HOI_LLK_Linear_Mixed_Modeling

2024-10-09

```
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.5
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.5.1     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.1
## ✔ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(ggplot2)
library(stringr)
library(lme4)
```

```
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
library(lmerTest)
```

```
##
## Attaching package: 'lmerTest'
##
## The following object is masked from 'package:lme4':
##
##     lmer
##
## The following object is masked from 'package:stats':
##
##     step
```

```
library(sjPlot)
```

```
## Install package "strengejacke" from GitHub (`devtools::install_github("strengejacke/strengejacke")`) to load a
ll sj-packages at once!
```

```
library(kableExtra)
```

```
##
## Attaching package: 'kableExtra'
##
## The following object is masked from 'package:dplyr':
##
##     group_rows
```

```
#rm(list = ls())
```

```
#Load the dataframes
features_1H_raw<- read_csv("Features_1H.csv")
```

```
## New names:
## Rows: 30 Columns: 27
## ── Column specification
## ──────────────────────────────────────────────────────── Delimiter: "," chr
## (2): subject_id, Group dbl (25): ...1, Alpha_DTC, Alpha_O, Alpha_S, Alpha_TC,
## Beta_DTC, Beta_O, Bet...
## ℹ Use `spec()` to retrieve the full column specification for this data. ℹ
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## • `` -> `...1`
```

```
features_24H_raw<- read_csv("Features_24H.csv")
```

```
## New names:
## Rows: 30 Columns: 27
## ── Column specification
## ──────────────────────────────────────────────────────── Delimiter: "," chr
## (2): subject_id, Group dbl (25): ...1, Alpha_DTC, Alpha_O, Alpha_S, Alpha_TC,
## Beta_DTC, Beta_O, Bet...
## ℹ Use `spec()` to retrieve the full column specification for this data. ℹ
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## • `` -> `...1`
```

```
features_Day7_raw<- read_csv("Features_Day7.csv")
```

```
## New names:
## Rows: 30 Columns: 27
## ── Column specification
## ──────────────────────────────────────────────────────── Delimiter: "," chr
## (2): subject_id, Group dbl (25): ...1, Alpha_DTC, Alpha_O, Alpha_S, Alpha_TC,
## Beta_DTC, Beta_O, Bet...
## ℹ Use `spec()` to retrieve the full column specification for this data. ℹ
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## • `` -> `...1`
```

Data Wrangling

Converting into binary factors and imputing missing data

```
#Convert the group into a binary factor variables for all 3 datasets
features_1H_raw<-features_1H_raw%>%
  mutate(Group= factor(ifelse(Group == "Ketamine", 1, 0)))
features_24H_raw<-features_24H_raw%>%
  mutate(Group= factor(ifelse(Group == "Ketamine", 1, 0)))
features_Day7_raw<-features_Day7_raw%>%
  mutate(Group= factor(ifelse(Group == "Ketamine", 1, 0)))


#Impute missing data by calculating mean for the rest of the column
#1H
features_1H_imputed <- features_1H_raw %>%
  mutate(across(-all_of("Group"), ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)))
#24H
#RS_024 in 24H data has bad data; replace all values with NA and then impute
features_24H_raw <- features_24H_raw %>%
  mutate(across(-c(1:3), ~ ifelse(subject_id == "RS_024_deltas", NA, .)))
#Impute
features_24H_imputed <- features_24H_raw %>%
  mutate(across(-all_of("Group"), ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)))
#Day 7
features_Day7_imputed <- features_Day7_raw %>%
  mutate(across(-all_of("Group"), ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)))
```

Converting into one long dataframe

```
# Combine timepoint datasets into one long format
features_combined <- bind_rows(
  mutate(features_1H_imputed, timepoint = "1H"),
  mutate(features_24H_imputed, timepoint = "24H"),
  mutate(features_Day7_imputed, timepoint = "Day7")
)

# Gather measures and frequency bands
features_long <- features_combined %>%
  pivot_longer(
    cols = -c(subject_id, Group, timepoint, ...1),  # Keep 'subject' and 'timepoint' columns
    names_to = c("frequency_band", "measure"),  # Separate column names into 'frequency_band' and 'measure'
    names_pattern = "([A-Za-z]+)_([A-Z]+)",
    values_to = "value"  # The new column for the values
  )

# View the structure of the long-format dataset
str(features_long)
```

```
## tibble [2,160 × 7] (S3: tbl_df/tbl/data.frame)
##  $ ...1          : num [1:2160] 0 0 0 0 0 0 0 0 0 0 ...
##  $ subject_id    : chr [1:2160] "RS_006_deltas" "RS_006_deltas" "RS_006_deltas" "RS_006_deltas" ...
##  $ Group         : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
##  $ timepoint     : chr [1:2160] "1H" "1H" "1H" "1H" ...
##  $ frequency_band: chr [1:2160] "Alpha" "Alpha" "Alpha" "Alpha" ...
##  $ measure       : chr [1:2160] "DTC" "O" "S" "TC" ...
##  $ value         : num [1:2160] -0.226 0.131 -0.418 0.566 0.104 ...
```

```
# Preview the first few rows
head(features_long)
```

```
## # A tibble: 6 × 7
##    ...1 subject_id    Group timepoint frequency_band measure    value
##   <dbl> <chr>         <fct> <chr>     <chr>          <chr>      <dbl>
## 1     0 RS_006_deltas 1     1H        Alpha          DTC     -0.226
## 2     0 RS_006_deltas 1     1H        Alpha          O        0.131
## 3     0 RS_006_deltas 1     1H        Alpha          S       -0.418
## 4     0 RS_006_deltas 1     1H        Alpha          TC       0.566
## 5     0 RS_006_deltas 1     1H        Beta           DTC      0.104
## 6     0 RS_006_deltas 1     1H        Beta           O       -0.00102
```

Separate the frequency bands into 6 dataframes

```
alpha_features <- features_long %>% filter(frequency_band == 'Alpha')
beta_features <- features_long %>% filter(frequency_band == 'Beta')
gamma_features <- features_long %>% filter(frequency_band == 'Gamma')
delta_features <- features_long %>% filter(frequency_band == 'Delta')
theta_features <- features_long %>% filter(frequency_band == 'Theta')
wholeband_features <- features_long %>% filter(frequency_band == 'Wholeband')
```

Separate the frequency bands and measures and loop through a list of models

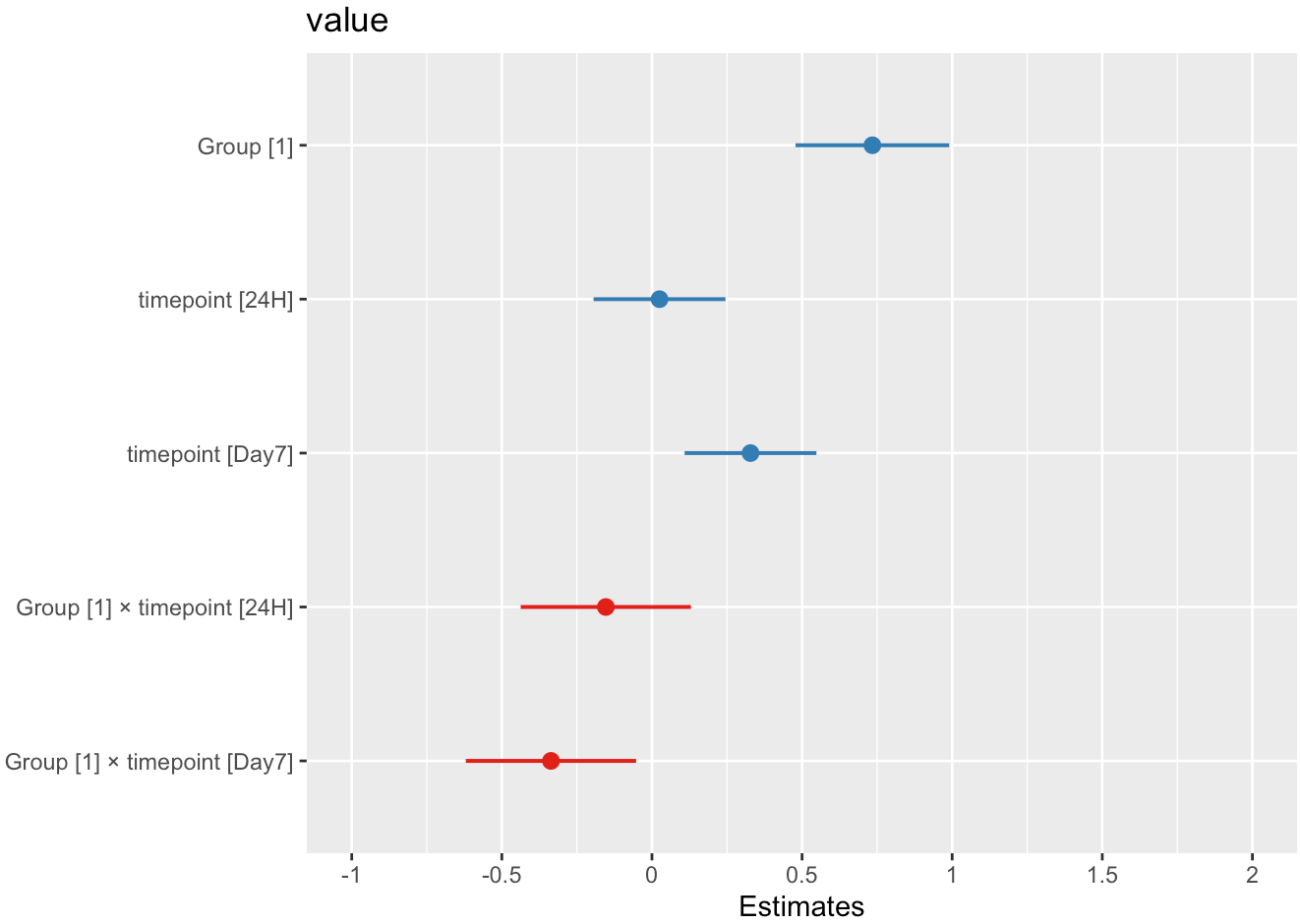
```
# Define frequency bands and measures
frequency_bands <- unique(features_long$frequency_band)
measures <- c("O", "S", "TC", "DTC")

models <- list()

# Loop over frequency bands and measures to create and store models
for (band in frequency_bands) {
  for (measure in measures) {
    data_subset <- subset(features_long, frequency_band == band & measure == measure)
    model <- lmer(value ~ Group * timepoint + (1 | subject_id), data = data_subset)
    models[[paste(band, measure, sep = "_")]] <- model
  }
}



# Alpha models
tab_model(models[["Alpha_O"]])
```

	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.67 – -0.28	**<0.001**
Group [1]	0.73	0.48 – 0.99	**<0.001**
timepoint [24H]	0.03	-0.19 – 0.24	0.822
timepoint [Day7]	0.33	0.11 – 0.55	**0.004**
Group [1] × timepoint [24H]	-0.15	-0.44 – 0.13	0.287
Group [1] × timepoint [Day7]	-0.34	-0.62 – -0.05	**0.020**

Random Effects

σ^2	0.30
$\tau_{00\ subject_id}$	0.05
ICC	0.14
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.205 / 0.313

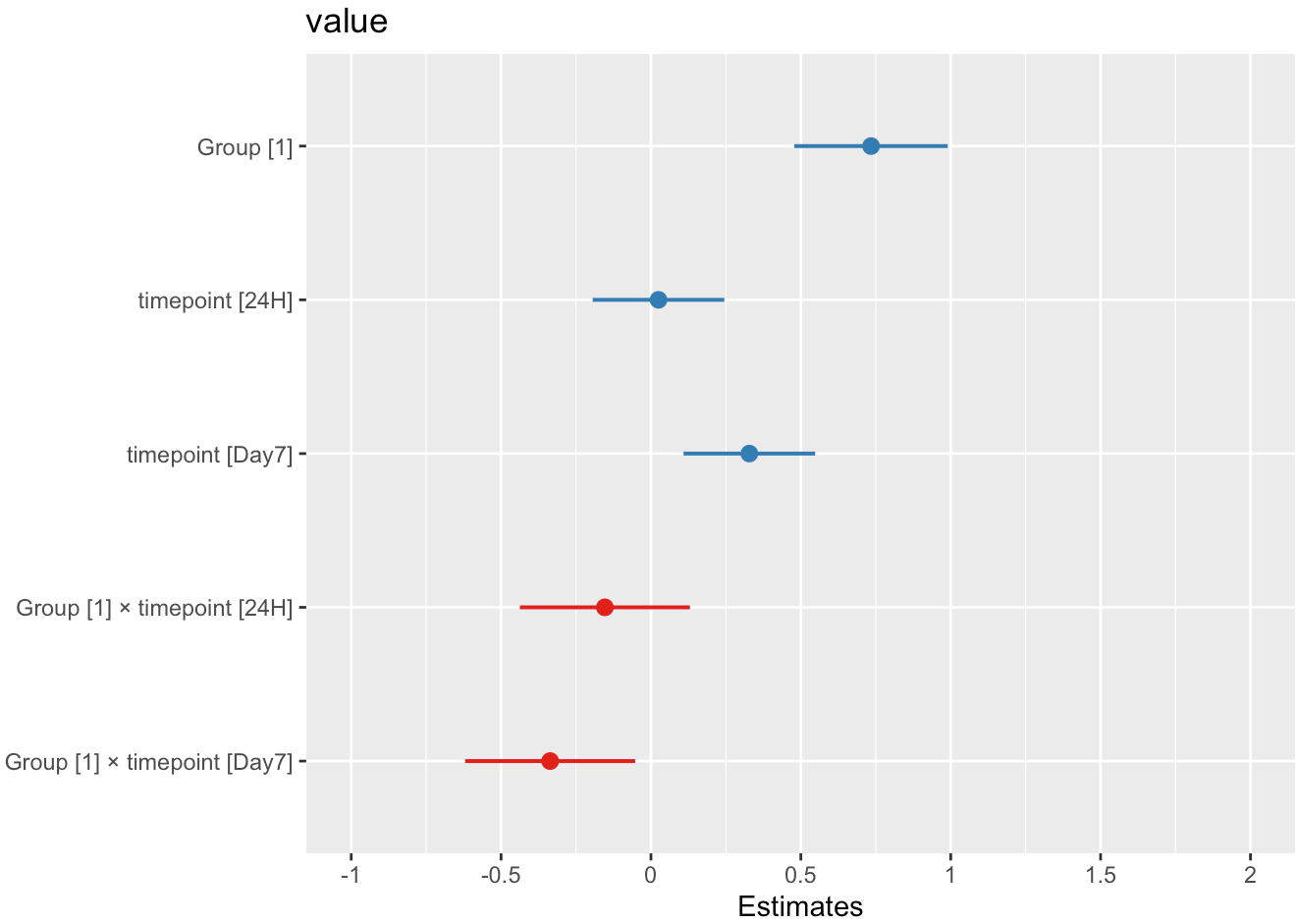
```
plot_model(models["Alpha_0"])
```



```
tab_model(models["Alpha_S"])
```

	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.67 – -0.28	**<0.001**
Group [1]	0.73	0.48 – 0.99	**<0.001**
timepoint [24H]	0.03	-0.19 – 0.24	0.822
timepoint [Day7]	0.33	0.11 – 0.55	**0.004**
Group [1] × timepoint [24H]	-0.15	-0.44 – 0.13	0.287
Group [1] × timepoint [Day7]	-0.34	-0.62 – -0.05	**0.020**
Random Effects			
σ^2	0.30		
$\tau_{00\ subject_id}$	0.05		
ICC	0.14		
$N_{\ subject_id}$	30		
Observations	360		
Marginal R^2 / Conditional R^2	0.205 / 0.313		

```
plot_model(models["Alpha_S"])
```




```
tab_model(models[["Alpha_TC"]])
```

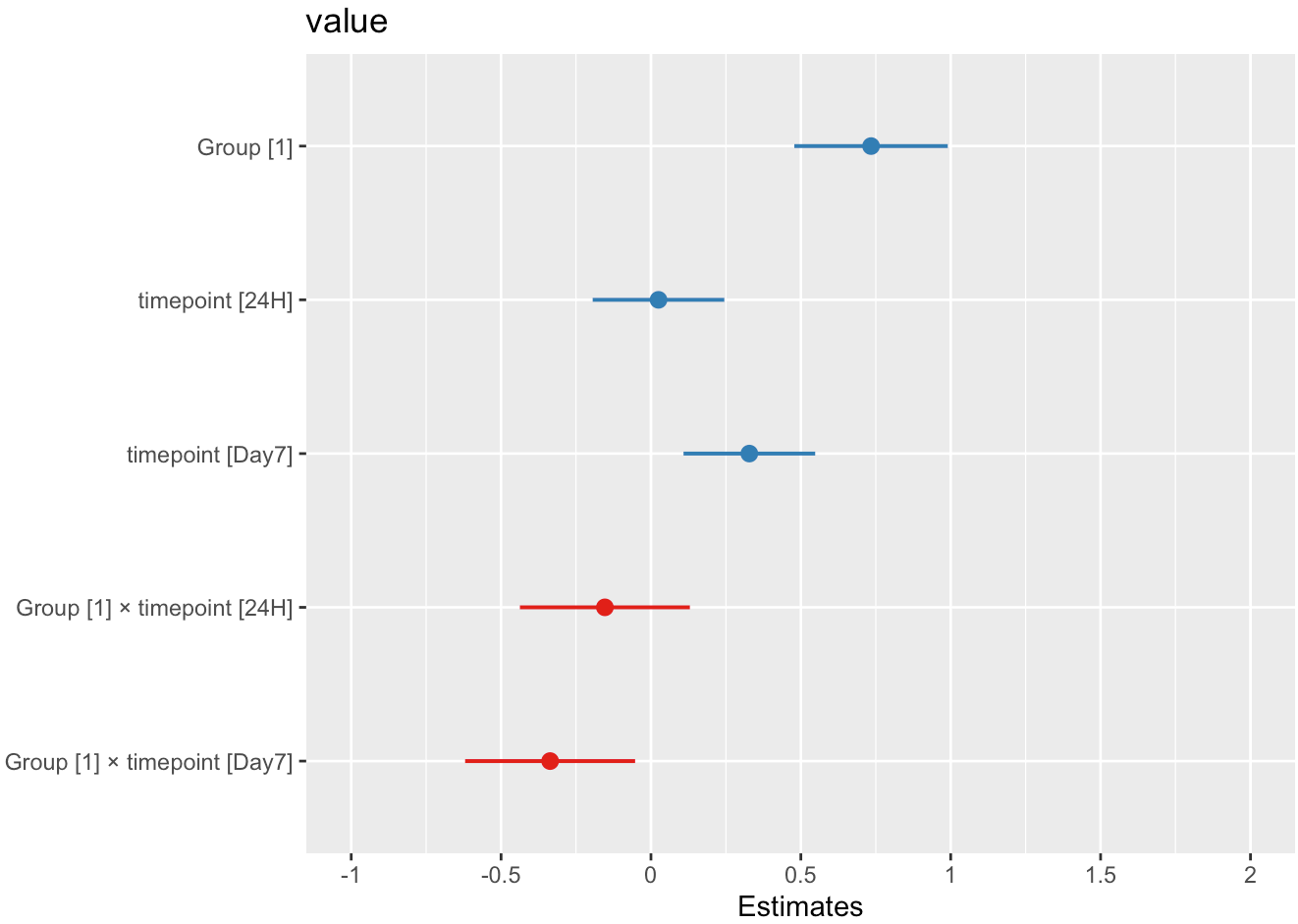
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.67 – -0.28	**<0.001**
Group [1]	0.73	0.48 – 0.99	**<0.001**
timepoint [24H]	0.03	-0.19 – 0.24	0.822
timepoint [Day7]	0.33	0.11 – 0.55	**0.004**

Group [1] × timepoint [24H]	-0.15	-0.44 – 0.13	0.287
Group [1] × timepoint [Day7]	-0.34	-0.62 – -0.05	**0.020**

Random Effects

σ^2	0.30
$\tau_{00\ subject_id}$	0.05
ICC	0.14
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.205 / 0.313

```
plot_model(models["Alpha_TC"])
```




```
tab_model(models[["Alpha_DTC"]])
```

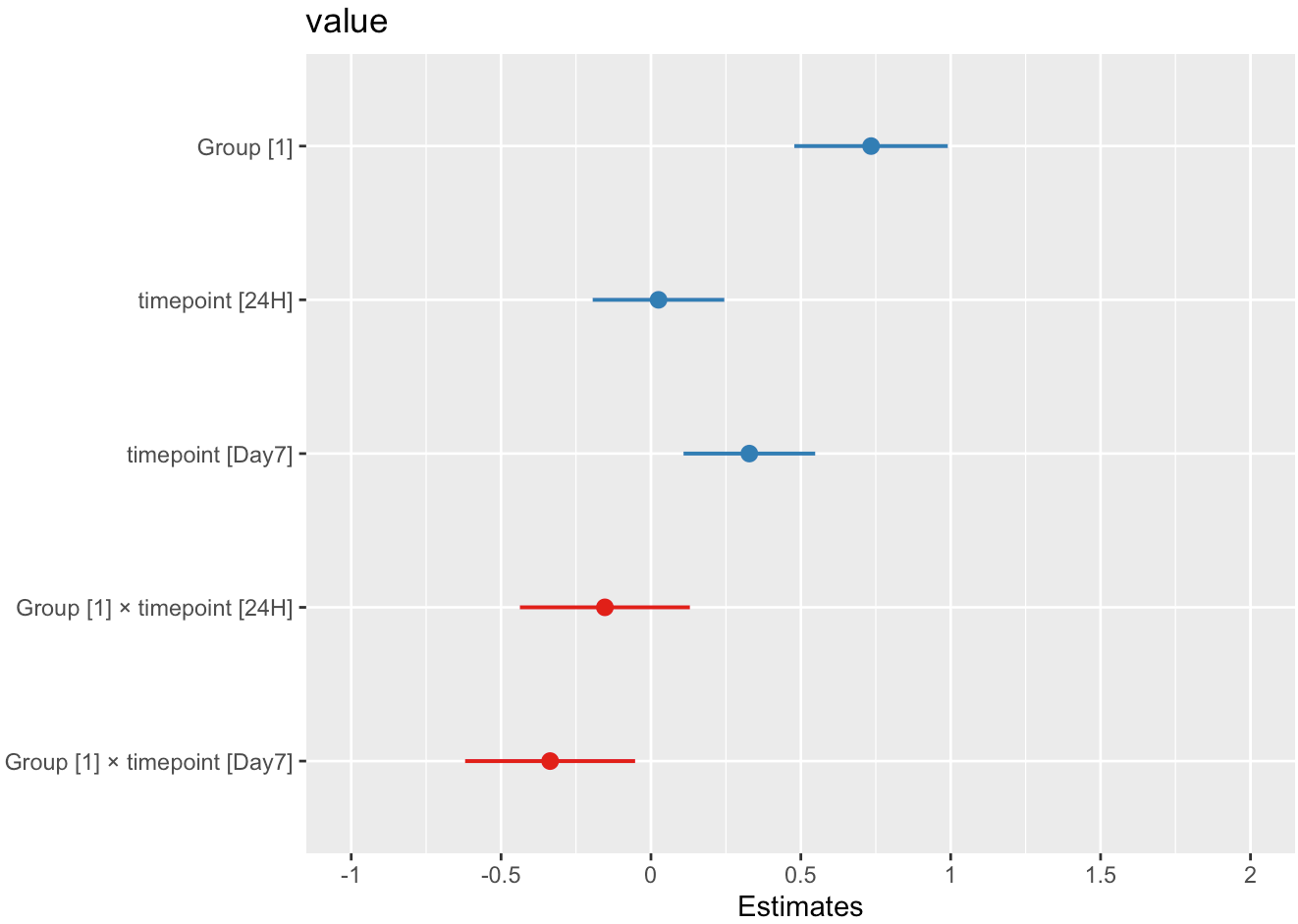
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.67 – -0.28	**<0.001**
Group [1]	0.73	0.48 – 0.99	**<0.001**
timepoint [24H]	0.03	-0.19 – 0.24	0.822
timepoint [Day7]	0.33	0.11 – 0.55	**0.004**

Group [1] × timepoint [24H]	-0.15	-0.44 – 0.13	0.287
Group [1] × timepoint [Day7]	-0.34	-0.62 – -0.05	**0.020**

Random Effects

σ^2	0.30
$\tau_{00\ subject_id}$	0.05
ICC	0.14
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.205 / 0.313

```
plot_model(models["Alpha_DTC"])
```




```
# Beta models
tab_model(models[["Beta_0"]])
```

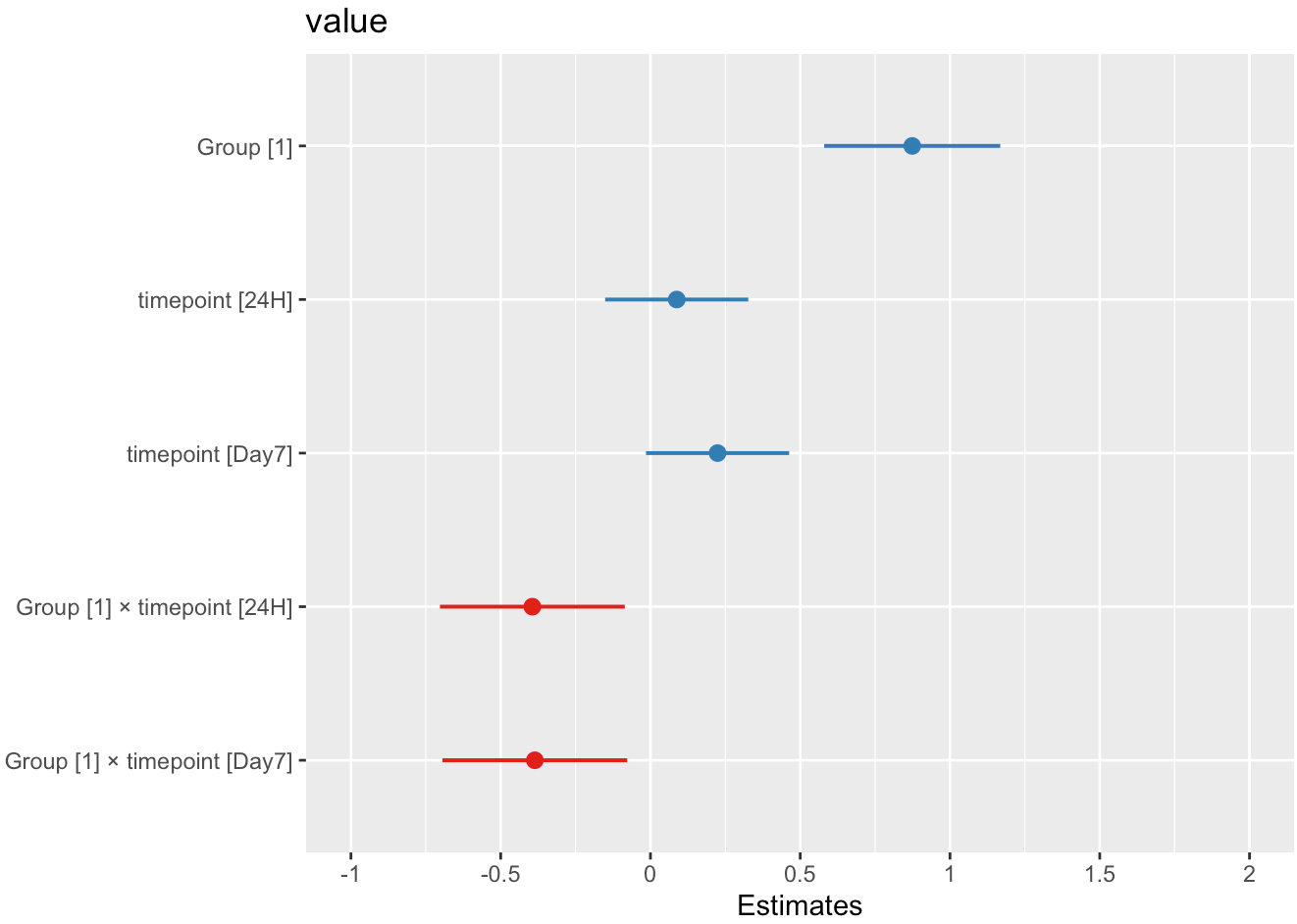
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.71 – -0.26	**<0.001**
Group [1]	0.87	0.58 – 1.17	**<0.001**
timepoint [24H]	0.09	-0.15 – 0.33	0.471

timepoint [Day7]	0.22	-0.01 – 0.46	0.066
Group [1] × timepoint [24H]	-0.39	-0.70 – -0.09	**0.012**
Group [1] × timepoint [Day7]	-0.39	-0.69 – -0.08	**0.014**

Random Effects

σ^2	0.35
$\tau_{00\ subject_id}$	0.07
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.195 / 0.332

```
plot_model(models["Beta_0"])
```




```
tab_model(models["Beta_S"])
```

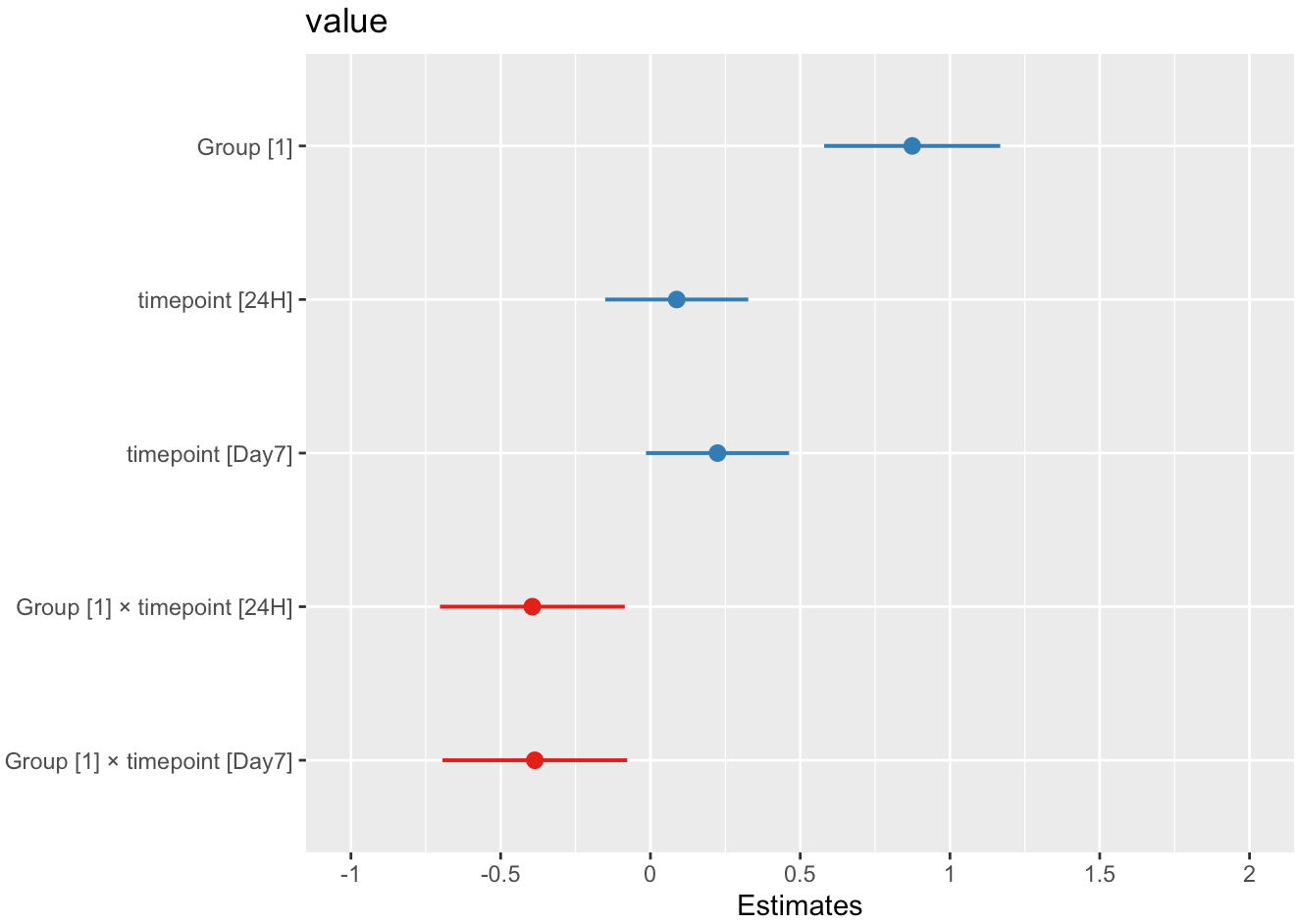
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.71 – -0.26	**<0.001**
Group [1]	0.87	0.58 – 1.17	**<0.001**
timepoint [24H]	0.09	-0.15 – 0.33	0.471
timepoint [Day7]	0.22	-0.01 – 0.46	0.066

Group [1] × timepoint [24H]	-0.39	-0.70 – -0.09	**0.012**
Group [1] × timepoint [Day7]	-0.39	-0.69 – -0.08	**0.014**

Random Effects

σ^2	0.35
$\tau_{00\ subject_id}$	0.07
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.195 / 0.332

```
plot_model(models["Beta_S"])
```




```
tab_model(models[["Beta_TC"]])
```

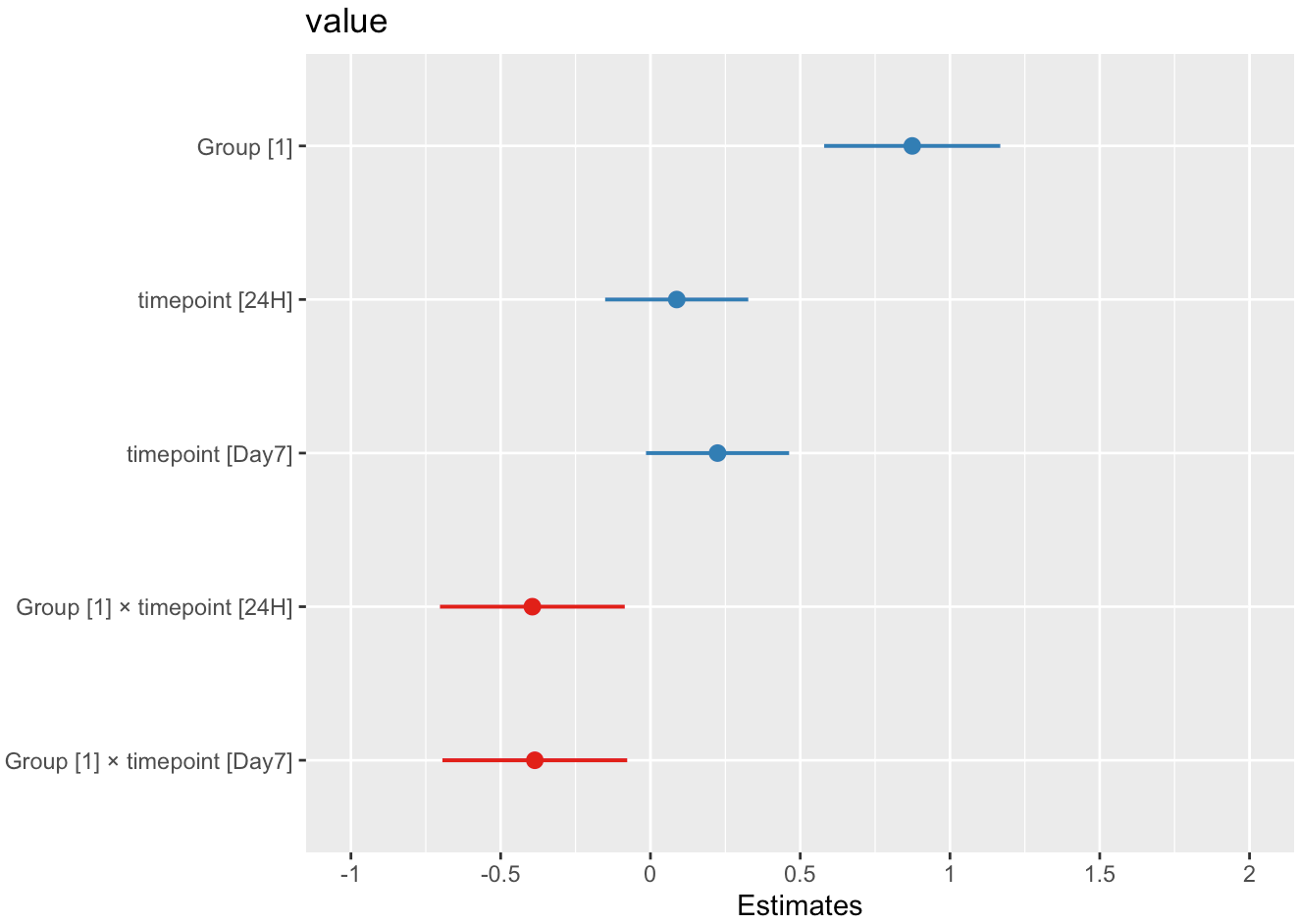
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.71 – -0.26	**<0.001**
Group [1]	0.87	0.58 – 1.17	**<0.001**
timepoint [24H]	0.09	-0.15 – 0.33	0.471
timepoint [Day7]	0.22	-0.01 – 0.46	0.066

Group [1] × timepoint [24H]	-0.39	-0.70 – -0.09	**0.012**
Group [1] × timepoint [Day7]	-0.39	-0.69 – -0.08	**0.014**

Random Effects

σ^2	0.35
$\tau_{00\ subject_id}$	0.07
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.195 / 0.332

```
plot_model(models["Beta_TC"])
```




```
tab_model(models[["Beta_DTC"]])
```

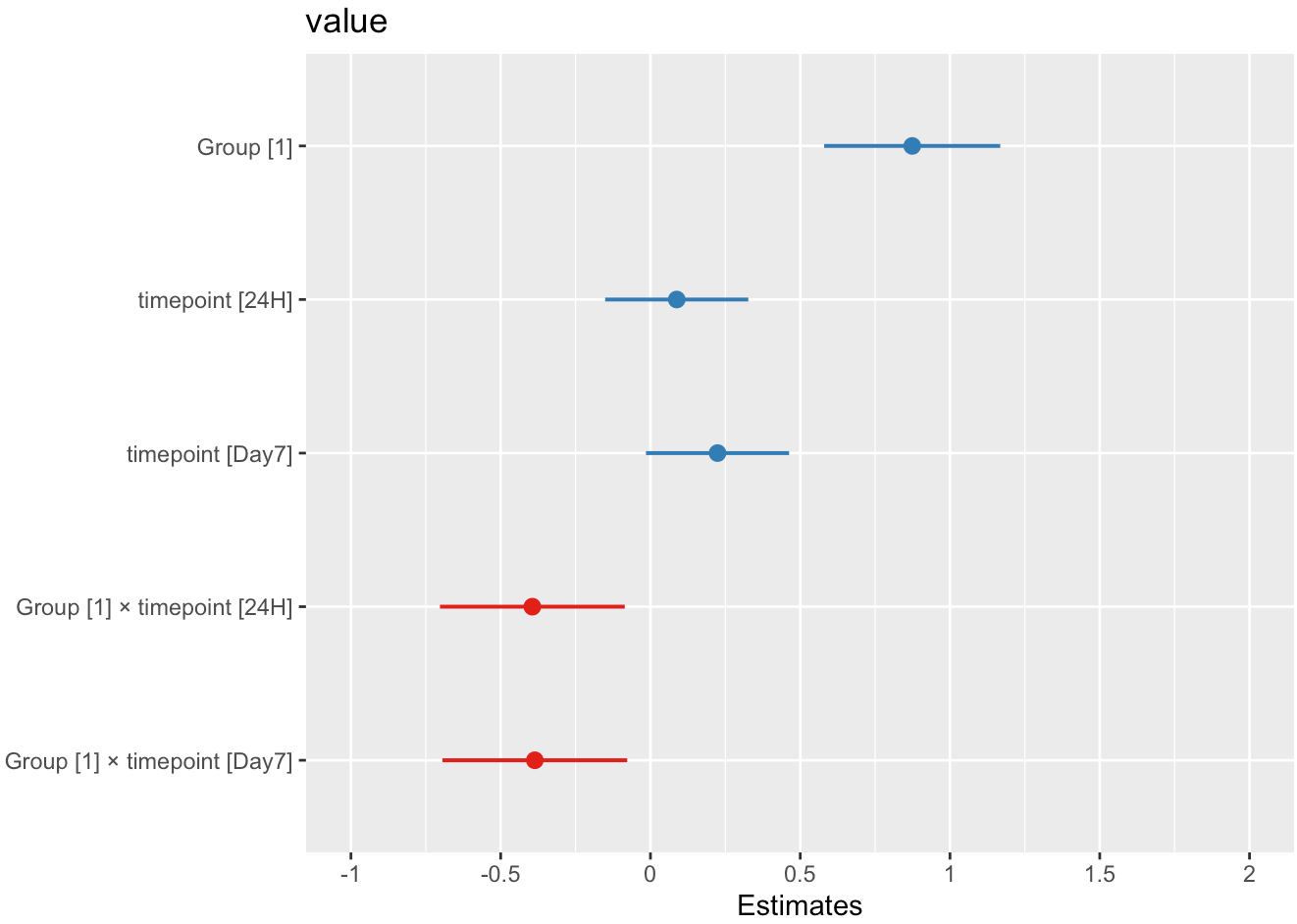
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-0.71 – -0.26	**<0.001**
Group [1]	0.87	0.58 – 1.17	**<0.001**
timepoint [24H]	0.09	-0.15 – 0.33	0.471
timepoint [Day7]	0.22	-0.01 – 0.46	0.066

Group [1] × timepoint [24H]	-0.39	-0.70 – -0.09	**0.012**
Group [1] × timepoint [Day7]	-0.39	-0.69 – -0.08	**0.014**

Random Effects

σ^2	0.35
$\tau_{00\ subject_id}$	0.07
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.195 / 0.332

```
plot_model(models["Beta_DTC"])
```




```
# Gamma models
tab_model(models[["Gamma_0"]])
```

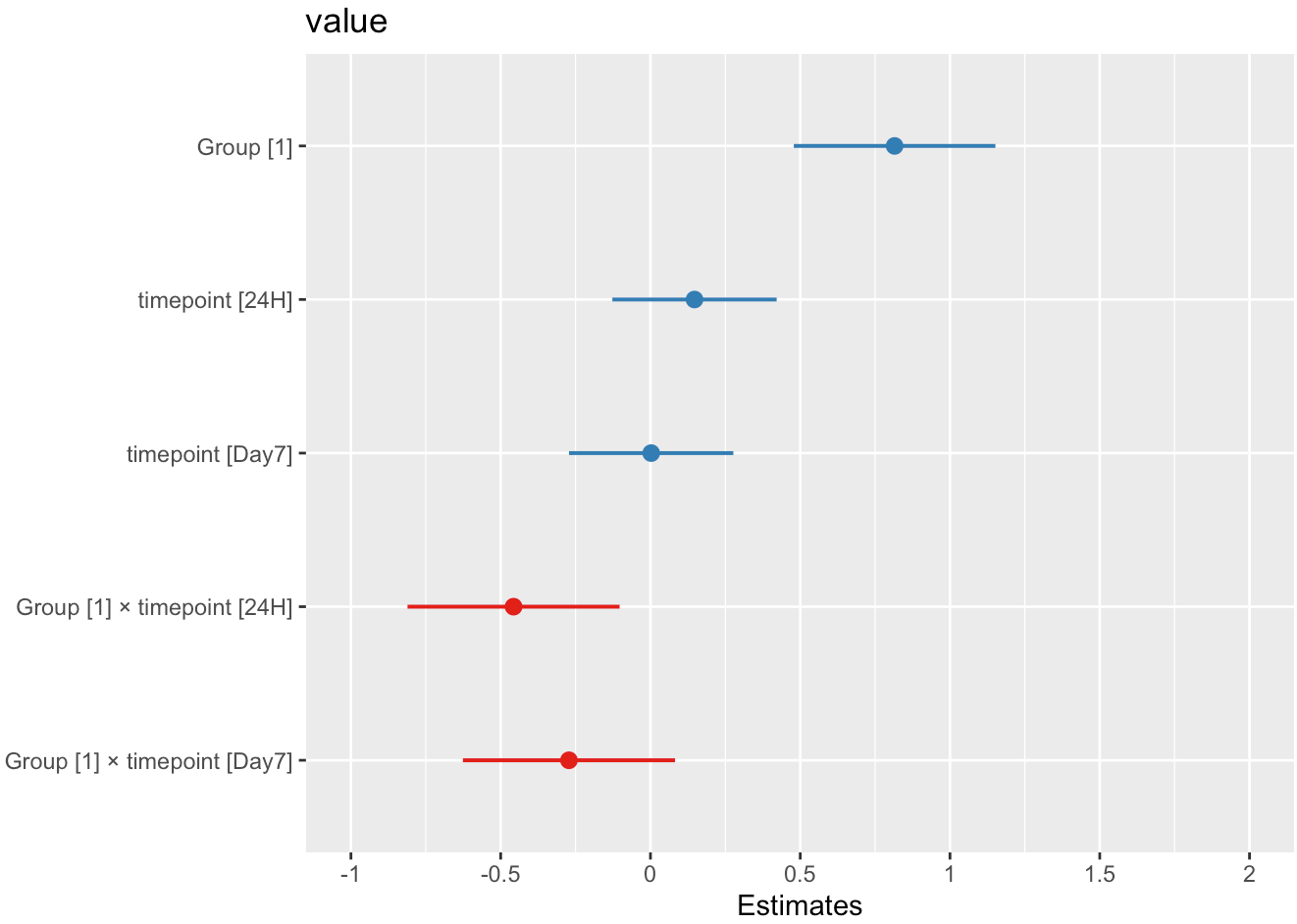
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.44	-0.70 – -0.18	**0.001**
Group [1]	0.82	0.48 – 1.15	**<0.001**
timepoint [24H]	0.15	-0.13 – 0.42	0.292

timepoint [Day7]	0.00	-0.27 – 0.28	0.986
Group [1] × timepoint [24H]	-0.46	-0.81 – -0.10	**0.012**
Group [1] × timepoint [Day7]	-0.27	-0.63 – 0.08	0.132

Random Effects

σ^2	0.47
$\tau_{00\ subject_id}$	0.09
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.285

```
plot_model(models["Gamma_0"])
```




```
tab_model(models["Gamma_S"])
```

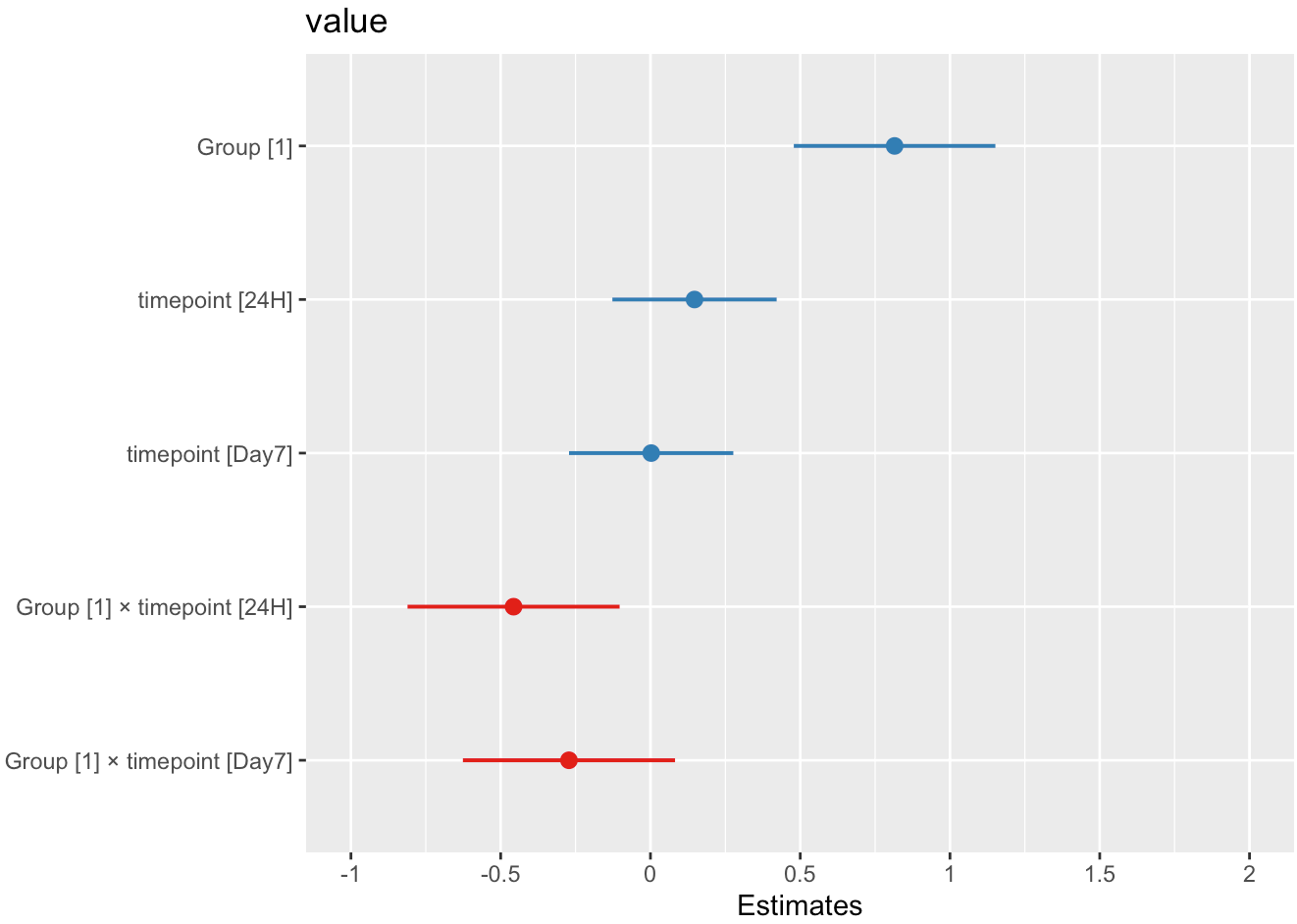
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.44	-0.70 – -0.18	**0.001**
Group [1]	0.82	0.48 – 1.15	**<0.001**
timepoint [24H]	0.15	-0.13 – 0.42	0.292
timepoint [Day7]	0.00	-0.27 – 0.28	0.986

Group [1] × timepoint [24H]	-0.46	-0.81 – -0.10	**0.012**
Group [1] × timepoint [Day7]	-0.27	-0.63 – 0.08	0.132

Random Effects

σ^2	0.47
$\tau_{00\ subject_id}$	0.09
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.285

```
plot_model(models["Gamma_S"])
```




```
tab_model(models["Gamma_TC"])
```

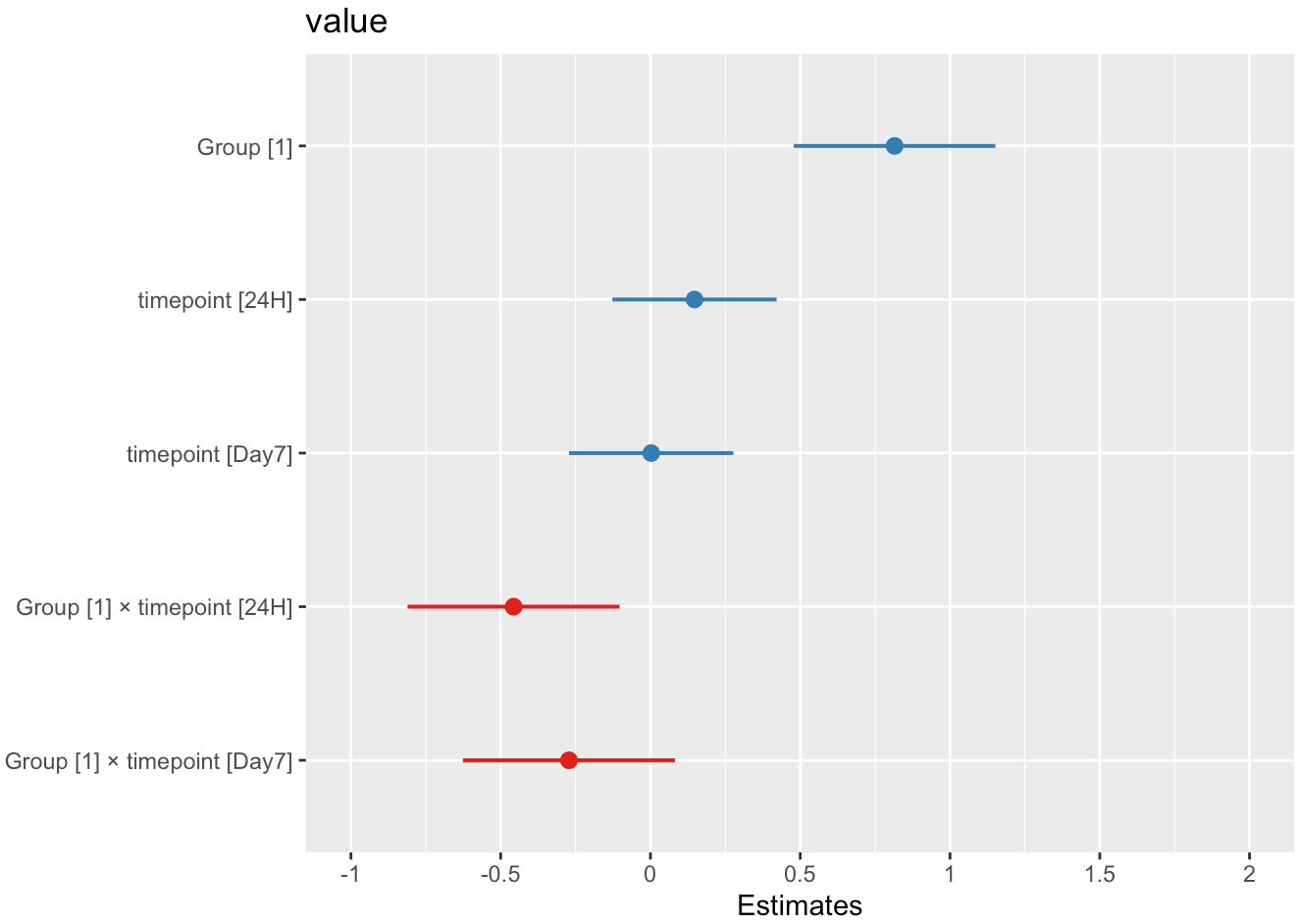
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.44	-0.70 – -0.18	**0.001**
Group [1]	0.82	0.48 – 1.15	**<0.001**
timepoint [24H]	0.15	-0.13 – 0.42	0.292
timepoint [Day7]	0.00	-0.27 – 0.28	0.986

Group [1] × timepoint [24H]	-0.46	-0.81 – -0.10	**0.012**
Group [1] × timepoint [Day7]	-0.27	-0.63 – 0.08	0.132

Random Effects

σ^2	0.47
$\tau_{00\ subject_id}$	0.09
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.285

```
plot_model(models["Gamma_TC"])
```




```
tab_model(models["Gamma_DTC"])
```

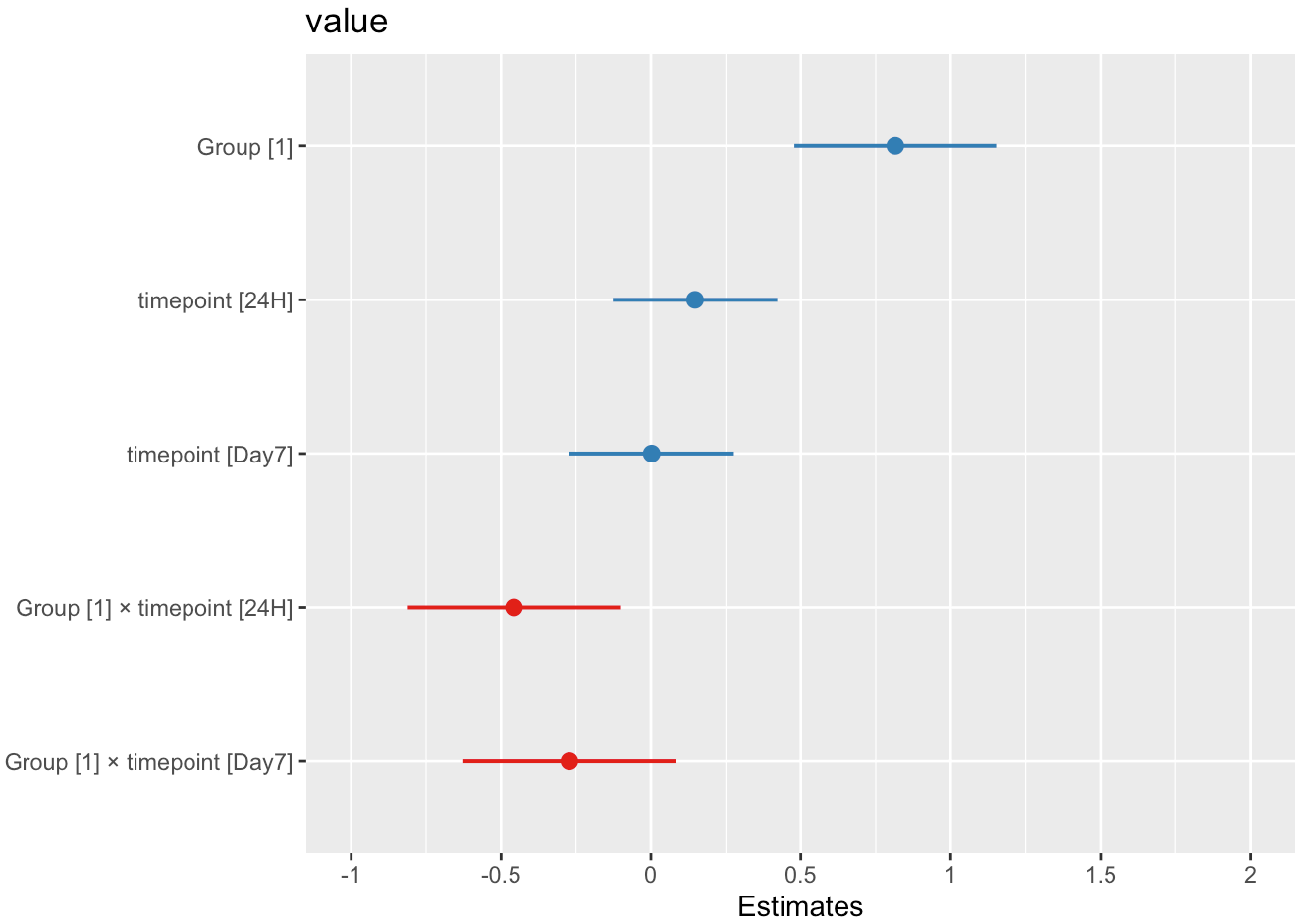
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.44	-0.70 – -0.18	**0.001**
Group [1]	0.82	0.48 – 1.15	**<0.001**
timepoint [24H]	0.15	-0.13 – 0.42	0.292
timepoint [Day7]	0.00	-0.27 – 0.28	0.986

Group [1] × timepoint [24H]	-0.46	-0.81 – -0.10	**0.012**
Group [1] × timepoint [Day7]	-0.27	-0.63 – 0.08	0.132

Random Effects

σ^2	0.47
$\tau_{00\ subject_id}$	0.09
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.285

```
plot_model(models["Gamma_DTC"])
```




```
# Delta models
tab_model(models[["Delta_0"]])
```

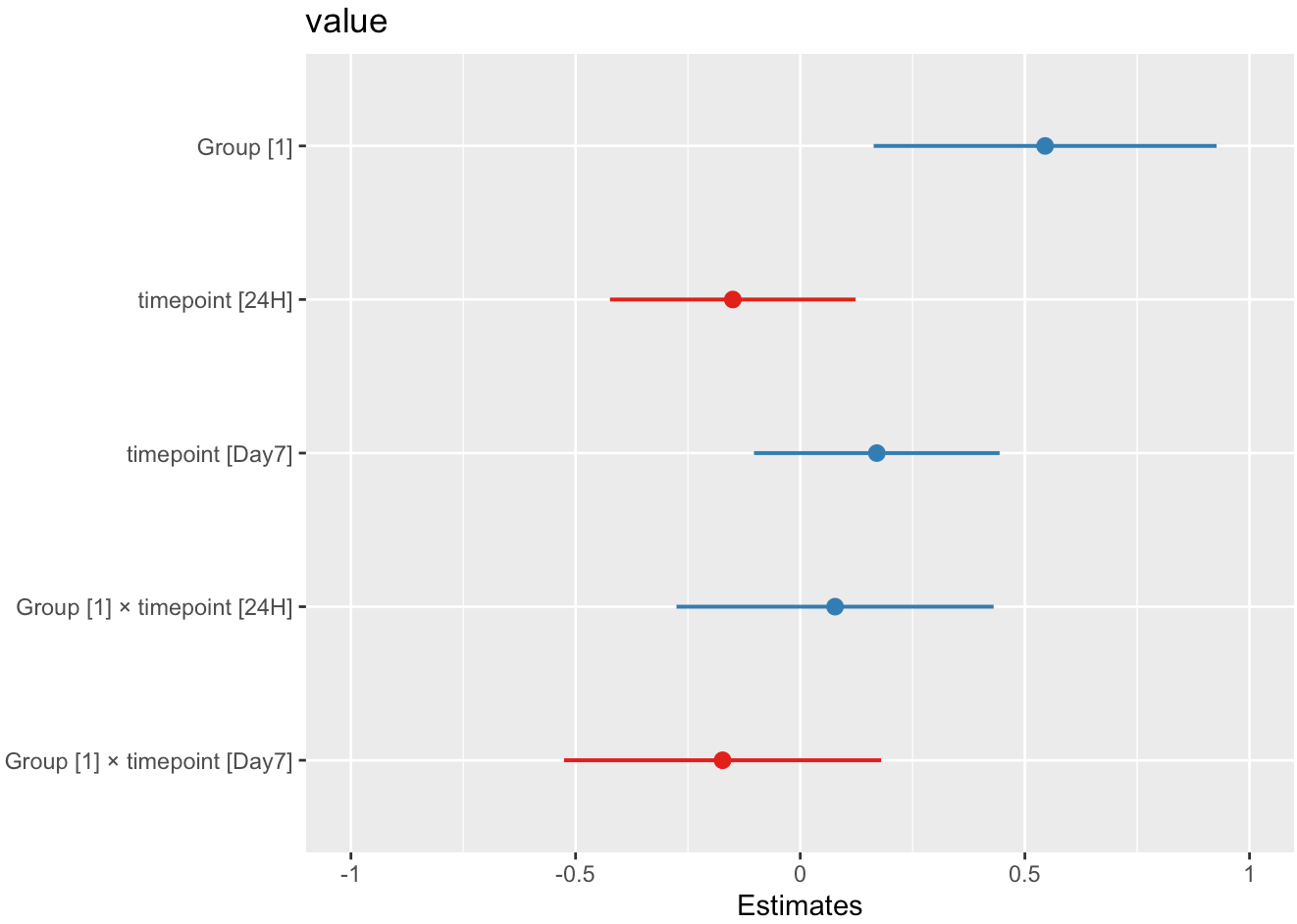
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.24	-0.54 – 0.05	0.107
Group [1]	0.55	0.16 – 0.93	**0.005**
timepoint [24H]	-0.15	-0.42 – 0.12	0.281

timepoint [Day7]	0.17	-0.10 – 0.44	0.221
Group [1] × timepoint [24H]	0.08	-0.28 – 0.43	0.666
Group [1] × timepoint [Day7]	-0.17	-0.53 – 0.18	0.336

Random Effects

σ^2	0.46
$\tau_{00\ subject_id}$	0.16
ICC	0.25
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.103 / 0.328

```
plot_model(models["Delta_0"])
```




```
tab_model(models[["Delta_S"]])
```

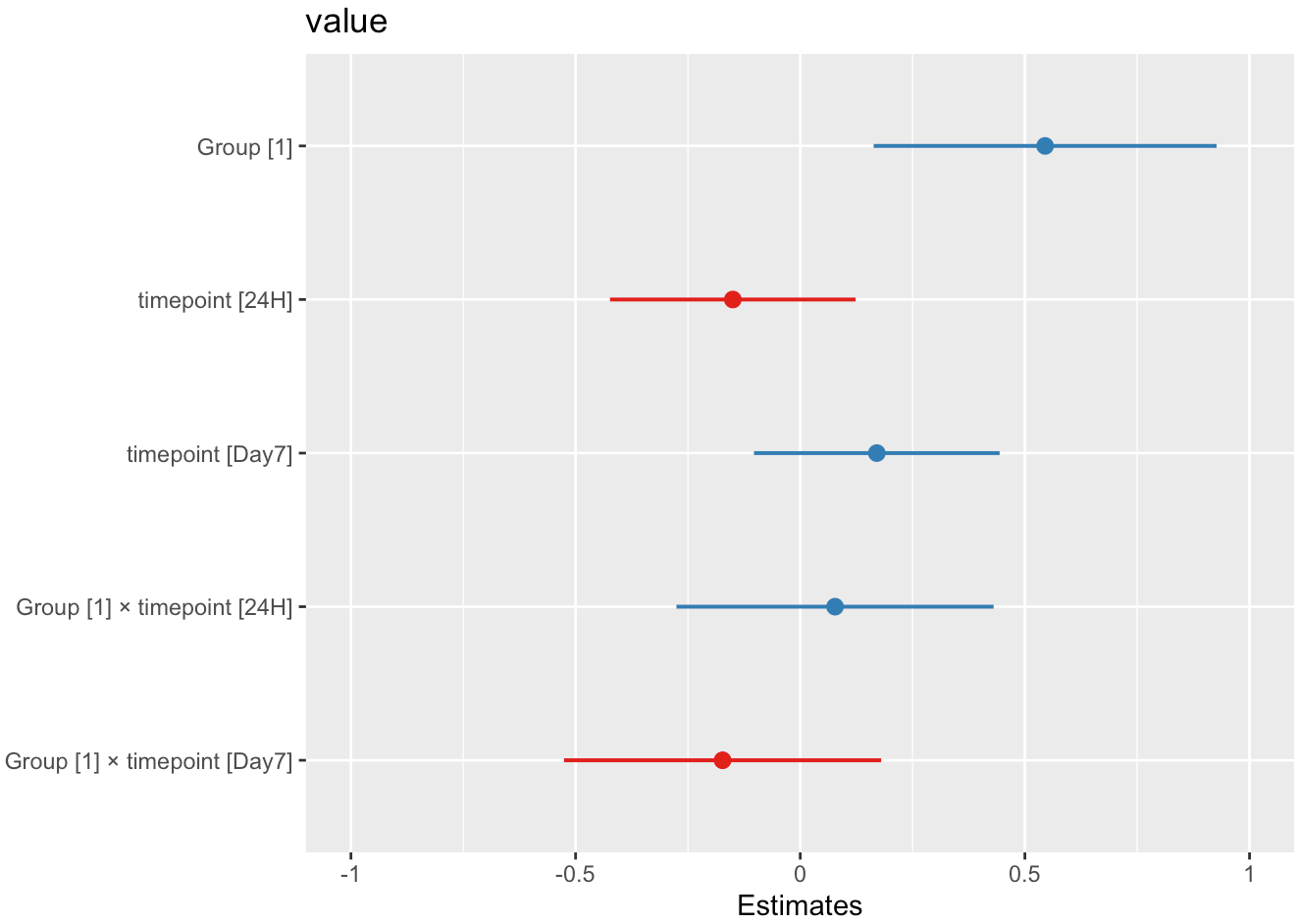
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.24	-0.54 – 0.05	0.107
Group [1]	0.55	0.16 – 0.93	**0.005**
timepoint [24H]	-0.15	-0.42 – 0.12	0.281
timepoint [Day7]	0.17	-0.10 – 0.44	0.221

Group [1] × timepoint [24H]	0.08	-0.28 – 0.43	0.666
Group [1] × timepoint [Day7]	-0.17	-0.53 – 0.18	0.336

Random Effects

σ^2	0.46
$\tau_{00\ subject_id}$	0.16
ICC	0.25
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.103 / 0.328

```
plot_model(models["Delta_S"])
```




```
tab_model(models[["Delta_TC"]])
```

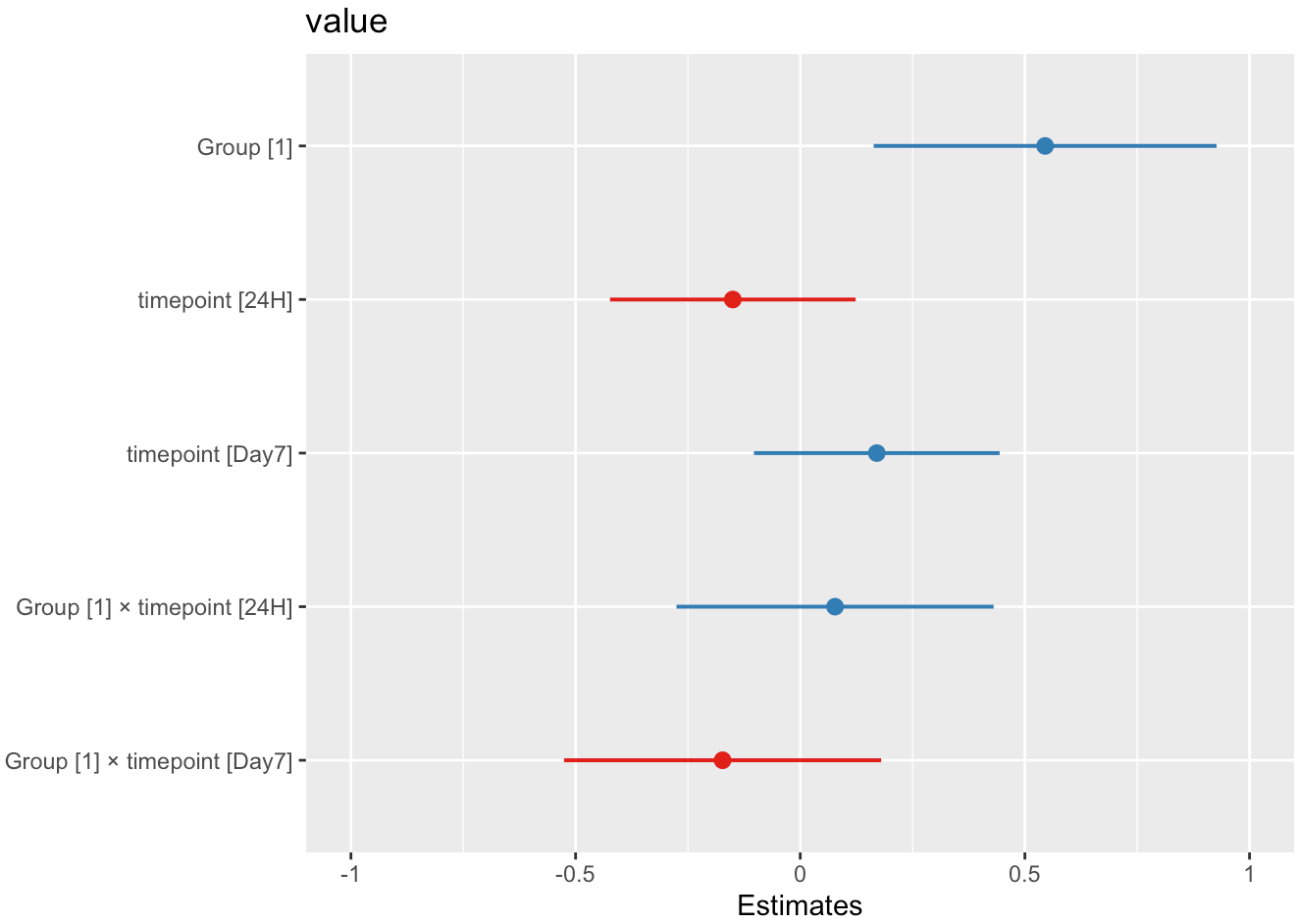
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.24	-0.54 – 0.05	0.107
Group [1]	0.55	0.16 – 0.93	**0.005**
timepoint [24H]	-0.15	-0.42 – 0.12	0.281
timepoint [Day7]	0.17	-0.10 – 0.44	0.221

Group [1] × timepoint [24H]	0.08	-0.28 – 0.43	0.666
Group [1] × timepoint [Day7]	-0.17	-0.53 – 0.18	0.336

Random Effects

σ^2	0.46
$\tau_{00\ subject_id}$	0.16
ICC	0.25
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.103 / 0.328

```
plot_model(models["Delta_TC"])
```




```
tab_model(models[["Delta_DTC"]])
```

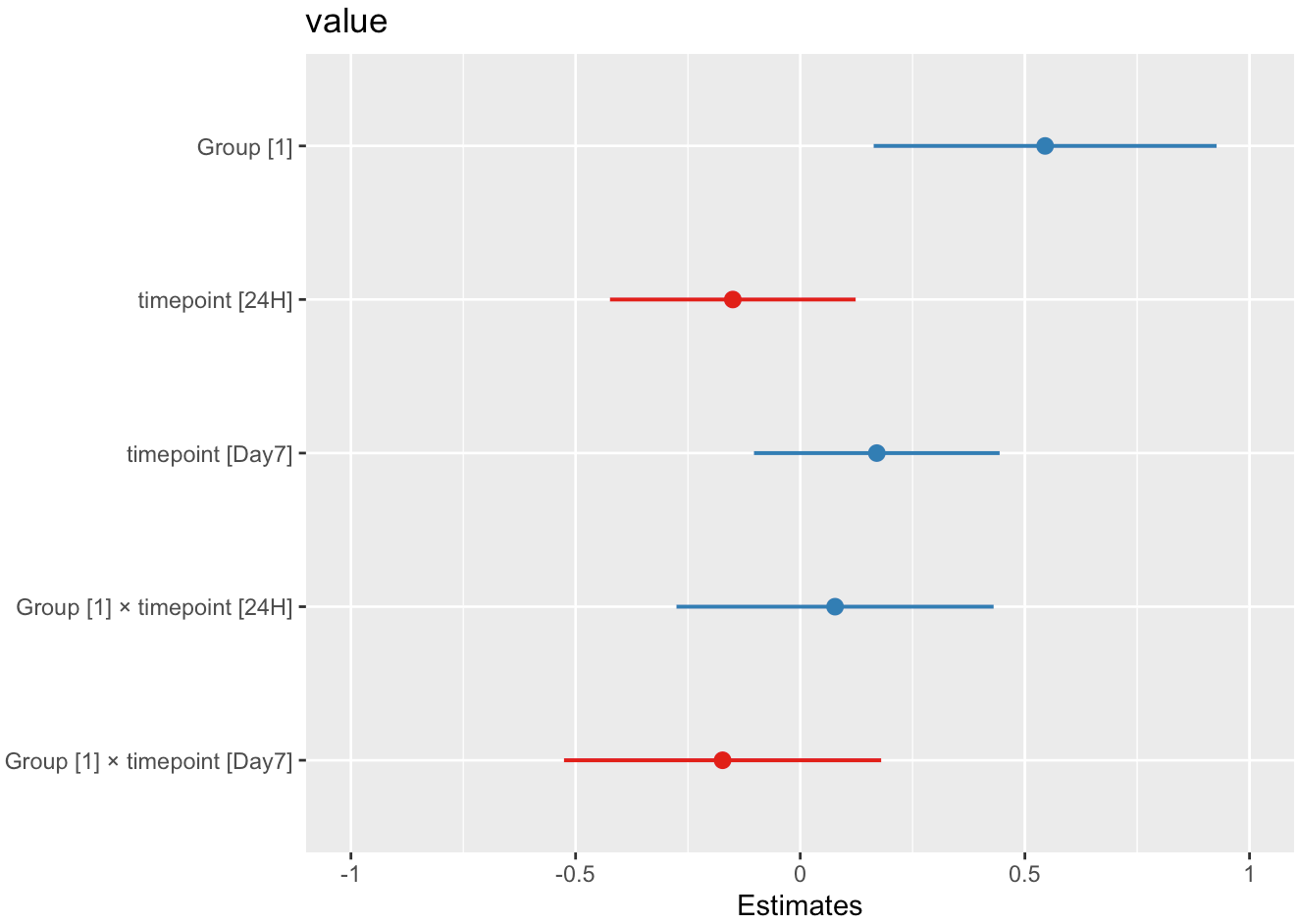
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.24	-0.54 – 0.05	0.107
Group [1]	0.55	0.16 – 0.93	**0.005**
timepoint [24H]	-0.15	-0.42 – 0.12	0.281
timepoint [Day7]	0.17	-0.10 – 0.44	0.221

Group [1] × timepoint [24H]	0.08	-0.28 – 0.43	0.666
Group [1] × timepoint [Day7]	-0.17	-0.53 – 0.18	0.336

Random Effects

σ^2	0.46
$\tau_{00\ subject_id}$	0.16
ICC	0.25
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.103 / 0.328

```
plot_model(models["Delta_DTC"])
```




```
# Theta models
tab_model(models[["Theta_0"]])
```

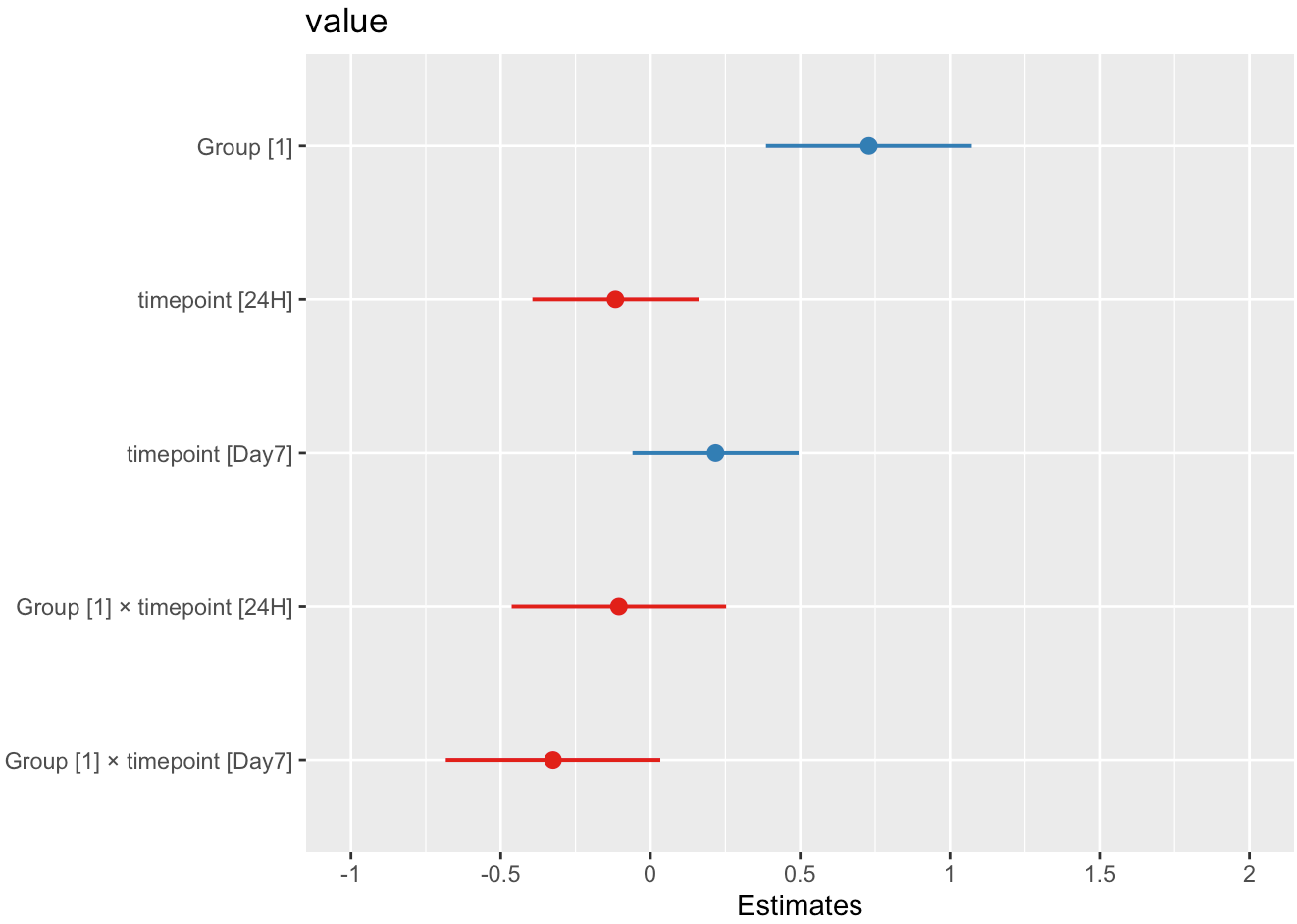
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.41	-0.67 – -0.14	**0.003**
Group [1]	0.73	0.39 – 1.07	**<0.001**
timepoint [24H]	-0.12	-0.39 – 0.16	0.408

timepoint [Day7]	0.22	-0.06 – 0.49	0.124
Group [1] × timepoint [24H]	-0.11	-0.46 – 0.25	0.563
Group [1] × timepoint [Day7]	-0.33	-0.68 – 0.03	0.075

Random Effects

σ^2	0.48
$\tau_{00\ subject_id}$	0.10
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.291

```
plot_model(models["Theta_0"])
```




```
tab_model(models[["Theta_S"]])
```

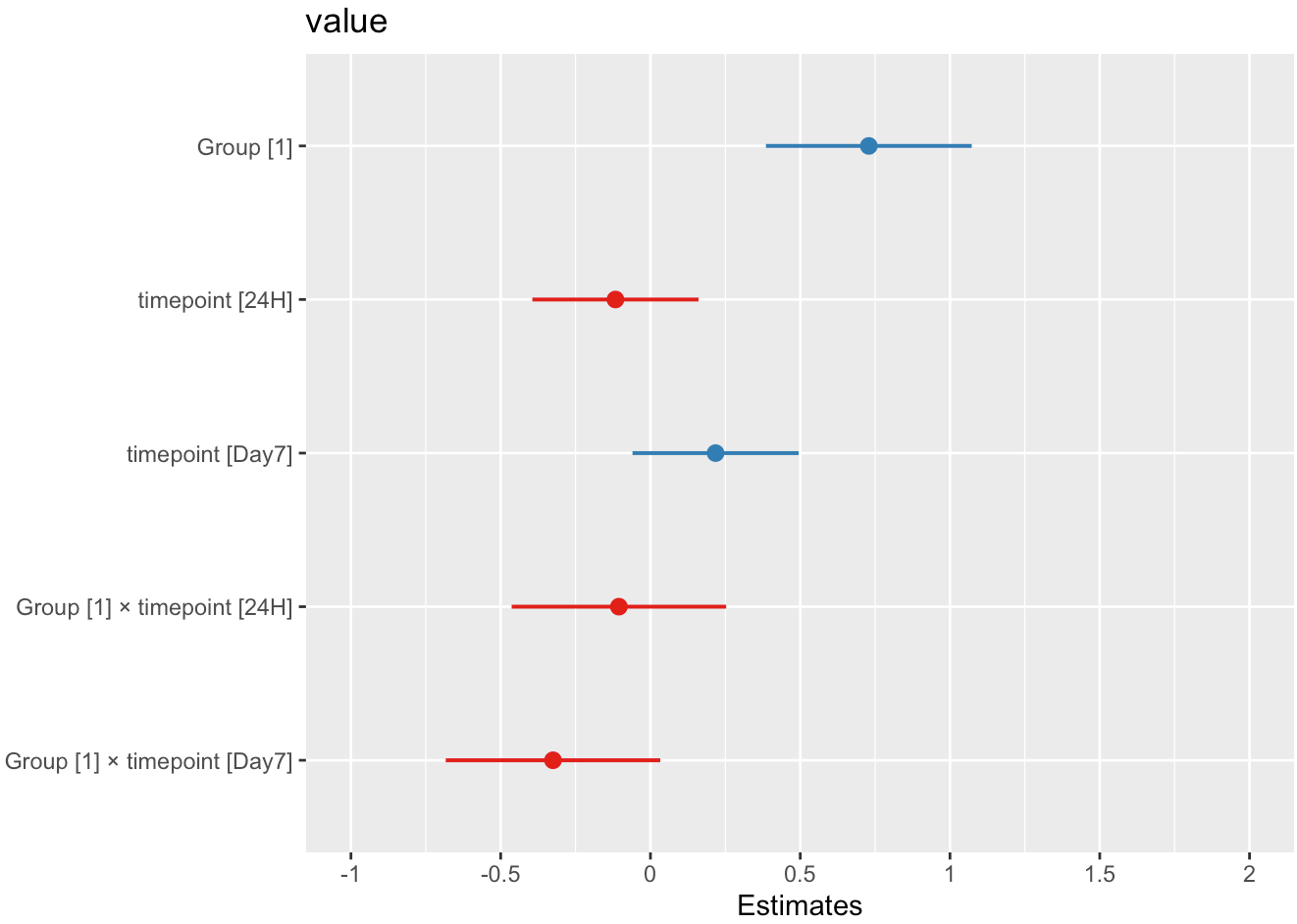
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.41	-0.67 – -0.14	**0.003**
Group [1]	0.73	0.39 – 1.07	**<0.001**
timepoint [24H]	-0.12	-0.39 – 0.16	0.408
timepoint [Day7]	0.22	-0.06 – 0.49	0.124

Group [1] × timepoint [24H]	-0.11	-0.46 – 0.25	0.563
Group [1] × timepoint [Day7]	-0.33	-0.68 – 0.03	0.075

Random Effects

σ^2	0.48
$\tau_{00\ subject_id}$	0.10
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.291

```
plot_model(models["Theta_S"])
```




```
tab_model(models[["Theta_TC"]])
```

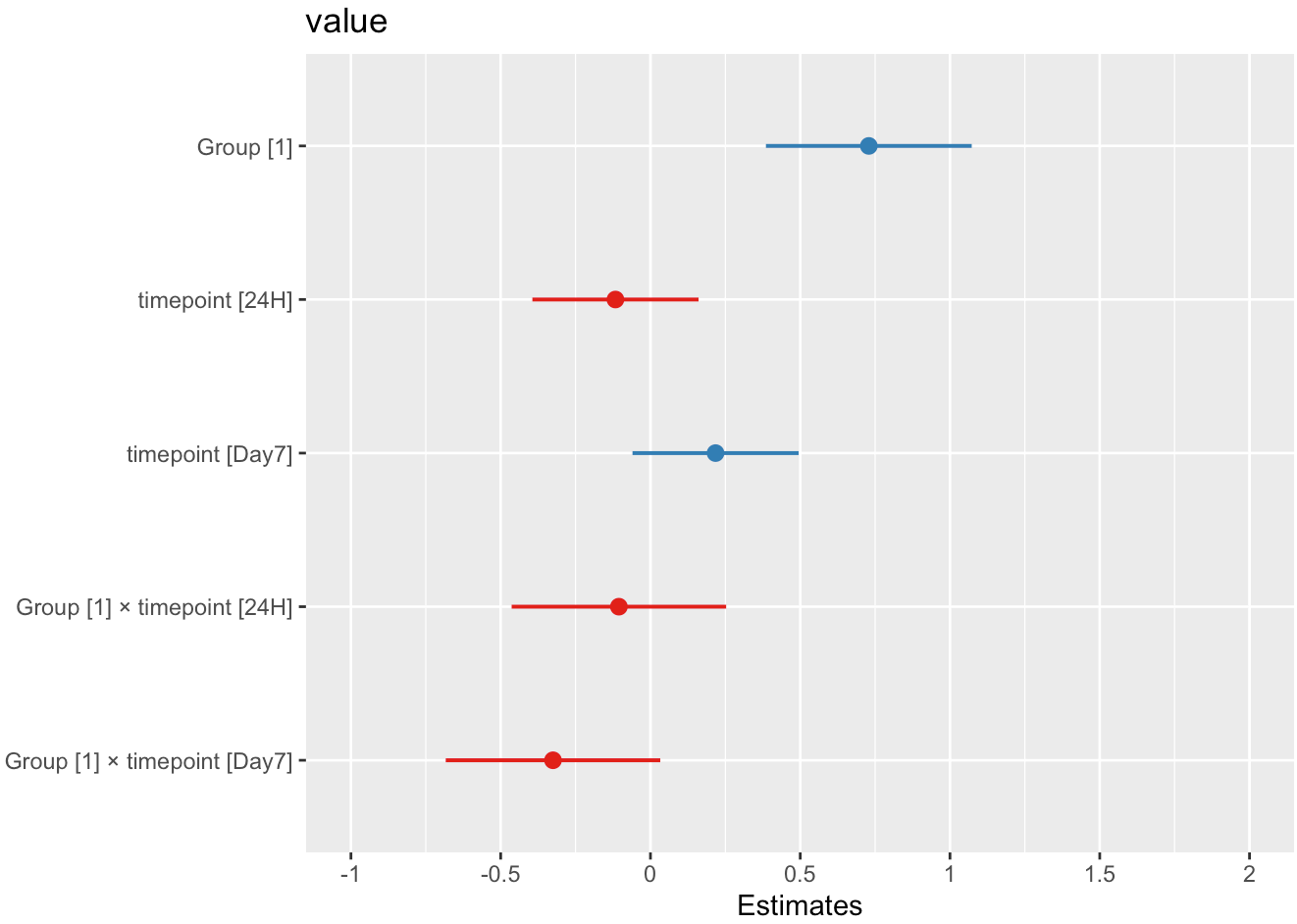
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.41	-0.67 – -0.14	**0.003**
Group [1]	0.73	0.39 – 1.07	**<0.001**
timepoint [24H]	-0.12	-0.39 – 0.16	0.408
timepoint [Day7]	0.22	-0.06 – 0.49	0.124

Group [1] × timepoint [24H]	-0.11	-0.46 – 0.25	0.563
Group [1] × timepoint [Day7]	-0.33	-0.68 – 0.03	0.075

Random Effects

σ^2	0.48
$\tau_{00\ subject_id}$	0.10
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.291

```
plot_model(models["Theta_TC"])
```




```
tab_model(models[["Theta_DTC"]])
```

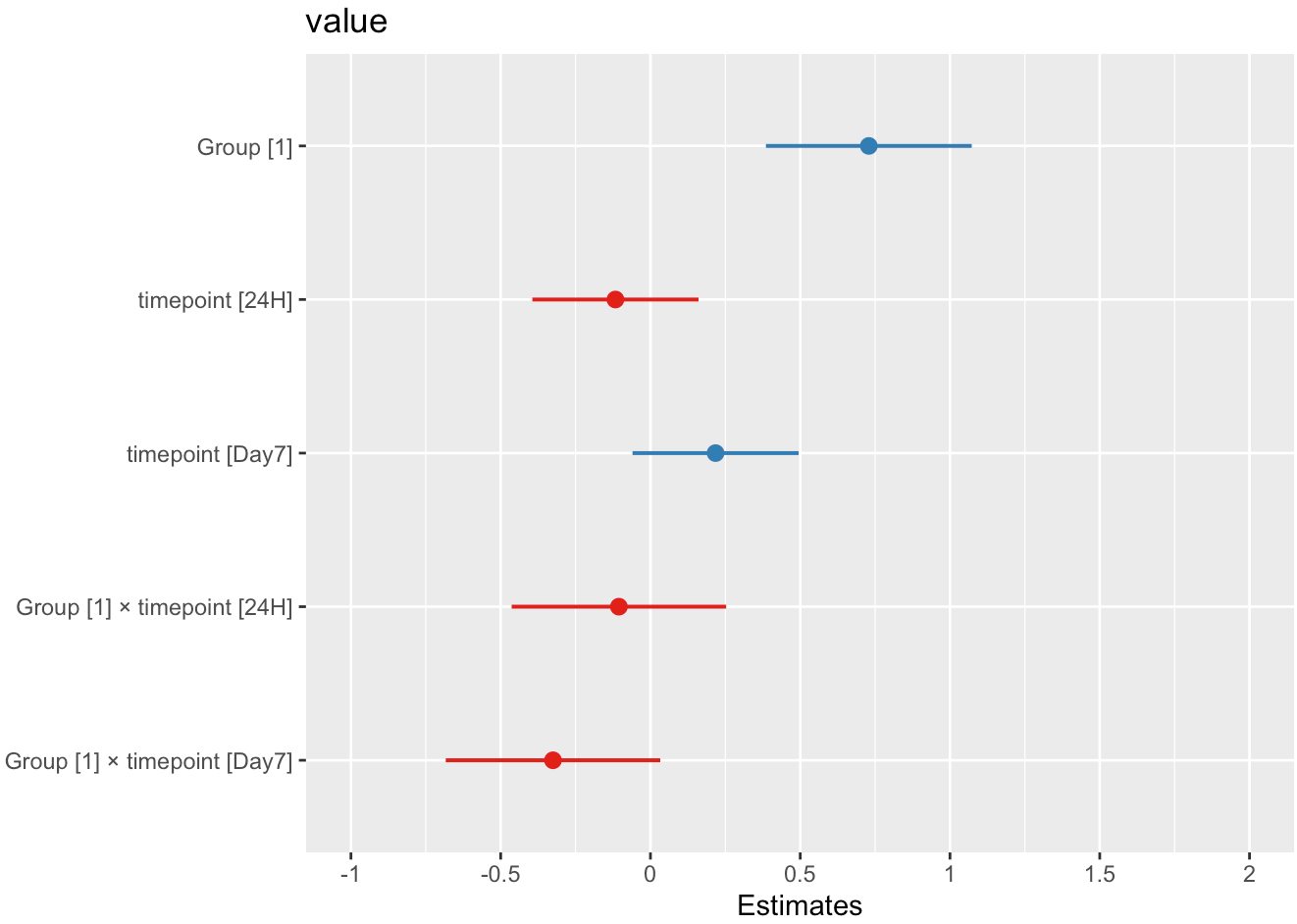
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.41	-0.67 – -0.14	**0.003**
Group [1]	0.73	0.39 – 1.07	**<0.001**
timepoint [24H]	-0.12	-0.39 – 0.16	0.408
timepoint [Day7]	0.22	-0.06 – 0.49	0.124

Group [1] × timepoint [24H]	-0.11	-0.46 – 0.25	0.563
Group [1] × timepoint [Day7]	-0.33	-0.68 – 0.03	0.075

Random Effects

σ^2	0.48
$\tau_{00\ subject_id}$	0.10
ICC	0.17
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.141 / 0.291

```
plot_model(models["Theta_DTC"])
```




```
# Wholeband models
tab_model(models[["Wholeband_0"]])
```

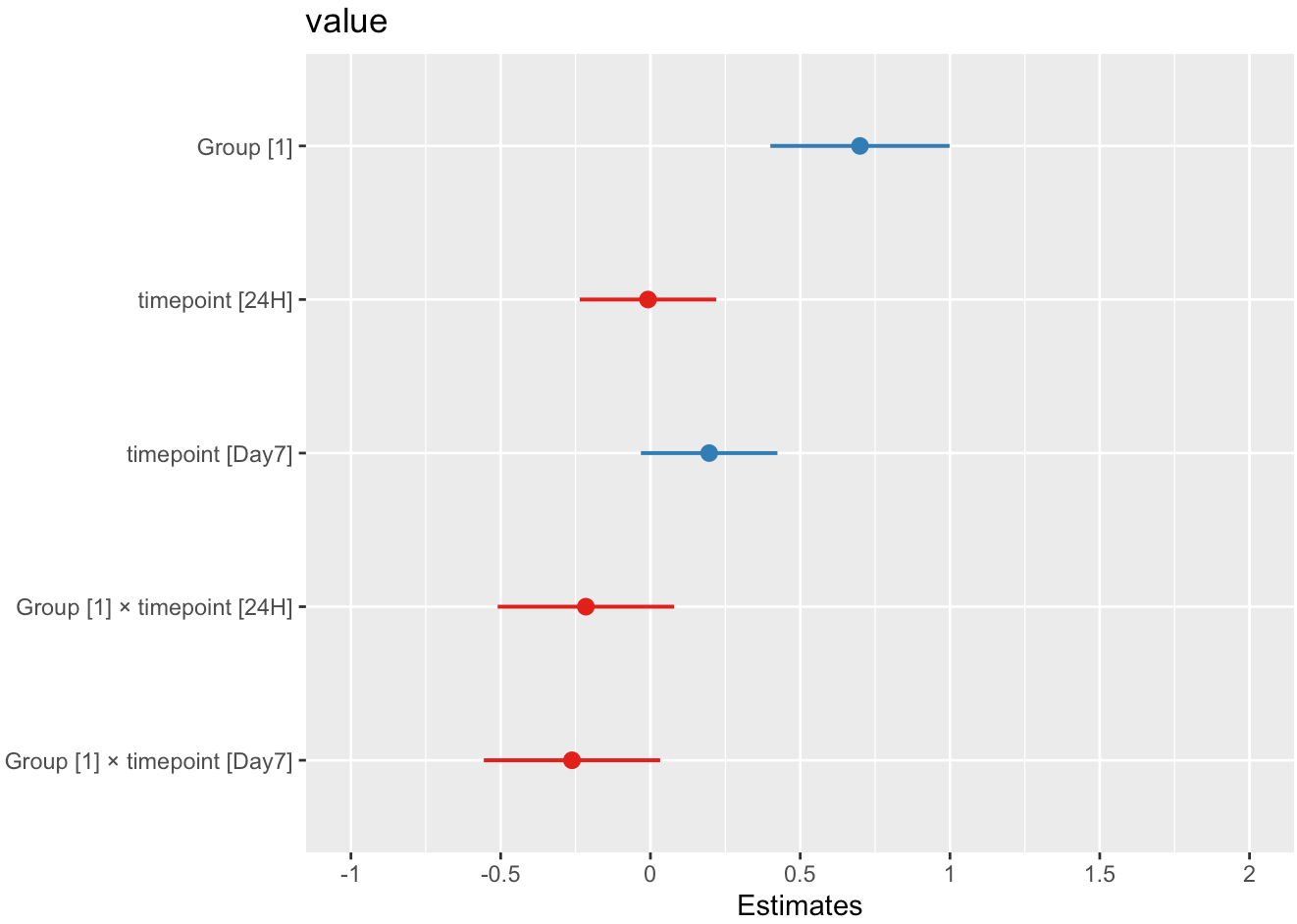
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.40	-0.63 – -0.16	**0.001**
Group [1]	0.70	0.40 – 1.00	**<0.001**
timepoint [24H]	-0.01	-0.24 – 0.22	0.944

timepoint [Day7]	0.20	-0.03 – 0.42	0.092
Group [1] × timepoint [24H]	-0.22	-0.51 – 0.08	0.150
Group [1] × timepoint [Day7]	-0.26	-0.56 – 0.03	0.081

Random Effects

σ^2	0.32
$\tau_{00\ subject_id}$	0.09
ICC	0.21
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.162 / 0.339

```
plot_model(models["Wholeband_0"])
```




```
tab_model(models["Wholeband_S"])
```

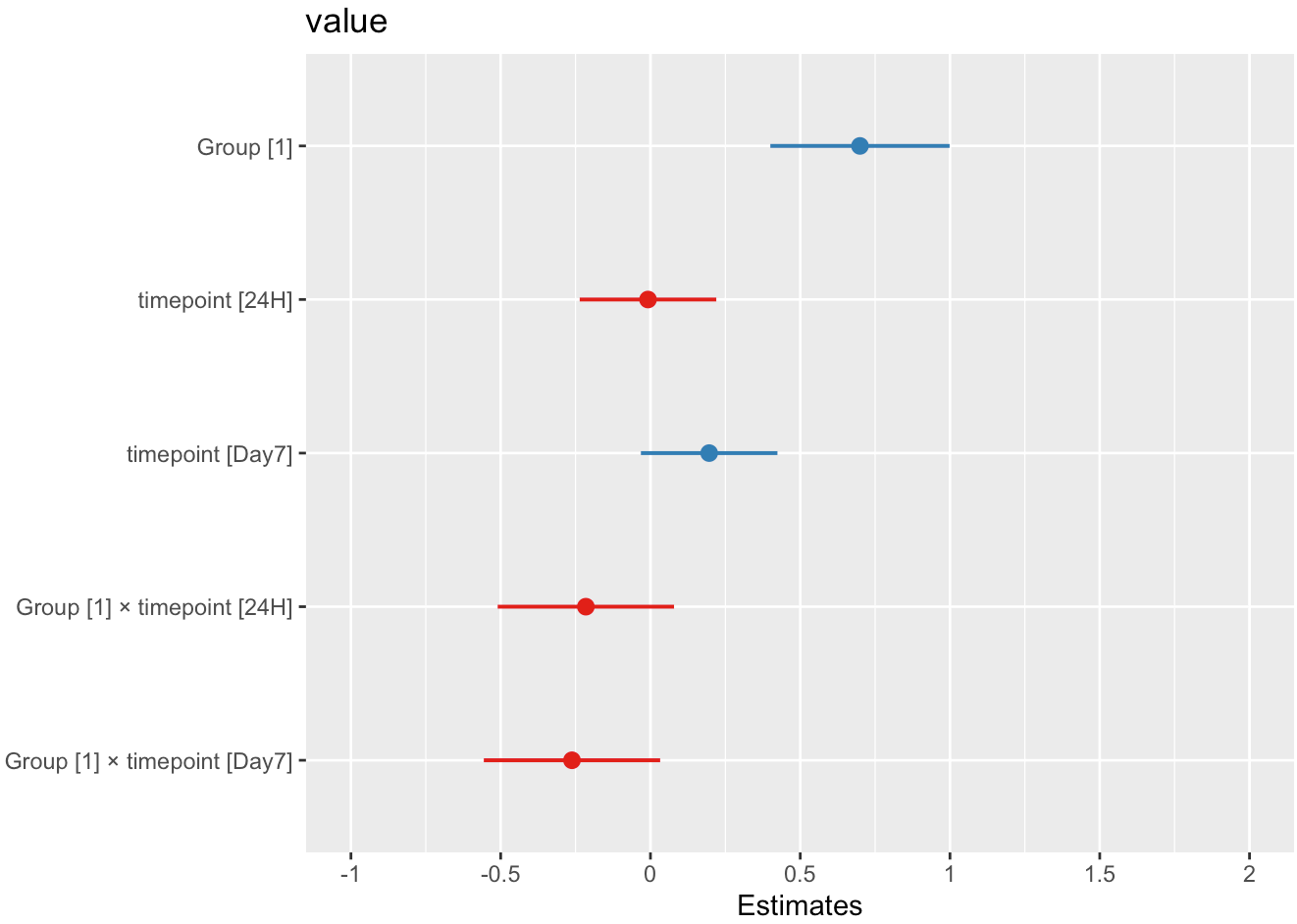
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.40	-0.63 – -0.16	**0.001**
Group [1]	0.70	0.40 – 1.00	**<0.001**
timepoint [24H]	-0.01	-0.24 – 0.22	0.944
timepoint [Day7]	0.20	-0.03 – 0.42	0.092

Group [1] × timepoint [24H]	-0.22	-0.51 – 0.08	0.150
Group [1] × timepoint [Day7]	-0.26	-0.56 – 0.03	0.081

Random Effects

σ^2	0.32
$\tau_{00\ subject_id}$	0.09
ICC	0.21
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.162 / 0.339

```
plot_model(models["Wholeband_S"])
```




```
tab_model(models["Wholeband_TC"])
```

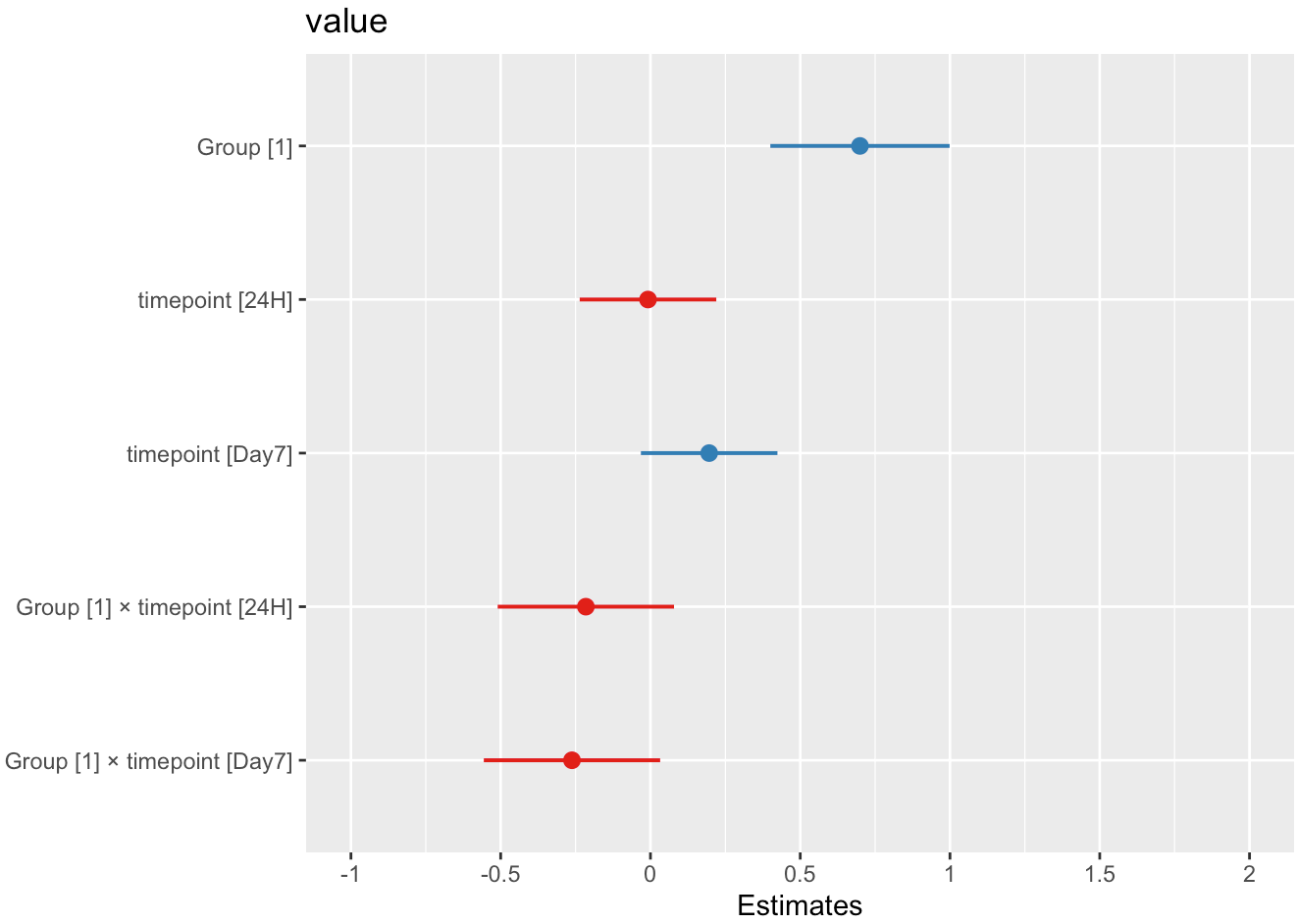
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.40	-0.63 – -0.16	**0.001**
Group [1]	0.70	0.40 – 1.00	**<0.001**
timepoint [24H]	-0.01	-0.24 – 0.22	0.944
timepoint [Day7]	0.20	-0.03 – 0.42	0.092

Group [1] × timepoint [24H]	-0.22	-0.51 – 0.08	0.150
Group [1] × timepoint [Day7]	-0.26	-0.56 – 0.03	0.081

Random Effects

σ^2	0.32
$\tau_{00\ subject_id}$	0.09
ICC	0.21
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.162 / 0.339

```
plot_model(models["Wholeband_TC"])
```




```
tab_model(models["Wholeband_DTC"])
```

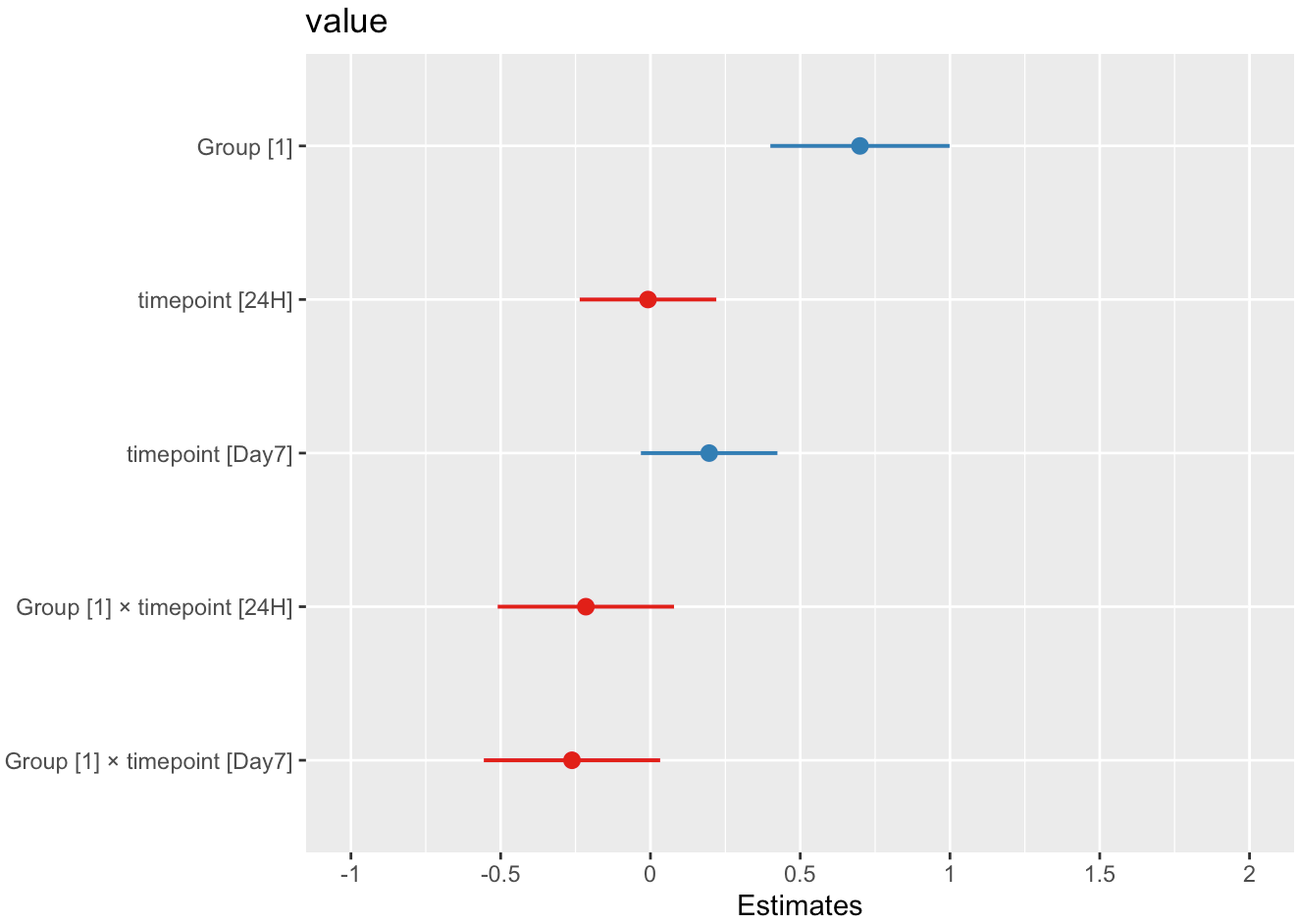
	value		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.40	-0.63 – -0.16	**0.001**
Group [1]	0.70	0.40 – 1.00	**<0.001**
timepoint [24H]	-0.01	-0.24 – 0.22	0.944
timepoint [Day7]	0.20	-0.03 – 0.42	0.092

Group [1] × timepoint [24H]	-0.22	-0.51 – 0.08	0.150
Group [1] × timepoint [Day7]	-0.26	-0.56 – 0.03	0.081

Random Effects

σ^2	0.32
$\tau_{00\ subject_id}$	0.09
ICC	0.21
$N_{\ subject_id}$	30
Observations	360
Marginal R^2 / Conditional R^2	0.162 / 0.339

```
plot_model(models["Wholeband_DTC"])
```



> Run the linear mixed models