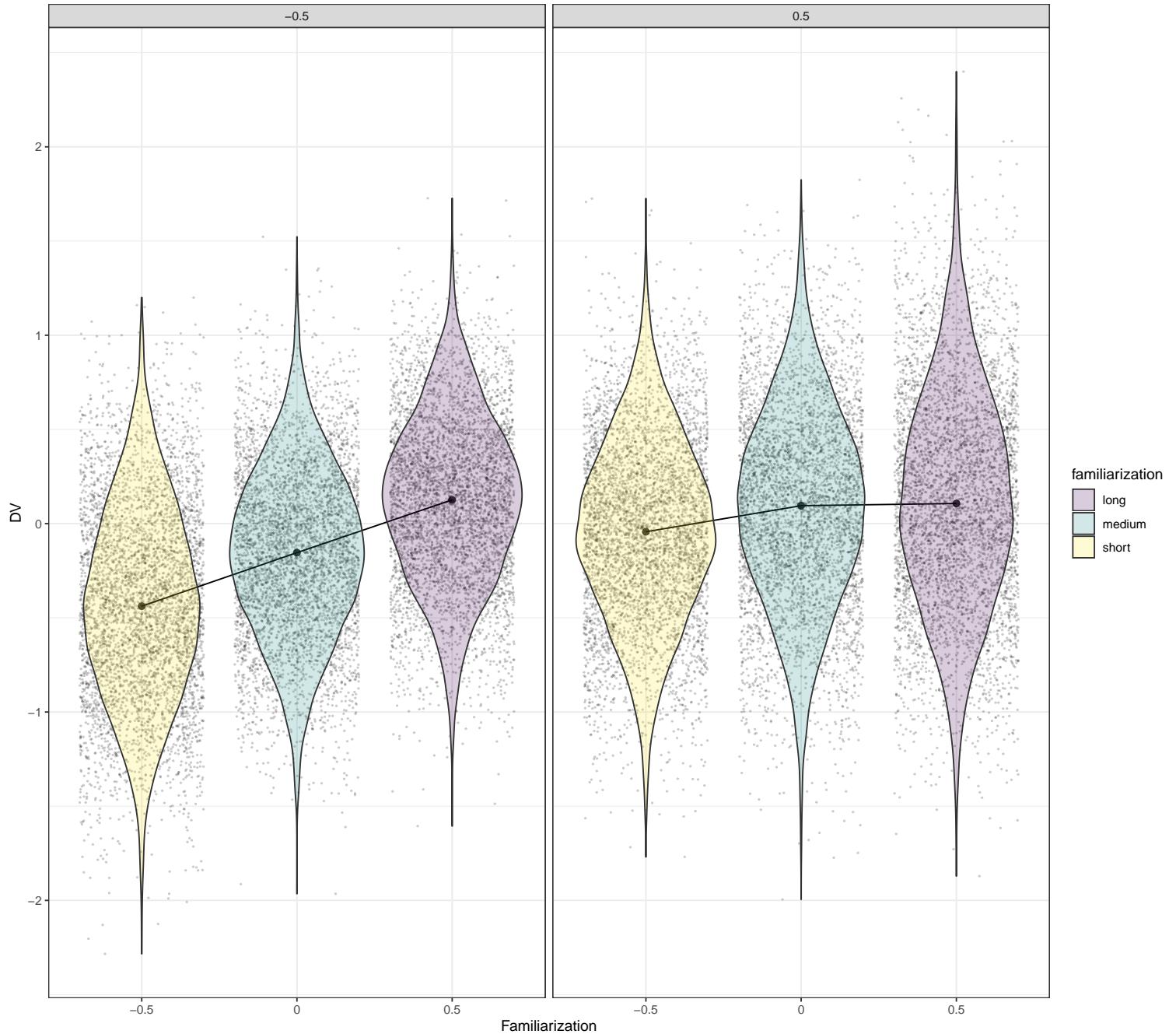
```
plot_familiarization_complexity <- dat_sim %>%
  mutate(X_c = as.factor(X_c)) %>%
  mutate(X_f = as.factor(X_f)) %>%
  ggplot() + geom_point(aes(y = DV, x = X_f), position = "jitter",
```

```

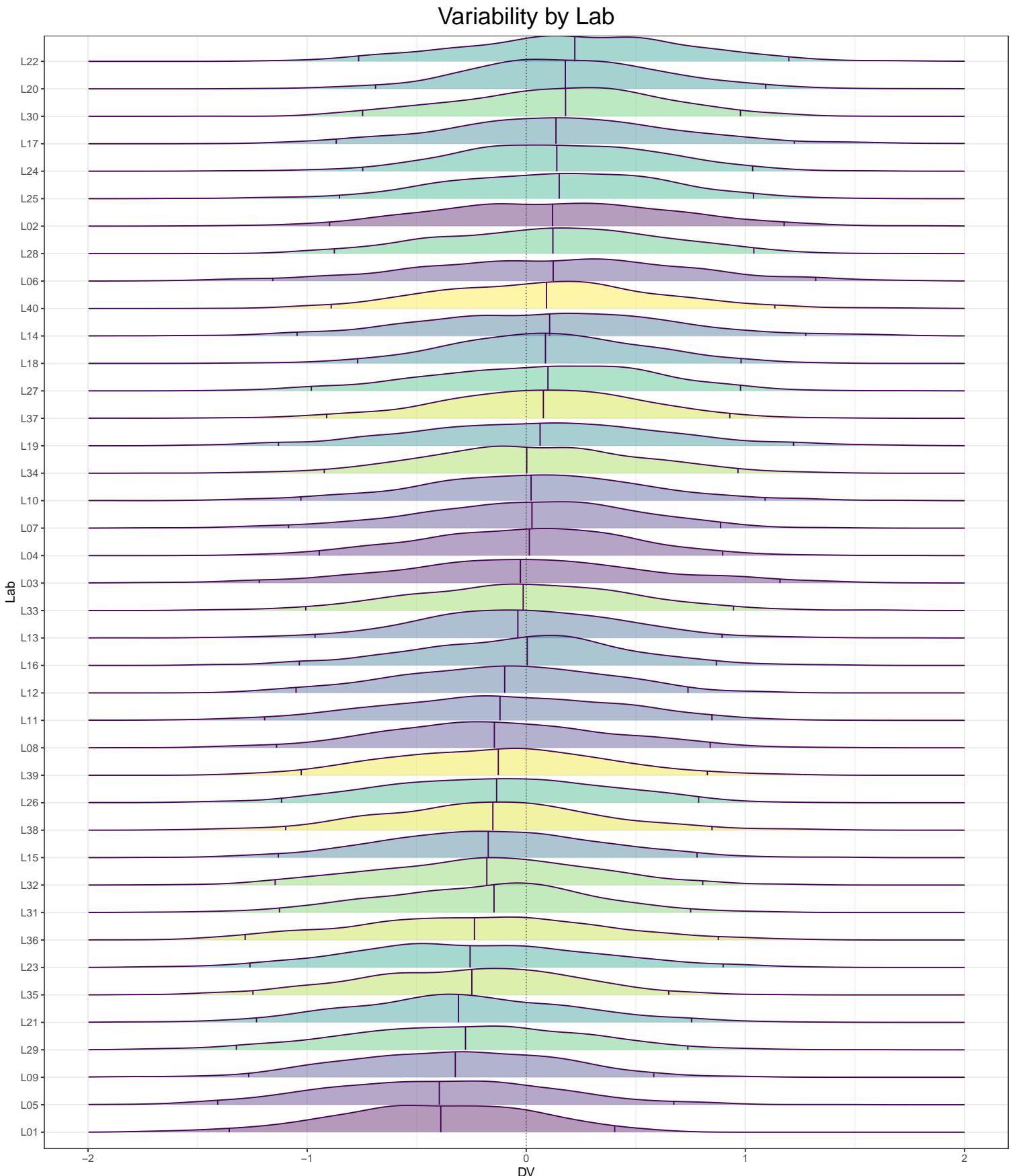
alpha = 0.2, size = 0.2) + geom_point(aes(y = med_DV, x = as.factor(X_f)),
alpha = 0.8, size = 2, data = dat_f_c_interaction) + geom_line(aes(y = med_DV,
x = as.factor(X_f), group = 1), data = dat_f_c_interaction) +
geom_violin(aes(y = DV, x = X_f, fill = familiarization),
alpha = 0.2) + scale_fill_manual(values = viridis(n = 3)) +
facet_wrap(~X_c) + ggtitle("Familiarization x Complexity Interaction") +
xlab("Familiarization") + theme_bw()
plot_familiarization_complexity <- plot_familiarization_complexity +
theme(plot.title = element_text(hjust = 0.5, size = 20))
plot_familiarization_complexity

```

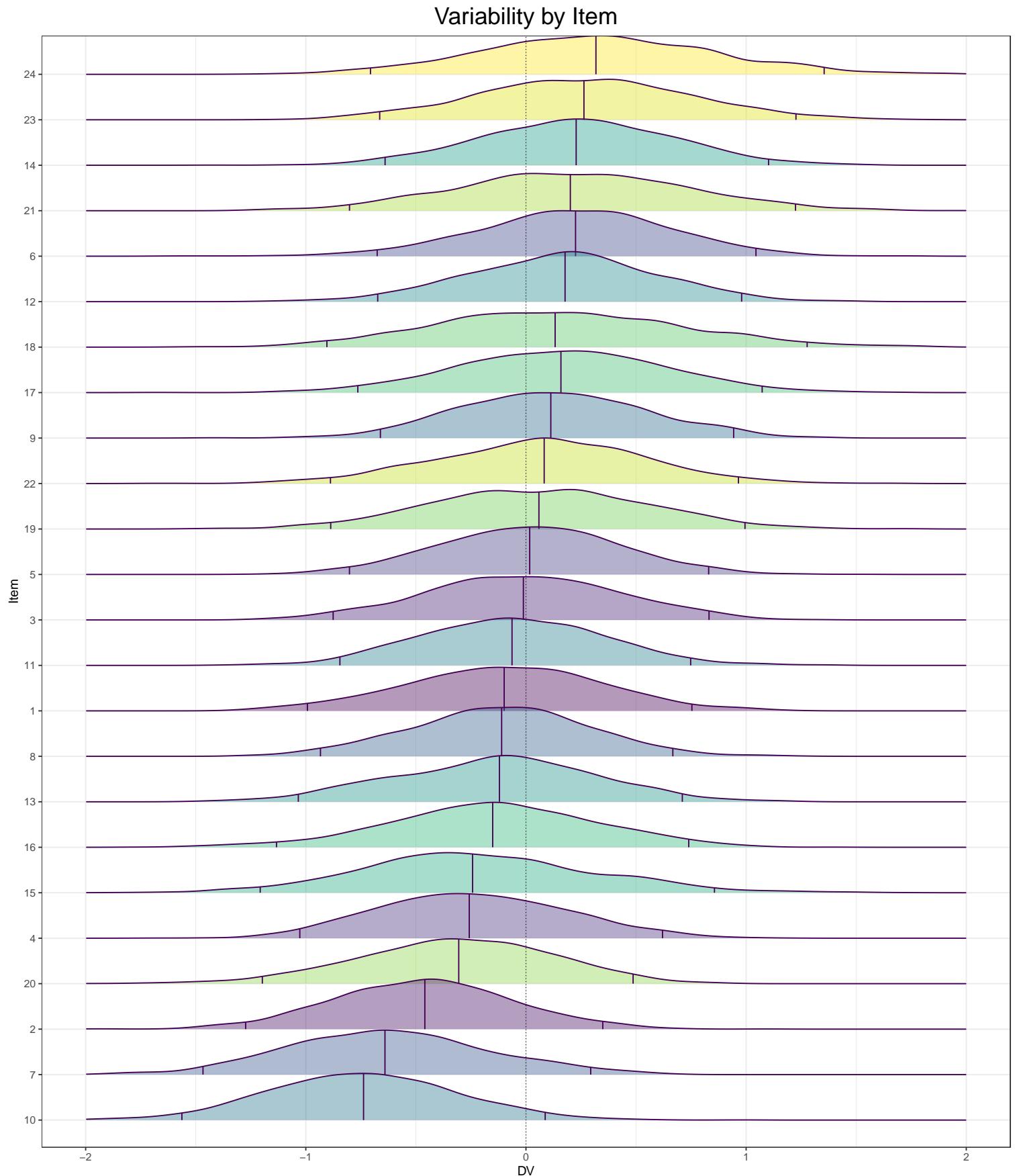
Familiarization x Complexity Interaction



2.7 Variability by Lab



2.8 Variability by Item



3 Power Calculation with Full Data and Varying Intercepts and Varying Slopes

3.1 Effect Size = 0.5

```
# Number of simulations:  
reps <- 350  
  
# Simulation function:  
run_sims <- function(filename_full, ef) {  
  
  dat_sim <- my_sim_data(beta_c = ef,  
                          beta_f = ef,  
                          beta_a = ef,  
  
                          beta_ca = ef,  
                          beta_af = ef,  
                          beta_cf = ef,  
  
                          beta_cfa = ef)  
  
  mod_sim <- lmer(DV ~ 1 + X_a * X_c * X_f +  
                    (1 + X_c * X_f | subj_id) +  
                    (1 | lab_id) +  
                    (1 | item_id),  
                    data=dat_sim)  
  
  sim_results <- broom.mixed::tidy(mod_sim)  
  
  # append the results to a file  
  append <- file.exists(filename_full)  
  write_csv(sim_results, filename_full, append = append)  
  
  # return the tidy table  
  sim_results  
}  
  
filename_full_0.5 = 'run_sims_full_0.5.csv'  
start_time <- Sys.time()  
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_0.5, ef = 0.5))  
end_time <- Sys.time()  
end_time - start_time
```

3.2 Effect Size = 0.4

```
filename_full_0.4 = "run_sims_full_0.4.csv"  
start_time <- Sys.time()  
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_0.4,  
                                         ef = 0.4))  
end_time <- Sys.time()  
end_time - start_time
```

3.3 Effect Size = 0.3

```
filename_full_0.3 = "run_sims_full_0.3.csv"  
start_time <- Sys.time()  
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_0.3,
```

```
    ef = 0.3))
end_time <- Sys.time()
end_time - start_time
```

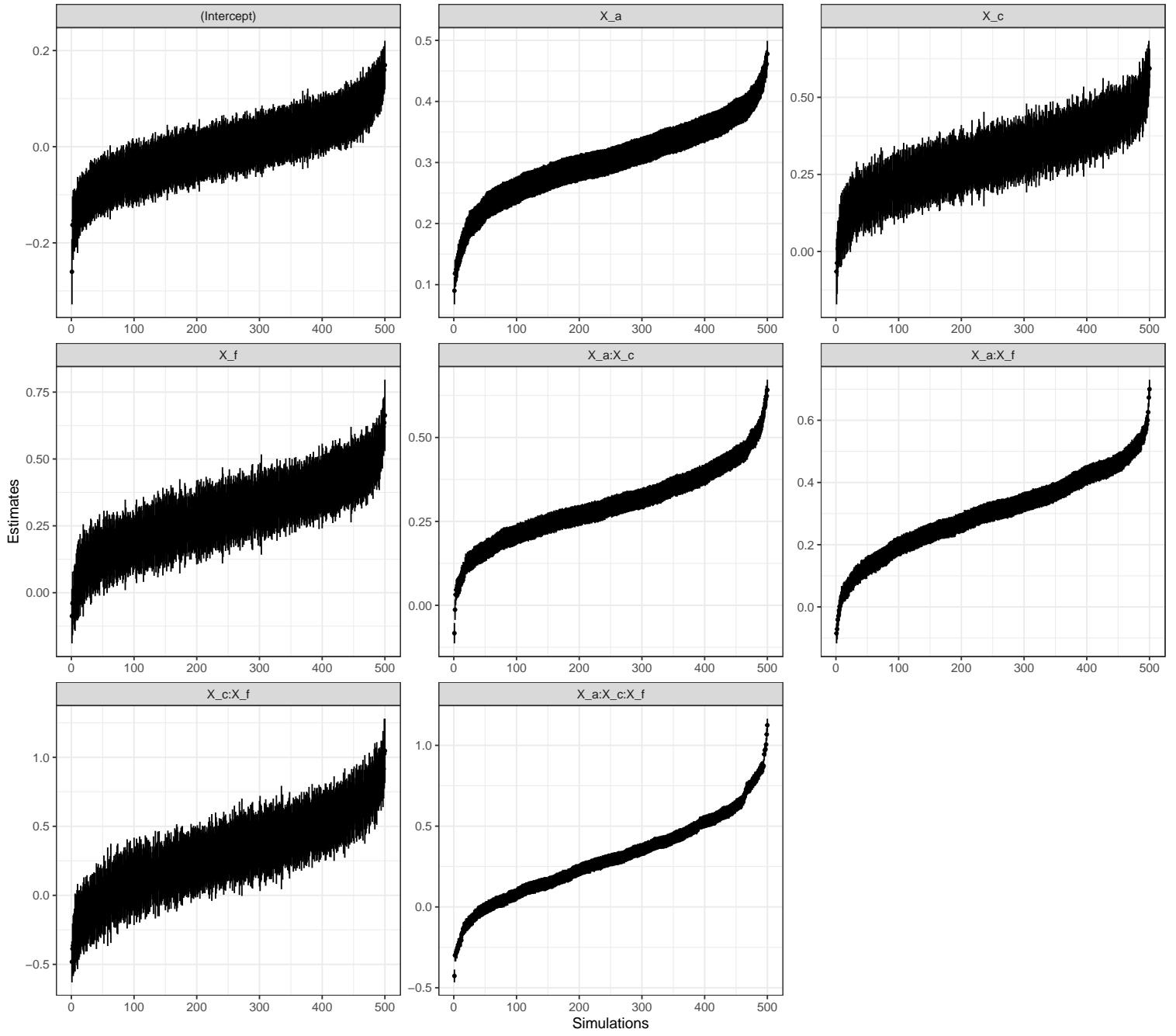
3.3.1 Visualise Estimates for Fixed Effects:

```
sims_full_0.3 <- read_csv(filename_full_0.3, col_types = cols(group = col_factor(ordered = TRUE),
  term = col_factor(ordered = TRUE)))

fixed_full_plot <- sims_full_0.3 %>%
  filter(effect == "fixed") %>%
  ungroup() %>%
  arrange(term, estimate) %>%
  mutate(row = rep(seq(1:reps), 8)) %>%
  ggplot(aes(x = row, y = estimate, ymin = estimate - std.error,
    ymax = estimate + std.error)) + facet_wrap(~term, scales = "free") +
  geom_pointrange(fatten = 1/2) + ylab("Estimates") + xlab("Simulations") +
  ggtitle("Estimates of Fixed Effects for Full Data and Varying Intercepts and Varying Slopes, ef = 0.3") +
  theme_bw()

fixed_full_plot <- fixed_full_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
fixed_full_plot
```

Estimates of Fixed Effects for Full Data and Varying Intercepts and Varying Slopes, ef = 0.3



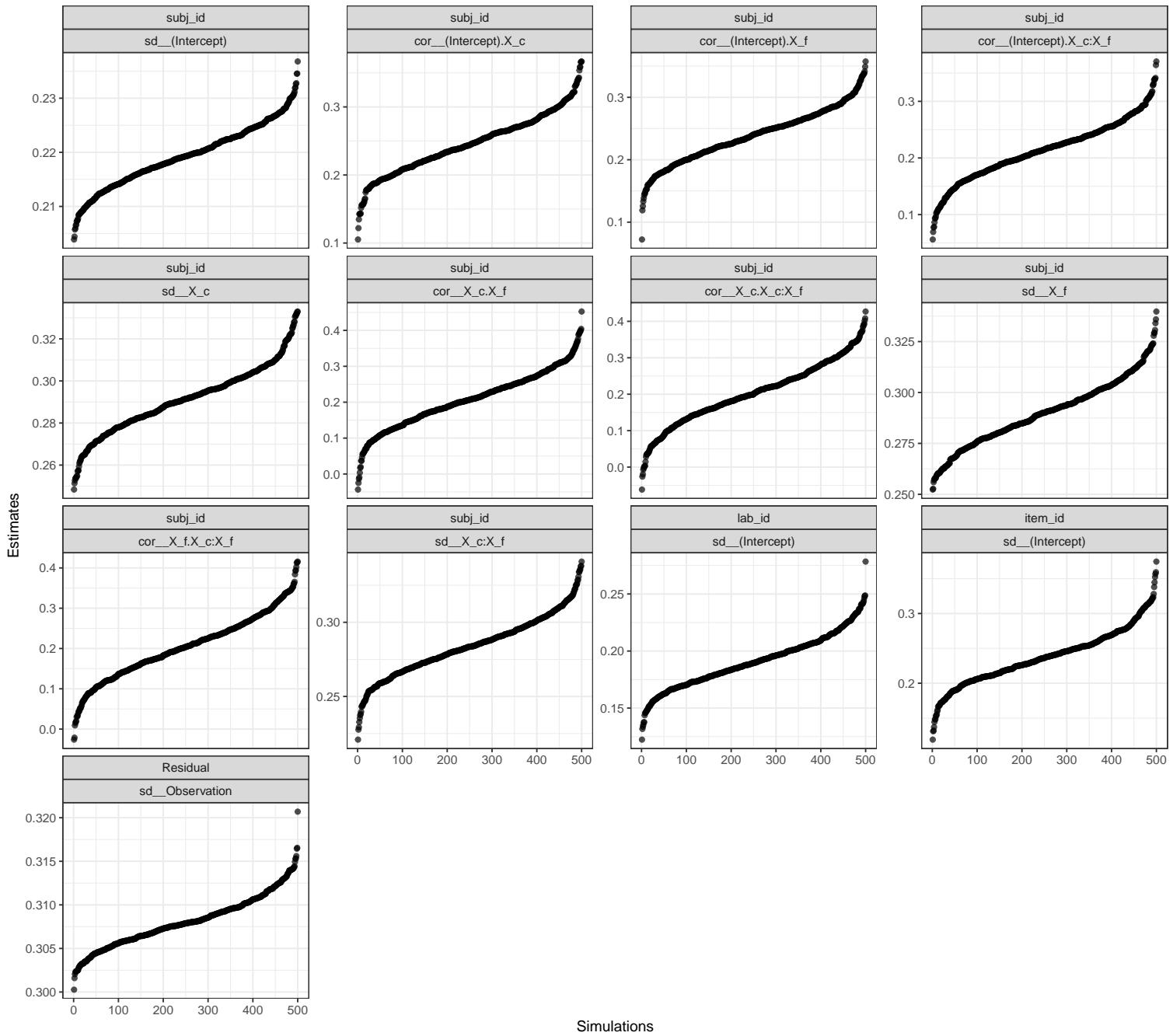
3.3.2 Visualise Estimates for Random Effects:

```

ran_full_plot <- sims_full_0.3 %>%
  filter(effect == "ran_pars") %>%
  ungroup() %>%
  arrange(group, term, estimate) %>%
  mutate(row = rep(seq(1:reps), 13)) %>%
  ggplot(aes(x = row, y = estimate)) + geom_point(alpha = 0.7) +
  facet_wrap(~group + term, scales = "free_y") + theme_bw() +
  ylab("Estimates") + xlab("Simulations") + ggtitle("Estimates of Random Effects Full Random-Effects Structure",
  theme_bw())
ran_full_plot <- ran_full_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
ran_full_plot

```

Estimates of Random Effects Full Random–Effects Structure, ef = 0.3



3.4 Effect Size = 0.2

```
filename_full_0.2 = "run_sims_full_0.2.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_0.2,
  ef = 0.2))
end_time <- Sys.time()
end_time - start_time
```

3.5 Effect Size = 0.1

```
filename_full_0.1 = "run_sims_full_0.1.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_0.1,
```

```

ef = 0.1))
end_time <- Sys.time()
end_time - start_time

```

4 Power Calculation with Full Data and Varying Intercepts

4.1 Effect Size = 0.5

```

# Simulation function:
run_sims <- function(filename_full, ef) {

  dat_sim <- my_sim_data(beta_c = ef,
                         beta_f = ef,
                         beta_a = ef,
                         beta_ca = ef,
                         beta_af = ef,
                         beta_cf = ef,
                         beta_cfa = ef)

  mod_sim <- lmer(DV ~ 1 + X_a * X_c * X_f +
                    (1 | subj_id) +
                    (1 | lab_id) +
                    (1 | item_id),
                    data=dat_sim)

  sim_results <- broom.mixed::tidy(mod_sim)

  # append the results to a file
  append <- file.exists(filename_full)
  write_csv(sim_results, filename_full, append = append)

  # return the tidy table
  sim_results
}

filename_full_int_0.5 = 'run_sims_full_int_0.5.csv'
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_int_0.5, ef = 0.5))
end_time <- Sys.time()
end_time - start_time

```

4.2 Effect Size = 0.4

```

filename_full_int_0.4 = "run_sims_full_int_0.4.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_int_0.4,
                                         ef = 0.4))
end_time <- Sys.time()
end_time - start_time

```

4.3 Effect Size = 0.3

```

filename_full_int_0.3 = "run_sims_full_int_0.3.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_int_0.3,
                                         ef = 0.3))
end_time <- Sys.time()
end_time - start_time

```

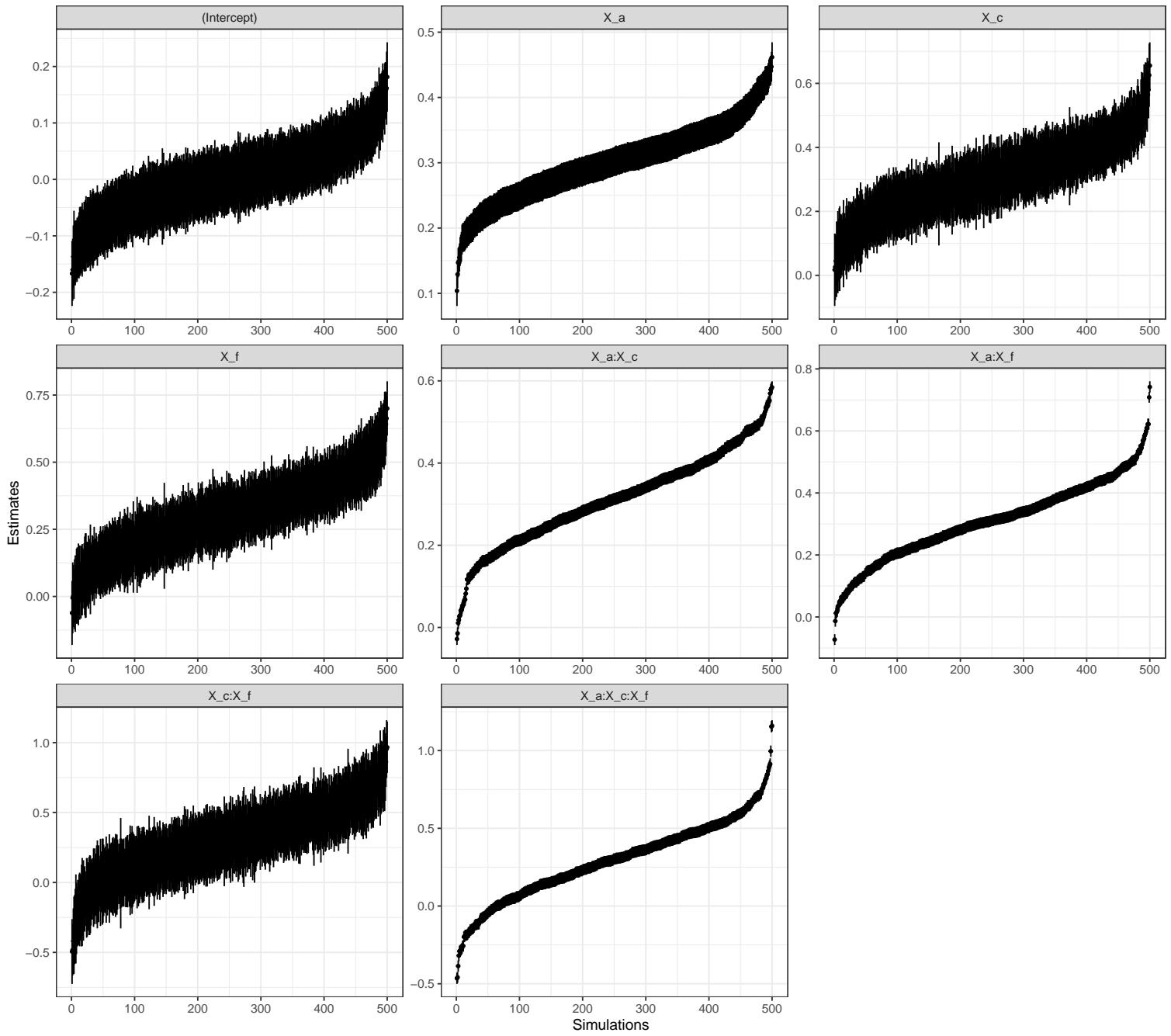
4.3.1 Visualise Estimates for Fixed Effects:

```
sims_full_int_0.3 <- read_csv(filename_full_int_0.3, col_types = cols(group = col_factor(ordered = TRUE),
  term = col_factor(ordered = TRUE)))

fixed_full_int_plot <- sims_full_int_0.3 %>%
  filter(effect == "fixed") %>%
  ungroup() %>%
  arrange(term, estimate) %>%
  mutate(row = rep(seq(1:reps), 8)) %>%
  ggplot(aes(x = row, y = estimate, ymin = estimate - std.error,
    ymax = estimate + std.error)) + facet_wrap(~term, scales = "free") +
  geom_pointrange(fatten = 1/2) + ylab("Estimates") + xlab("Simulations") +
  ggtitle("Estimates of Fixed Effects for Full Data and Random Intercepts, ef = 0.3") +
  theme_bw()

fixed_full_int_plot <- fixed_full_int_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
fixed_full_int_plot
```

Estimates of Fixed Effects for Full Data and Random Intercepts, ef = 0.3



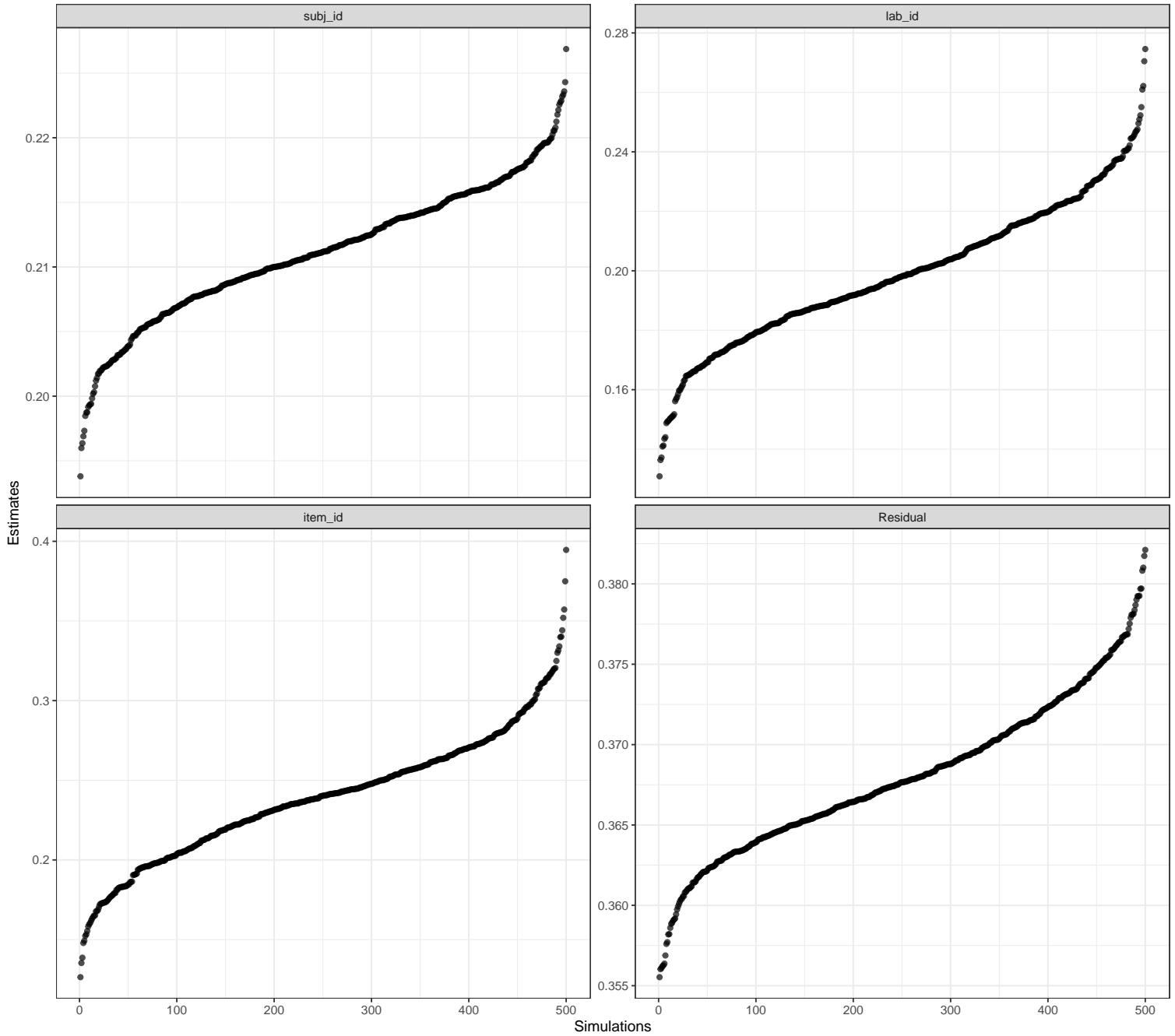
4.3.2 Visualise Estimates for Random Effects:

```

ran_full_int_plot <- sims_full_int_0.3 %>%
  filter(effect == "ran_pars") %>%
  ungroup() %>%
  arrange(group, estimate) %>%
  mutate(row = rep(seq(1:reps), 4)) %>%
  ggplot(aes(x = row, y = estimate)) + geom_point(alpha = 0.7) +
  facet_wrap(~group, scales = "free_y") + theme_bw() + ylab("Estimates") +
  xlab("Simulations") + ggtitle("Estimates of Random Effects for Full Data, ef = 0.3") +
  theme_bw()
ran_full_int_plot <- ran_full_int_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
ran_full_int_plot

```

Estimates of Random Effects for Full Data, ef = 0.3



4.4 Effect Size = 0.2

```
filename_full_int_0.2 = "run_sims_full_int_0.2.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_int_0.2,
  ef = 0.2))
end_time <- Sys.time()
end_time - start_time
```

4.5 Effect Size = 0.1

```
filename_full_int_0.1 = "run_sims_full_int_0.1.csv"
start_time <- Sys.time()
sims <- purrr::map_df(1:reps, ~run_sims(filename_full = filename_full_int_0.1,
```

```

ef = 0.1))
end_time <- Sys.time()
end_time - start_time

```

5 Power Calculation with 20 pct. Missing Data and Varying Intercepts and Varying Slopes

5.1 Effect Size = 0.5

```

run_sims_missing <- function(filename_missing, ef) {

  dat_sim <- my_sim_data(beta_c = ef,
                         beta_f = ef,
                         beta_a = ef,
                         beta_ca = ef,
                         beta_af = ef,
                         beta_cf = ef,
                         beta_cfa = ef)

  missing_samples <- dat_sim %>%
    mutate(nas = rbinom(nrow(dat_sim), 1, 1 - .20)) %>%
    mutate(DV = ifelse(nas == 1, DV, NA)) %>%
    drop_na()

  mod_sim <- lmer(DV ~ 1 + X_a * X_c * X_f +
                  (1 + X_c * X_f | subj_id) +
                  (1 | lab_id) +
                  (1 | item_id),
                  data=missing_samples)

  sim_results <- broom.mixed::tidy(mod_sim)

  # append the results to a file
  append <- file.exists(filename_missing)
  write_csv(sim_results, filename_missing, append = append)

  # return the tidy table
  sim_results
}

filename_20_missing_0.5 = 'run_sims_20_missing_0.5.csv'
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_20_missing_0.5, ef = 0.5))
end_time <- Sys.time()
end_time - start_time

```

5.2 Effect Size = 0.4

```

filename_20_missing_0.4 = "run_sims_20_missing_0.4.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_20_missing_0.4,
                                                       ef = 0.4))
end_time <- Sys.time()
end_time - start_time

```

5.3 Effect Size = 0.3

```
filename_20_missing_0.3 = "run_sims_20_missing_0.3.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_20_missing_0.3,
  ef = 0.3))
end_time <- Sys.time()
end_time - start_time
```

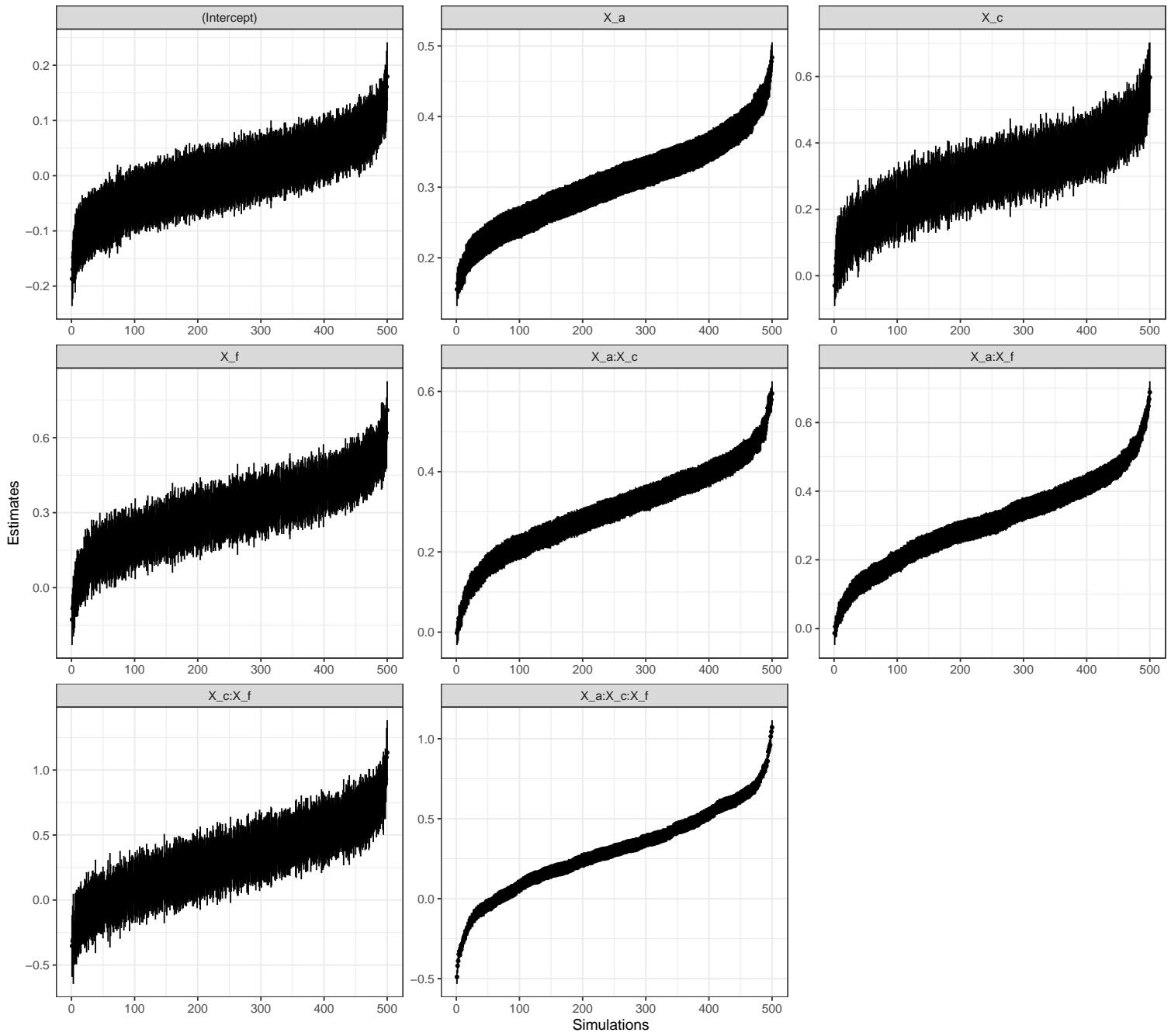
5.3.1 Visualise Estimates for Fixed Effects:

```
# read saved simulation data
sims_20_missing_0.3 <- read_csv(filename_20_missing_0.3, col_types = cols(
  # makes sure plots display in this order
  group = col_factor(ordered = TRUE),
  term = col_factor(ordered = TRUE)
))

fixed_missing_plot <- sims_20_missing_0.3 %>%
  filter(effect == "fixed") %>%
  ungroup() %>%
  arrange(term, estimate) %>%
  mutate(row = rep(seq(1:reps), 8)) %>%
  ggplot(aes(x = row, y = estimate, ymin = estimate-std.error, ymax = estimate+std.error)) +
  facet_wrap(~term, scales = "free") +
  geom_pointrange(fatten = 1/2) +
  ylab("Estimates") +
  xlab("Simulations") +
  ggtitle('Estimates of Fixed Effects for 20 pct. Missing Data, ef = 0.3') +
  theme_bw()

fixed_missing_plot <- fixed_missing_plot + theme(plot.title = element_text(hjust = 0.5, size=20))
fixed_missing_plot
```

Estimates of Fixed Effects for 20 pct. Missing Data, ef = 0.3



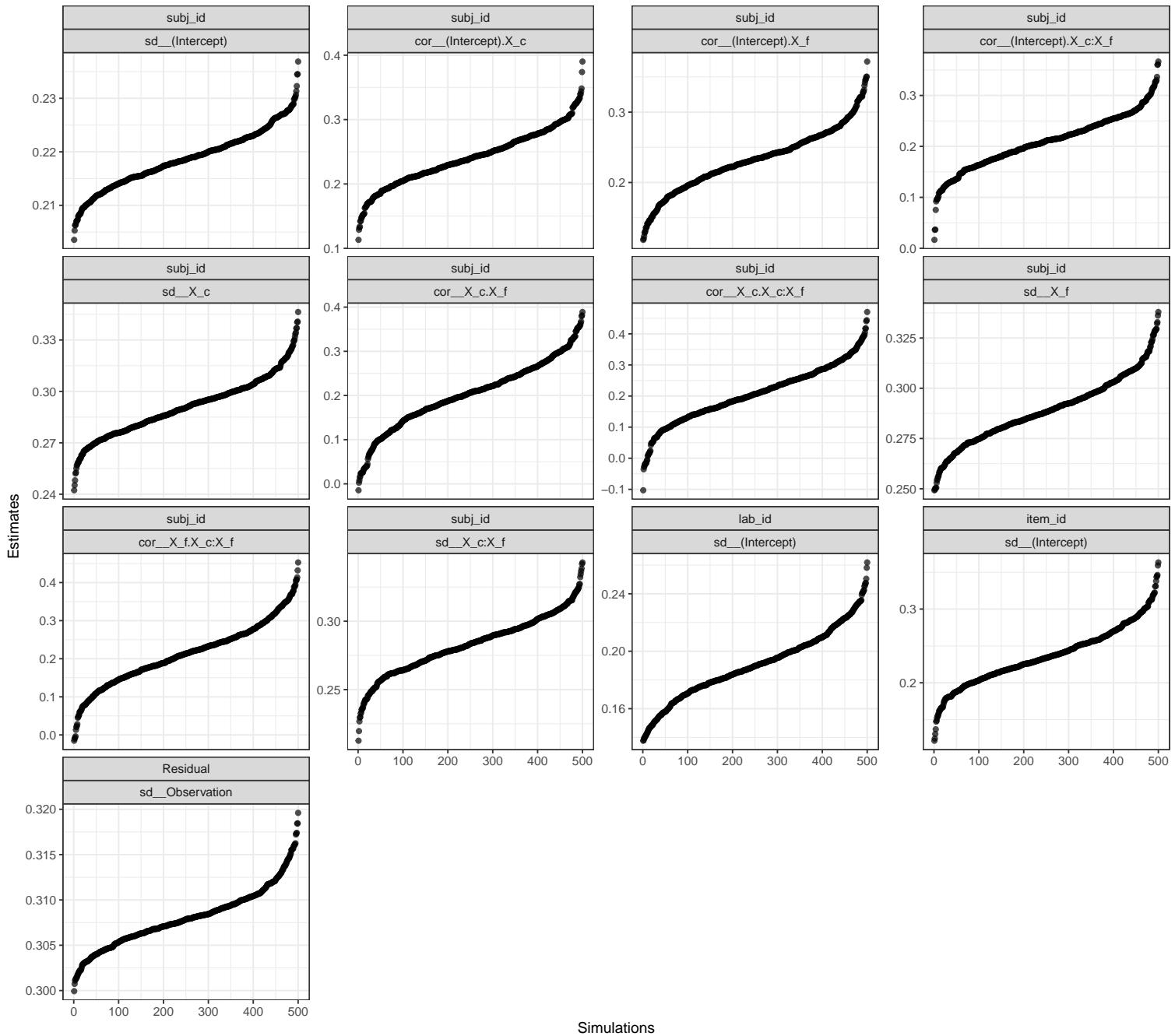
5.3.2 Visualise Estimates for Random Effects:

```

ran_missing_plot <- sims_20_missing_0.3 %>%
  filter(effect == "ran_pars") %>%
  ungroup() %>%
  arrange(group, term, estimate) %>%
  mutate(row = rep(seq(1:reps), 13)) %>%
  ggplot(aes(x = row, y = estimate)) + geom_point(alpha = 0.7) +
  facet_wrap(~group + term, scales = "free_y") + theme_bw() +
  ylab("Estimates") + xlab("Simulations") + ggtitle("Estimates of Random Effects for 20 pct. Missing Data, ef = 0.3") +
  theme_bw()
ran_missing_plot <- ran_missing_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
ran_missing_plot

```

Estimates of Random Effects for 20 pct. Missing Data, ef = 0.3



5.4 Effect Size = 0.2

```
filename_20_missing_0.2 = "run_sims_20_missing_0.2.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_20_missing_0.2,
  ef = 0.2))
end_time <- Sys.time()
end_time - start_time
```

5.5 Effect Size = 0.1

```
filename_20_missing_0.1 = "run_sims_20_missing_0.1.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_20_missing_0.1,
```

```

ef = 0.1))
end_time <- Sys.time()
end_time - start_time

```

6 Power Calculation with 50 pct. Missing Data and Varying Intercepts and Varying Slopes

6.1 Effect Size = 0.5

```

run_sims_missing <- function(filename_missing, ef) {

  dat_sim <- my_sim_data(beta_c = ef,
                         beta_f = ef,
                         beta_a = ef,
                         beta_ca = ef,
                         beta_af = ef,
                         beta_cf = ef,
                         beta_cfa = ef)

  missing_samples <- dat_sim %>%
    mutate(nas = rbinom(nrow(dat_sim), 1, 1 - .50)) %>%
    mutate(DV = ifelse(nas == 1, DV, NA)) %>%
    drop_na()

  mod_sim <- lmer(DV ~ 1 + X_a * X_c * X_f +
                  (1 + X_c * X_f | subj_id) +
                  (1 | lab_id) +
                  (1 | item_id),
                  data=missing_samples)

  sim_results <- broom.mixed::tidy(mod_sim)

  # append the results to a file
  append <- file.exists(filename_missing)
  write_csv(sim_results, filename_missing, append = append)

  # return the tidy table
  sim_results
}

filename_50_missing_0.5 = 'run_sims_50_missing_0.5.csv'
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_50_missing_0.5, ef = 0.5))
end_time <- Sys.time()
end_time - start_time

```

6.2 Effect Size = 0.4

```

filename_50_missing_0.4 = "run_sims_50_missing_0.4.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_50_missing_0.4,
                                                       ef = 0.4))
end_time <- Sys.time()
end_time - start_time

```

6.3 Effect Size = 0.3

```
filename_50_missing_0.3 = "run_sims_50_missing_0.3.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_50_missing_0.3,
  ef = 0.3))
end_time <- Sys.time()
end_time - start_time
```

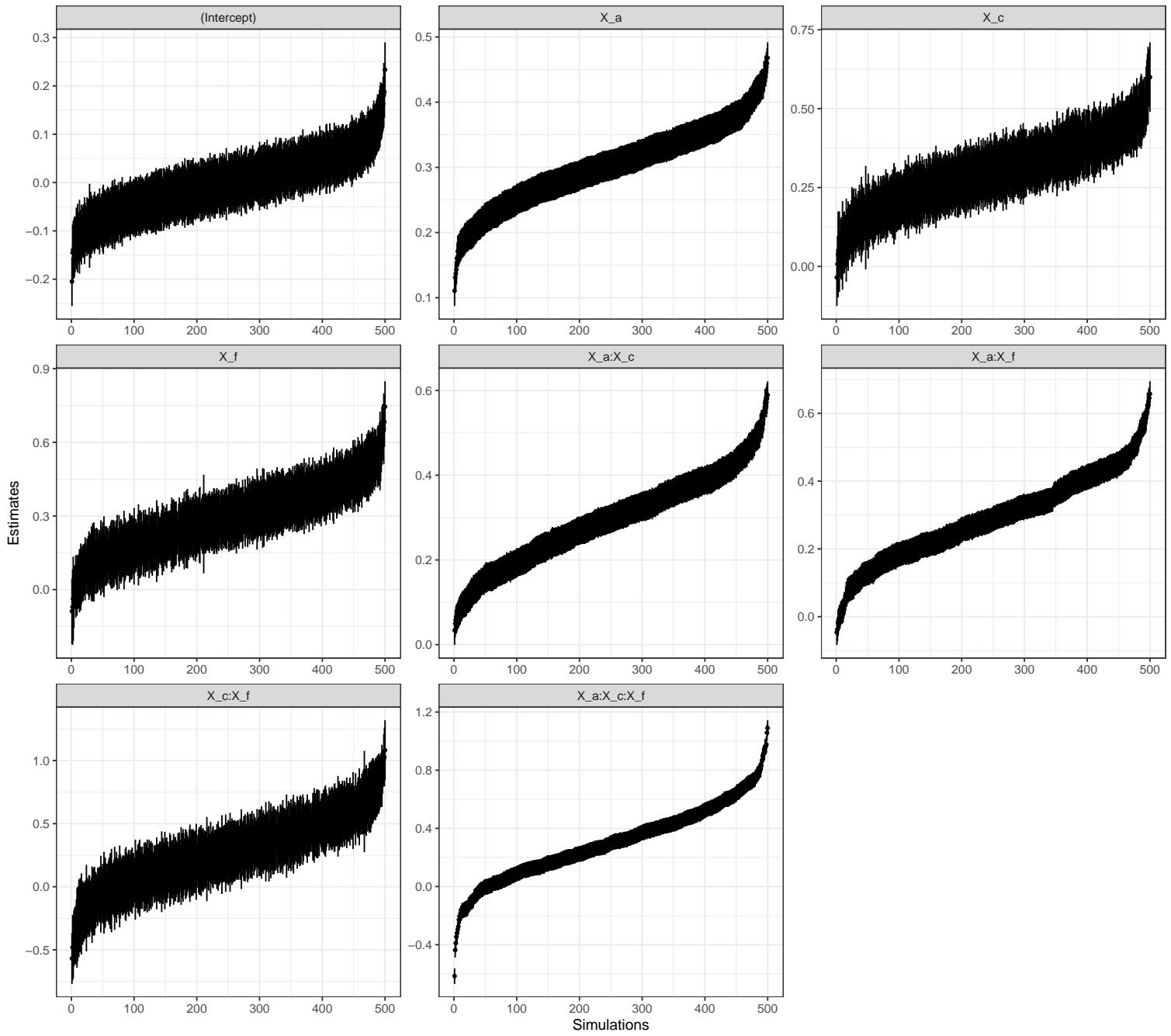
6.3.1 Visualise Estimates for Fixed Effects:

```
# read saved simulation data
sims_50_missing_0.3 <- read_csv(filename_50_missing_0.3, col_types = cols(
  # makes sure plots display in this order
  group = col_factor(ordered = TRUE),
  term = col_factor(ordered = TRUE)
))

fixed_missing_plot <- sims_50_missing_0.3 %>%
  filter(effect == "fixed") %>%
  ungroup() %>%
  arrange(term, estimate) %>%
  mutate(row = rep(seq(1:reps), 8)) %>%
  ggplot(aes(x = row, y = estimate, ymin = estimate-std.error, ymax = estimate+std.error)) +
  facet_wrap(~term, scales = "free") +
  geom_pointrange(fatten = 1/2) +
  ylab("Estimates") +
  xlab("Simulations") +
  ggtitle('Estimates of Fixed Effects for 50 pct. Missing Data, ef = 0.3') +
  theme_bw()

fixed_missing_plot <- fixed_missing_plot + theme(plot.title = element_text(hjust = 0.5, size=20))
fixed_missing_plot
```

Estimates of Fixed Effects for 50 pct. Missing Data, ef = 0.3



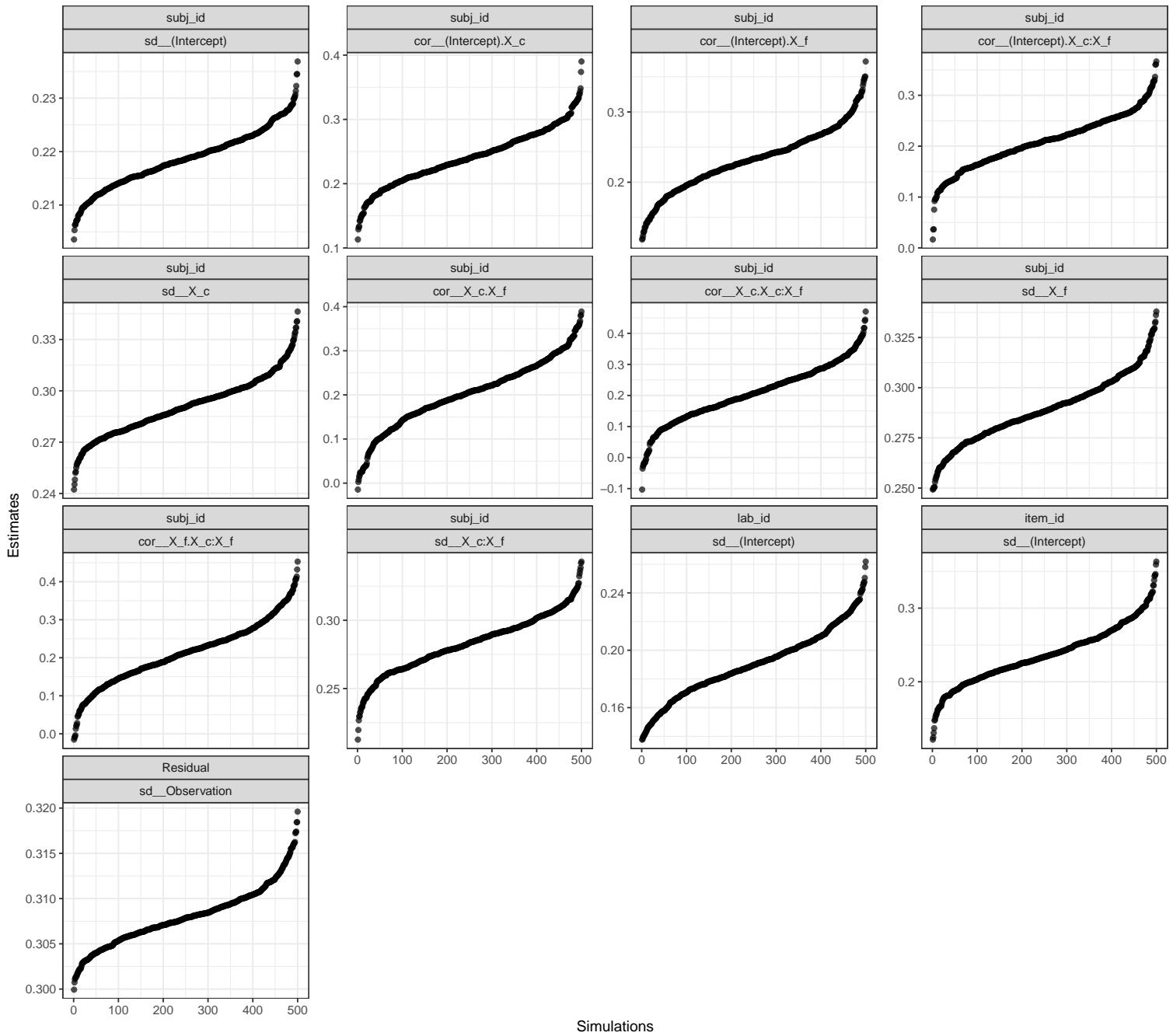
6.3.2 Visualise Estimates for Random Effects:

```

ran_missing_plot <- sims_20_missing_0.3 %>%
  filter(effect == "ran_pars") %>%
  ungroup() %>%
  arrange(group, term, estimate) %>%
  mutate(row = rep(seq(1:reps), 13)) %>%
  ggplot(aes(x = row, y = estimate)) + geom_point(alpha = 0.7) +
  facet_wrap(~group + term, scales = "free_y") + theme_bw() +
  ylab("Estimates") + xlab("Simulations") + ggtitle("Estimates of Random Effects for 50 pct. Missing Data, ef = 0.3") +
  theme_bw()
ran_missing_plot <- ran_missing_plot + theme(plot.title = element_text(hjust = 0.5,
  size = 20))
ran_missing_plot

```

Estimates of Random Effects for 50 pct. Missing Data, ef = 0.3



6.4 Effect Size = 0.2

```
filename_50_missing_0.2 = "run_sims_50_missing_0.2.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_50_missing_0.2,
  ef = 0.2))
end_time <- Sys.time()
end_time - start_time
```

6.5 Effect Size = 0.1

```
filename_50_missing_0.1 = "run_sims_50_missing_0.1.csv"
start_time <- Sys.time()
sims_missing <- purrr::map_df(1:reps, ~run_sims_missing(filename_missing = filename_50_missing_0.1,
```

```

ef = 0.1))
end_time <- Sys.time()
end_time - start_time

```

7 Overview of Power Simulation Results

7.1 Summary Statistics for Power Calculation with Full Data and Varying Intercepts and Varying Slopes:

Table 1: Power for Simulations with Full Data and Varying Intercepts and Varying Slopes

term	power, ef = 0.1	power, ef = 0.2	power, ef = 0.3	power, ef = 0.4	power, ef = 0.5
(Intercept)	0.050	0.056	0.070	0.056	0.026
X_a	0.844	0.990	1.000	1.000	1.000
X_c	0.170	0.474	0.838	0.966	0.992
X_f	0.118	0.360	0.634	0.864	0.968
X_a:X_c	0.690	0.894	0.986	1.000	1.000
X_a:X_f	0.748	0.864	0.966	0.994	1.000
X_c:X_f	0.072	0.124	0.244	0.350	0.486
X_a:X_c:X_f	0.770	0.808	0.856	0.938	0.956

7.2 Summary Statistics for Power Calculation with Full Data and Varying Intercepts:

Table 2: Power for Simulations with Full Data and Varying Intercepts

term	power, ef = 0.1	power, ef = 0.2	power, ef = 0.3	power, ef = 0.4	power, ef = 0.5
(Intercept)	0.050	0.056	0.050	0.080	0.058
X_a	0.822	0.994	1.000	1.000	1.000
X_c	0.162	0.482	0.810	0.998	0.966
X_f	0.136	0.352	0.644	0.970	0.884
X_a:X_c	0.868	0.958	0.990	1.000	0.998
X_a:X_f	0.848	0.932	0.990	1.000	0.998
X_c:X_f	0.092	0.136	0.220	0.564	0.348
X_a:X_c:X_f	0.798	0.832	0.882	0.964	0.934

7.3 Summary Statistics for Power Calculation with 20 pct. Missing Data and Varying Intercepts and Varying Slopes:

Table 3: Power for Simulations with 20 pct. Missing Data and Varying Intercepts and Slopes

term	power, ef = 0.1	power, ef = 0.2	power, ef = 0.3	power, ef = 0.4	power, ef = 0.5
(Intercept)	0.040	0.054	0.042	0.064	0.052
X_a	0.832	0.996	1.000	1.000	1.000
X_c	0.162	0.476	0.806	0.950	0.998
X_f	0.122	0.348	0.658	0.842	0.972
X_a:X_c	0.686	0.928	0.982	1.000	1.000
X_a:X_f	0.674	0.872	0.974	0.996	1.000
X_c:X_f	0.062	0.132	0.266	0.376	0.498
X_a:X_c:X_f	0.762	0.800	0.862	0.926	0.950

7.4 Summary Statistics for Power Calculation with 50 pct. Missing Data and Varying Intercepts and Varying Slopes:

Table 4: Power for Simulations with 50 pct. Missing Data and Varying Intercepts and Slopes

term	power, ef = 0.1	power, ef = 0.2	power, ef = 0.3	power, ef = 0.4	power, ef = 0.5
(Intercept)	0.036	0.058	0.054	0.044	0.046
X_a	0.822	0.986	1.000	1.000	1.000
X_c	0.168	0.540	0.840	0.970	0.996
X_f	0.120	0.366	0.658	0.836	0.964
X_a:X_c	0.666	0.902	0.992	0.998	1.000
X_a:X_f	0.680	0.826	0.966	0.992	1.000
X_c:X_f	0.066	0.174	0.232	0.372	0.460
X_a:X_c:X_f	0.690	0.754	0.840	0.896	0.942