

# Model Comparison and Interpretation

```
library(pracma)
library(posterior)
```

This is posterior version 1.2.1

Attaching package: 'posterior'

The following objects are masked from 'package:stats':

mad, sd, var

```
library(cmdstanr)
```

Warning: package 'cmdstanr' was built under R version 4.1.3

This is cmdstanr version 0.5.3

- CmdStanR documentation and vignettes: [mc-stan.org/cmdstanr](https://mc-stan.org/cmdstanr)
- CmdStan path: `/Users/stefano/.cmdstan/cmdstan-2.30.1`
- CmdStan version: 2.30.1

A newer version of CmdStan is available. See `?install_cmdstan()` to install it.  
To disable this check set option or environment variable `CMDSTANR_NO_VER_CHECK=TRUE`.

```
library(rstan)
```

Loading required package: StanHeaders

Loading required package: ggplot2

rstan (Version 2.21.5, GitRev: 2e1f913d3ca3)

For execution on a local, multicore CPU with excess RAM we recommend calling  
`options(mc.cores = parallel::detectCores())`.

To avoid recompilation of unchanged Stan programs, we recommend calling  
`rstan_options(auto_write = TRUE)`

Attaching package: 'rstan'

The following objects are masked from 'package:posterior':

`ess_bulk`, `ess_tail`

```
library(ggplot2)
```

```
library(loo)
```

This is loo version 2.5.1

- Online documentation and vignettes at [mc-stan.org/loo](http://mc-stan.org/loo)

- As of v2.0.0 loo defaults to 1 core but we recommend using as many as possible. Use the 'c

Attaching package: 'loo'

The following object is masked from 'package:rstan':

`loo`

```
library(dplyr)
```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

filter, lag

The following objects are masked from 'package:base':

intersect, setdiff, setequal, union

```
library(tidyr)
```

Attaching package: 'tidyr'

The following object is masked from 'package:rstan':

extract

```
library(brms)
```

Loading required package: Rcpp

Loading 'brms' package (version 2.18.0). Useful instructions can be found by typing `help('brms')`. A more detailed introduction to the package is available through `vignette('brms_overview')`.

Attaching package: 'brms'

The following object is masked from 'package:rstan':

loo

The following object is masked from 'package:posterior':

rhat

The following object is masked from 'package:pracma':

bernoulli

The following object is masked from 'package:stats':

ar

```
library(firatheme)
library(nlmeU)
```

Attaching package: 'nlmeU'

The following object is masked from 'package:stats':

sigma

```
library(corrplot)
```

corrplot 0.92 loaded

```
library(nlme)
```

Attaching package: 'nlme'

The following object is masked from 'package:dplyr':

collapse

```
library(lattice)
library(plot.matrix)
library(lme4)
```

Loading required package: Matrix

Attaching package: 'Matrix'

The following objects are masked from 'package:tidyr':

expand, pack, unpack

The following objects are masked from 'package:pracma':

expm, lu, tril, triu

Attaching package: 'lme4'

The following object is masked from 'package:nlme':

lmList

The following object is masked from 'package:brms':

ngrps

```
library(insight)
library(firatheme)
library(purrr)
```

Attaching package: 'purrr'

The following object is masked from 'package:pracma':

cross

```
library(patchwork)
library(glue)
library(tidyverse)
```

```
-- Attaching packages ----- tidyverse 1.3.1 --
```

```
v tibble 3.1.8      v stringr 1.4.0
v readr  2.1.1      v forcats 0.5.1
```

```
-- Conflicts ----- tidyverse_conflicts() --
```

```
x nlme::collapse() masks dplyr::collapse()
x purrr::cross()    masks pracma::cross()
x Matrix::expand() masks tidyr::expand()
x tidyr::extract() masks rstan::extract()
x dplyr::filter()   masks stats::filter()
x dplyr::lag()       masks stats::lag()
x Matrix::pack()     masks tidyr::pack()
x Matrix::unpack()  masks tidyr::unpack()
```

```
cmdstanr::check_cmdstan_toolchain(fix = TRUE)
```

The C++ toolchain required for CmdStan is setup properly!

```
register_knitr_engine(override = FALSE)
```

Data set-up

```
data = read.csv("./data/race_results_view.csv")

# Data processing
## Restricting my analysis to the period 2012-2021
data <- data %>% filter(
  position > 0,
  year > 2011
)
## convert to factors
data <- data %>% mutate(
```

```

    rider_name = as.factor(rider_name),
    team_name = as.factor(team_name)
  )

# New variables
data <- data %>% group_by(year, sequence) %>% mutate(
  position_prop = (n() - position) / (n() - 1),
  prop_trans = (position_prop * (n() - 1) + 0.5) / n()
) %>%
  ungroup()

prior2 <- c(
  prior(gamma(1,1), class = sd)
)

fit_year <- brm(
  formula = prop_trans ~ 0 + (1 | rider_name) + (1 | rider_name:year) + (1 | team_name) +
  family = Beta(),
  prior = prior2,
  data = data,
  backend = "cmdstanr",
  chains = 4,
  cores = 6,
  warmup = 1000,
  iter = 3500
)

```

Start sampling

Running MCMC with 4 chains, at most 6 in parallel...

```

Chain 1 Iteration:    1 / 3500 [ 0%] (Warmup)
Chain 2 Iteration:    1 / 3500 [ 0%] (Warmup)
Chain 3 Iteration:    1 / 3500 [ 0%] (Warmup)
Chain 4 Iteration:    1 / 3500 [ 0%] (Warmup)
Chain 2 Iteration:  100 / 3500 [ 2%] (Warmup)
Chain 3 Iteration:  100 / 3500 [ 2%] (Warmup)
Chain 4 Iteration:  100 / 3500 [ 2%] (Warmup)
Chain 1 Iteration:  100 / 3500 [ 2%] (Warmup)
Chain 2 Iteration:  200 / 3500 [ 5%] (Warmup)

```

Chain 4 Iteration: 200 / 3500 [ 5%] (Warmup)  
 Chain 3 Iteration: 200 / 3500 [ 5%] (Warmup)  
 Chain 1 Iteration: 200 / 3500 [ 5%] (Warmup)  
 Chain 2 Iteration: 300 / 3500 [ 8%] (Warmup)  
 Chain 4 Iteration: 300 / 3500 [ 8%] (Warmup)  
 Chain 2 Iteration: 400 / 3500 [ 11%] (Warmup)  
 Chain 3 Iteration: 300 / 3500 [ 8%] (Warmup)  
 Chain 4 Iteration: 400 / 3500 [ 11%] (Warmup)  
 Chain 1 Iteration: 300 / 3500 [ 8%] (Warmup)  
 Chain 4 Iteration: 500 / 3500 [ 14%] (Warmup)  
 Chain 3 Iteration: 400 / 3500 [ 11%] (Warmup)  
 Chain 1 Iteration: 400 / 3500 [ 11%] (Warmup)  
 Chain 2 Iteration: 500 / 3500 [ 14%] (Warmup)  
 Chain 4 Iteration: 600 / 3500 [ 17%] (Warmup)  
 Chain 1 Iteration: 500 / 3500 [ 14%] (Warmup)  
 Chain 2 Iteration: 600 / 3500 [ 17%] (Warmup)  
 Chain 4 Iteration: 700 / 3500 [ 20%] (Warmup)  
 Chain 3 Iteration: 500 / 3500 [ 14%] (Warmup)  
 Chain 1 Iteration: 600 / 3500 [ 17%] (Warmup)  
 Chain 4 Iteration: 800 / 3500 [ 22%] (Warmup)  
 Chain 2 Iteration: 700 / 3500 [ 20%] (Warmup)  
 Chain 3 Iteration: 600 / 3500 [ 17%] (Warmup)  
 Chain 1 Iteration: 700 / 3500 [ 20%] (Warmup)  
 Chain 4 Iteration: 900 / 3500 [ 25%] (Warmup)  
 Chain 1 Iteration: 800 / 3500 [ 22%] (Warmup)  
 Chain 3 Iteration: 700 / 3500 [ 20%] (Warmup)  
 Chain 2 Iteration: 800 / 3500 [ 22%] (Warmup)  
 Chain 4 Iteration: 1000 / 3500 [ 28%] (Warmup)  
 Chain 4 Iteration: 1001 / 3500 [ 28%] (Sampling)  
 Chain 1 Iteration: 900 / 3500 [ 25%] (Warmup)  
 Chain 3 Iteration: 800 / 3500 [ 22%] (Warmup)  
 Chain 4 Iteration: 1100 / 3500 [ 31%] (Sampling)  
 Chain 2 Iteration: 900 / 3500 [ 25%] (Warmup)  
 Chain 1 Iteration: 1000 / 3500 [ 28%] (Warmup)  
 Chain 1 Iteration: 1001 / 3500 [ 28%] (Sampling)  
 Chain 3 Iteration: 900 / 3500 [ 25%] (Warmup)  
 Chain 4 Iteration: 1200 / 3500 [ 34%] (Sampling)  
 Chain 1 Iteration: 1100 / 3500 [ 31%] (Sampling)  
 Chain 2 Iteration: 1000 / 3500 [ 28%] (Warmup)  
 Chain 4 Iteration: 1300 / 3500 [ 37%] (Sampling)  
 Chain 2 Iteration: 1001 / 3500 [ 28%] (Sampling)  
 Chain 3 Iteration: 1000 / 3500 [ 28%] (Warmup)  
 Chain 3 Iteration: 1001 / 3500 [ 28%] (Sampling)



Chain 1 Iteration: 1200 / 3500 [ 34%] (Sampling)  
Chain 2 Iteration: 1100 / 3500 [ 31%] (Sampling)  
Chain 4 Iteration: 1400 / 3500 [ 40%] (Sampling)  
Chain 3 Iteration: 1100 / 3500 [ 31%] (Sampling)  
Chain 1 Iteration: 1300 / 3500 [ 37%] (Sampling)  
Chain 2 Iteration: 1200 / 3500 [ 34%] (Sampling)  
Chain 4 Iteration: 1500 / 3500 [ 42%] (Sampling)  
Chain 3 Iteration: 1200 / 3500 [ 34%] (Sampling)  
Chain 1 Iteration: 1400 / 3500 [ 40%] (Sampling)  
Chain 2 Iteration: 1300 / 3500 [ 37%] (Sampling)  
Chain 4 Iteration: 1600 / 3500 [ 45%] (Sampling)  
Chain 3 Iteration: 1300 / 3500 [ 37%] (Sampling)  
Chain 1 Iteration: 1500 / 3500 [ 42%] (Sampling)  
Chain 2 Iteration: 1400 / 3500 [ 40%] (Sampling)  
Chain 4 Iteration: 1700 / 3500 [ 48%] (Sampling)  
Chain 3 Iteration: 1400 / 3500 [ 40%] (Sampling)  
Chain 1 Iteration: 1600 / 3500 [ 45%] (Sampling)  
Chain 2 Iteration: 1500 / 3500 [ 42%] (Sampling)  
Chain 4 Iteration: 1800 / 3500 [ 51%] (Sampling)  
Chain 3 Iteration: 1500 / 3500 [ 42%] (Sampling)  
Chain 1 Iteration: 1700 / 3500 [ 48%] (Sampling)  
Chain 2 Iteration: 1600 / 3500 [ 45%] (Sampling)  
Chain 4 Iteration: 1900 / 3500 [ 54%] (Sampling)  
Chain 3 Iteration: 1600 / 3500 [ 45%] (Sampling)  
Chain 1 Iteration: 1800 / 3500 [ 51%] (Sampling)  
Chain 2 Iteration: 1700 / 3500 [ 48%] (Sampling)  
Chain 3 Iteration: 1700 / 3500 [ 48%] (Sampling)  
Chain 4 Iteration: 2000 / 3500 [ 57%] (Sampling)  
Chain 1 Iteration: 1900 / 3500 [ 54%] (Sampling)  
Chain 2 Iteration: 1800 / 3500 [ 51%] (Sampling)  
Chain 3 Iteration: 1800 / 3500 [ 51%] (Sampling)  
Chain 4 Iteration: 2100 / 3500 [ 60%] (Sampling)  
Chain 1 Iteration: 2000 / 3500 [ 57%] (Sampling)  
Chain 2 Iteration: 1900 / 3500 [ 54%] (Sampling)  
Chain 3 Iteration: 1900 / 3500 [ 54%] (Sampling)  
Chain 4 Iteration: 2200 / 3500 [ 62%] (Sampling)  
Chain 1 Iteration: 2100 / 3500 [ 60%] (Sampling)  
Chain 2 Iteration: 2000 / 3500 [ 57%] (Sampling)  
Chain 3 Iteration: 2000 / 3500 [ 57%] (Sampling)  
Chain 4 Iteration: 2300 / 3500 [ 65%] (Sampling)  
Chain 1 Iteration: 2200 / 3500 [ 62%] (Sampling)  
Chain 2 Iteration: 2100 / 3500 [ 60%] (Sampling)  
Chain 3 Iteration: 2100 / 3500 [ 60%] (Sampling)

Chain 4 Iteration: 2400 / 3500 [ 68%] (Sampling)  
Chain 1 Iteration: 2300 / 3500 [ 65%] (Sampling)  
Chain 2 Iteration: 2200 / 3500 [ 62%] (Sampling)  
Chain 3 Iteration: 2200 / 3500 [ 62%] (Sampling)  
Chain 4 Iteration: 2500 / 3500 [ 71%] (Sampling)  
Chain 1 Iteration: 2400 / 3500 [ 68%] (Sampling)  
Chain 2 Iteration: 2300 / 3500 [ 65%] (Sampling)  
Chain 3 Iteration: 2300 / 3500 [ 65%] (Sampling)  
Chain 4 Iteration: 2600 / 3500 [ 74%] (Sampling)  
Chain 1 Iteration: 2500 / 3500 [ 71%] (Sampling)  
Chain 2 Iteration: 2400 / 3500 [ 68%] (Sampling)  
Chain 3 Iteration: 2400 / 3500 [ 68%] (Sampling)  
Chain 4 Iteration: 2700 / 3500 [ 77%] (Sampling)  
Chain 1 Iteration: 2600 / 3500 [ 74%] (Sampling)  
Chain 2 Iteration: 2500 / 3500 [ 71%] (Sampling)  
Chain 3 Iteration: 2500 / 3500 [ 71%] (Sampling)  
Chain 4 Iteration: 2800 / 3500 [ 80%] (Sampling)  
Chain 1 Iteration: 2700 / 3500 [ 77%] (Sampling)  
Chain 2 Iteration: 2600 / 3500 [ 74%] (Sampling)  
Chain 3 Iteration: 2600 / 3500 [ 74%] (Sampling)  
Chain 4 Iteration: 2900 / 3500 [ 82%] (Sampling)  
Chain 1 Iteration: 2800 / 3500 [ 80%] (Sampling)  
Chain 2 Iteration: 2700 / 3500 [ 77%] (Sampling)  
Chain 3 Iteration: 2700 / 3500 [ 77%] (Sampling)  
Chain 4 Iteration: 3000 / 3500 [ 85%] (Sampling)  
Chain 1 Iteration: 2900 / 3500 [ 82%] (Sampling)  
Chain 2 Iteration: 2800 / 3500 [ 80%] (Sampling)  
Chain 3 Iteration: 2800 / 3500 [ 80%] (Sampling)  
Chain 4 Iteration: 3100 / 3500 [ 88%] (Sampling)  
Chain 1 Iteration: 3000 / 3500 [ 85%] (Sampling)  
Chain 2 Iteration: 2900 / 3500 [ 82%] (Sampling)  
Chain 3 Iteration: 2900 / 3500 [ 82%] (Sampling)  
Chain 4 Iteration: 3200 / 3500 [ 91%] (Sampling)  
Chain 1 Iteration: 3100 / 3500 [ 88%] (Sampling)  
Chain 2 Iteration: 3000 / 3500 [ 85%] (Sampling)  
Chain 3 Iteration: 3000 / 3500 [ 85%] (Sampling)  
Chain 4 Iteration: 3300 / 3500 [ 94%] (Sampling)  
Chain 1 Iteration: 3200 / 3500 [ 91%] (Sampling)  
Chain 2 Iteration: 3100 / 3500 [ 88%] (Sampling)  
Chain 3 Iteration: 3100 / 3500 [ 88%] (Sampling)  
Chain 4 Iteration: 3400 / 3500 [ 97%] (Sampling)  
Chain 1 Iteration: 3300 / 3500 [ 94%] (Sampling)  
Chain 2 Iteration: 3200 / 3500 [ 91%] (Sampling)

```

Chain 3 Iteration: 3200 / 3500 [ 91%] (Sampling)
Chain 4 Iteration: 3500 / 3500 [100%] (Sampling)
Chain 4 finished in 183.4 seconds.
Chain 1 Iteration: 3400 / 3500 [ 97%] (Sampling)
Chain 2 Iteration: 3300 / 3500 [ 94%] (Sampling)
Chain 3 Iteration: 3300 / 3500 [ 94%] (Sampling)
Chain 1 Iteration: 3500 / 3500 [100%] (Sampling)
Chain 1 finished in 189.3 seconds.
Chain 2 Iteration: 3400 / 3500 [ 97%] (Sampling)
Chain 3 Iteration: 3400 / 3500 [ 97%] (Sampling)
Chain 2 Iteration: 3500 / 3500 [100%] (Sampling)
Chain 2 finished in 195.8 seconds.
Chain 3 Iteration: 3500 / 3500 [100%] (Sampling)
Chain 3 finished in 196.1 seconds.

```

All 4 chains finished successfully.  
 Mean chain execution time: 191.1 seconds.  
 Total execution time: 196.3 seconds.

Warning: 34 of 10000 (0.0%) transitions ended with a divergence.  
 See <https://mc-stan.org/misc/warnings> for details.

## Model fits

```

#fit_basic = readRDS("./fit/fit_basic.rds")
#summary(fit_basic)

```

```

#fit_year = readRDS("./fit/fit_year.rds")
summary(fit_year)

```

Warning: There were 34 divergent transitions after warmup. Increasing  
 adapt\_delta above 0.8 may help. See <http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup>

```

Family: beta
Links: mu = logit; phi = identity
Formula: prop_trans ~ 0 + (1 | rider_name) + (1 | rider_name:year) + (1 | team_name) + (1 | 1
Data: data (Number of observations: 3184)
Draws: 4 chains, each with iter = 3500; warmup = 1000; thin = 1;

```

```
total post-warmup draws = 10000
```

Group-Level Effects:

~rider\_name (Number of levels: 89)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(Intercept)	0.99	0.12	0.76	1.25	1.00	2167	3825

~rider\_name:year (Number of levels: 298)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(Intercept)	0.45	0.05	0.37	0.54	1.00	1580	3817

~team\_name (Number of levels: 74)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(Intercept)	0.51	0.09	0.36	0.70	1.00	2777	4593

~team\_name:year (Number of levels: 158)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(Intercept)	0.20	0.09	0.02	0.35	1.00	763	1615

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
phi	5.97	0.15	5.69	6.28	1.00	13519	6678

Draws were sampled using `sample(hmc)`. For each parameter, Bulk\_ESS and Tail\_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

## Inference about Rider skills

```
riders_focus <- c("Rossi","Crutchlow","Marquez")
rider_mean <- as_draws_df(fit_year) %>% select(-.chain, -.iteration) %>% select(contains("r
```

Warning: Dropping 'draws\_df' class as required metadata was removed.

```
rider_form <- as_draws_df(fit_year) %>% select(-.chain, -.iteration) %>% select(contains("r
```

Warning: Dropping 'draws\_df' class as required metadata was removed.

```

rider_mean_long <-
  rider_mean %>%
  pivot_longer(-.draw, names_to = "Rider", values_to = "Skill",
    names_pattern = "\\[(\\w{1,10}.*?),..*?\\]") %>%
  mutate(Rider = as.factor(Rider))

rider_form_long <-
  rider_form %>%
  pivot_longer(-.draw, names_to = c("Rider", "Year"), values_to = "Form",
    names_pattern = "\\[(\\w{1,10}).*?(\\d{1,4}).*?,") %>%
  mutate(Rider = as.factor(Rider), Year = as.integer(Year))

rider_skill_summary <-
  merge(x=rider_form_long, y=rider_mean_long, by = c("Rider", ".draw")) %>%
  mutate(skill_yr = Form + Skill) %>%
  group_by(Rider, Year) %>%
  summarise(
    est = mean(skill_yr),
    lower = quantile(skill_yr, 0.055),
    upper = quantile(skill_yr, 0.945),
  )

```

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

```

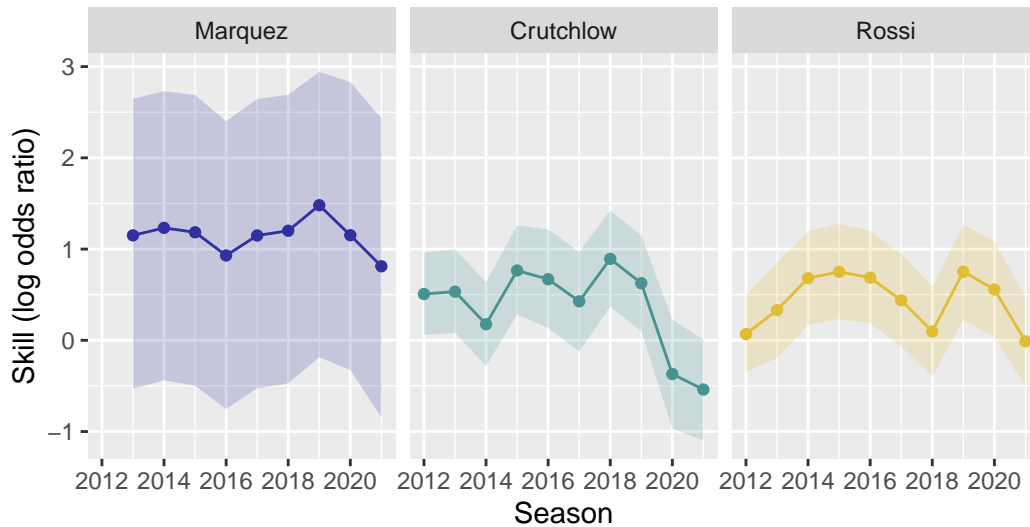
plt_skill_trajectory <-
  rider_skill_summary %>%
  ungroup() %>%
  filter(Rider %in% riders_focus) %>%
  mutate(Rider = fct_reorder(Rider, -est)) %>%
  ggplot(aes(x = Year, y = est, ymin = lower, ymax = upper)) +
  geom_ribbon(aes(fill = Rider), alpha = .2) +
  geom_line(aes(colour = Rider)) +
  geom_point(aes(colour = Rider)) +
  scale_fill_fira(guide = "none") +
  scale_colour_fira(guide = "none") +
  #theme_fira() +
  facet_wrap(~Rider) +
  labs(x = "Season", y = "Skill (log odds ratio)", title = "MotoGP Rider skill trajectories",
    subtitle = "era (2011-2021) Rider skill, \naccounting for yearly team advantage.")

```

```
plt_skill_trajectory
```

## MotoGP Rider skill trajectories

era (2011–2021) Rider skill,  
accounting for yearly team advantage.

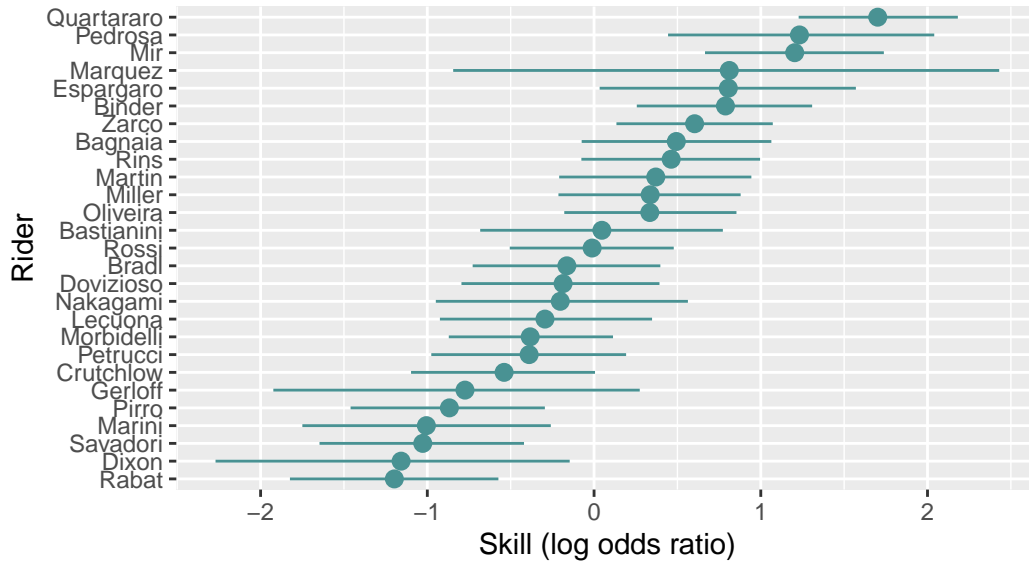


```
plt_rider_skill_2021 <-  
  rider_skill_summary %>%  
  ungroup() %>%  
  filter(Year == 2021) %>%  
  mutate(Rider = fct_reorder(Rider, est)) %>%  
  ggplot(aes(y = Rider, x = est, xmin = lower, xmax = upper)) +  
  geom_pointrange(colour = firaCols[3]) +  
  #theme_fira() +  
  labs(title = "2021 MotoGP rider skill",  
        subtitle = "Accounting for yearly team advantage.",  
        x = "Skill (log odds ratio)",  
        y = "Rider")
```

```
plt_rider_skill_2021
```

## 2021 MotoGP rider skill

Accounting for yearly team advantage.



```
sfit <- summary(fit_year, prob = 0.89)
```

Warning: There were 34 divergent transitions after warmup. Increasing adapt\_delta above 0.8 may help. See <http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup>

```
ranef_summary <- rbind(
  "team" = sfit$random$team_name,
  "team form" = sfit$random$`team_name:year`,
  "rider" = sfit$random$rider_name,
  "rider form" = sfit$random$`rider_name:year`
)[1:4, 1:4]
xtable::xtable(ranef_summary)
```

```
% latex table generated in R 4.1.2 by xtable 1.8-4 package
% Thu Dec 1 19:41:38 2022
\begin{table}[ht]
\centering
\begin{tabular}{rrrrr}
\hline
```

```

& Estimate & Est.Error & l-89\% CI & u-89\% CI \\
\hline
team & 0.51 & 0.09 & 0.38 & 0.66 \\
team form & 0.20 & 0.09 & 0.04 & 0.32 \\
rider & 0.99 & 0.12 & 0.80 & 1.20 \\
rider form & 0.45 & 0.05 & 0.38 & 0.52 \\
\hline
\end{tabular}
\end{table}

```

```

# how much of variance is due to car?
colSums(ranef_summary[1:2,]^2)/colSums(ranef_summary^2)

```

```

Estimate Est.Error l-89% CI u-89% CI
0.2033896 0.4660817 0.1592090 0.2414985

```

```

# and how much due to the driver?
colSums(ranef_summary[3:4,]^2)/colSums(ranef_summary^2)

```

```

Estimate Est.Error l-89% CI u-89% CI
0.7966104 0.5339183 0.8407910 0.7585015

```