

# Supplementary Materials: Search strategies improve with practice, but not with time pressure or financial incentives

ADF Clarke

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These supplementary materials contain more details of the Bayesian analysis, including power analysis. Please see the source Rmd file for full code.

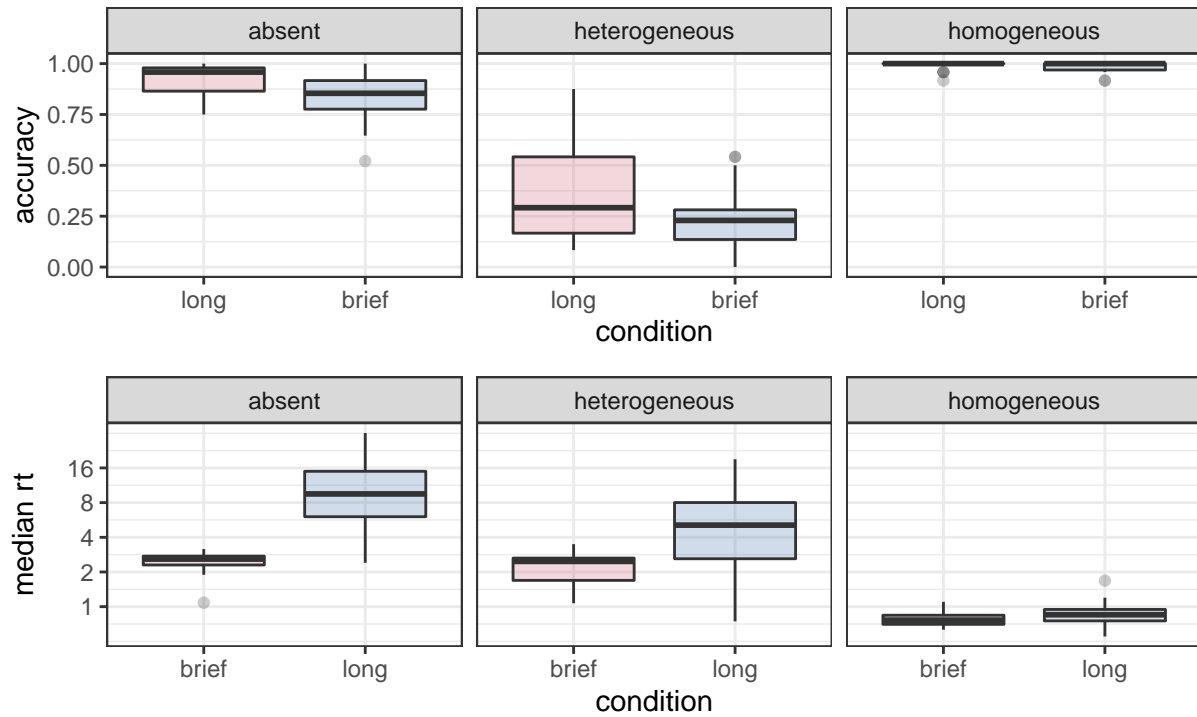
## 1 Experiment 1: Deadline

### 1.1 Descriptive Statistics

We will first look at descriptive statistics for accuracy and reaction time data, to check that it looks sensible and inline with our expectations.

#### 1.1.1 Accuracy and Reaction Time

After plotting the accuracy data, incorrect trials are removed from all further analysis.

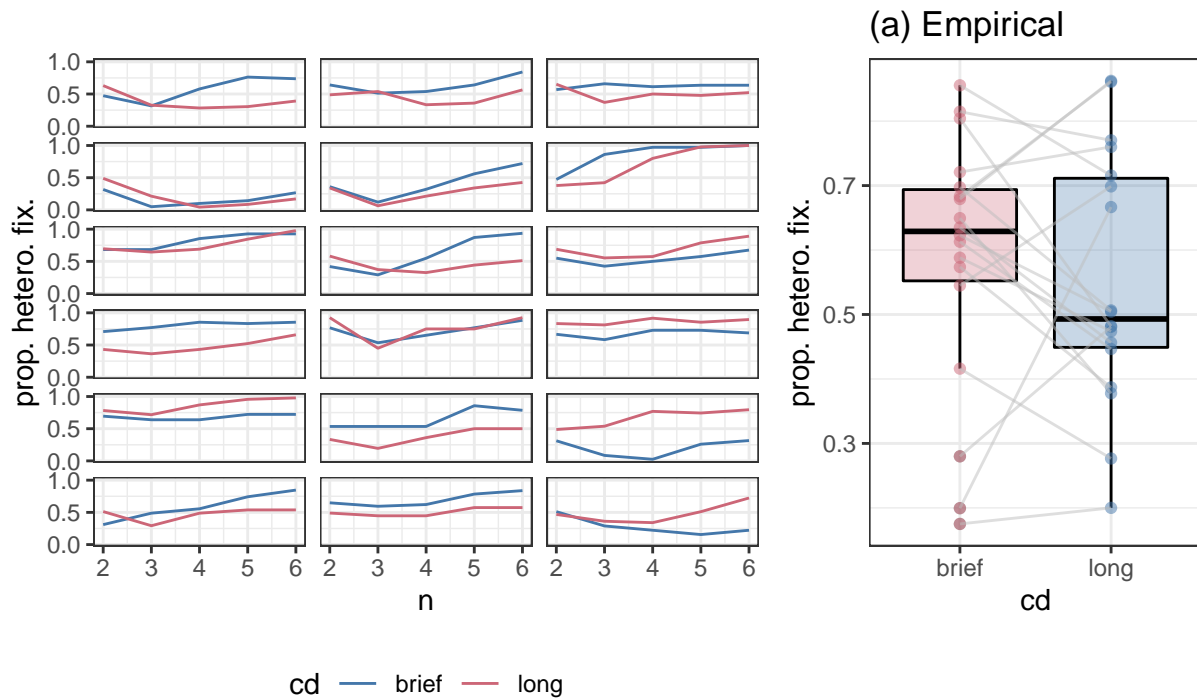


### 1.1.2 Saccadic Strategy

First, we need to merge (join) the fixation and accuracy data, so that we can take only correct target absent trials. We will compute the proportion of fixations to the heterogeneous side of the display for each fixation number, over all trials made by a participant.

Create a facet plot of each individual's strategy.

We can further summarise the data by creating a strategy measure, which is the proportion of all (2 - 6) fixations made by an observer over all trials.



## 1.2 Bayesian Model of Saccadic Strategy

Summarise data so that we have one strategy score per trial per observer.

Note, as beta distributions are only defined over  $(0, 1)$ , values of 0 and 1 are impossible. To get around this, we will set any such values to 0.001 and 0.999 respectively.

### 1.2.1 Define function for plotting model output

I will want to reuse this plotting code, so I will put it in a function here.

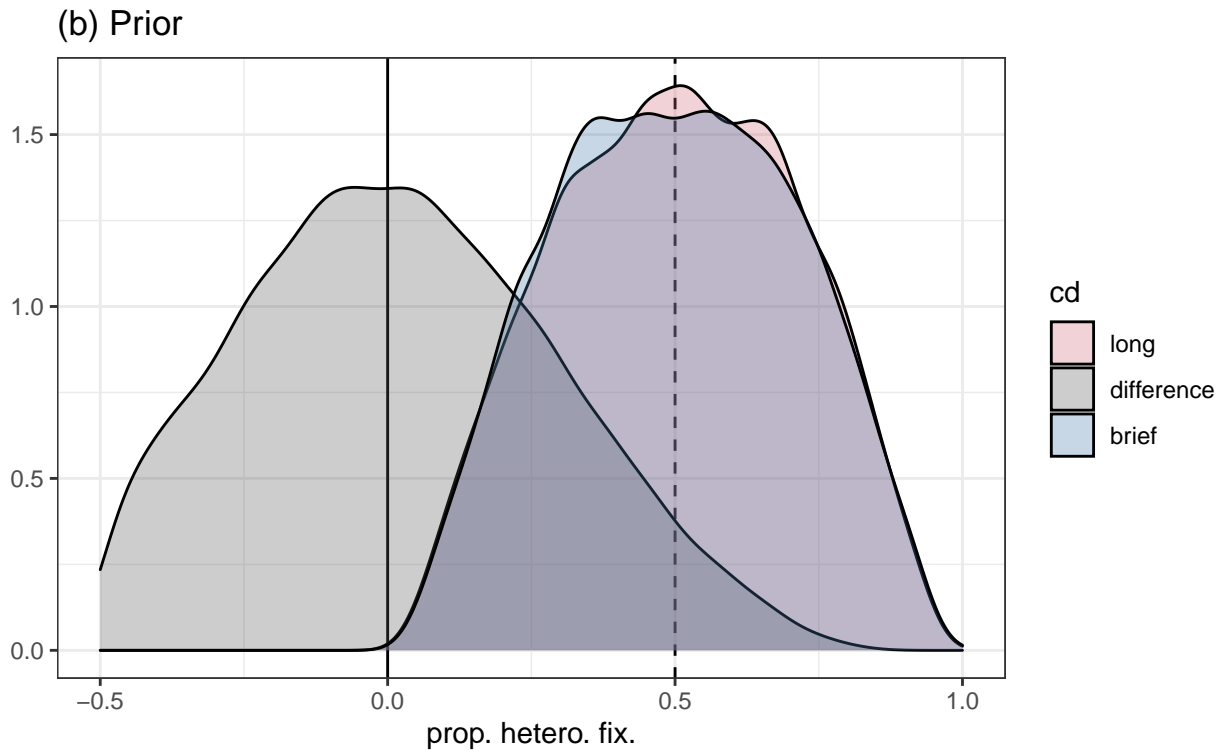
### 1.2.2 Define Priors

We will use  $N(0, 1)$ , weakly informative priors, illustrated in the plot below.

```
model_priors <- c(
  prior(normal(0, 1), class = "b"))

prior_model <- brm(
  data = d_strat,
  prop_hetero ~ 0 + cd + (cd | observer),
  family = "beta",
  sample_prior = "only",
  prior = model_priors,
  iter = 5000,
  control = list(adapt_delta = 0.95))
```

```
## Warning: Removed 460 rows containing non-finite values (stat_density).
```



### 1.2.3 Power Analysis

We will carry out our power analysis by simulating our experiment assuming the distributions below.

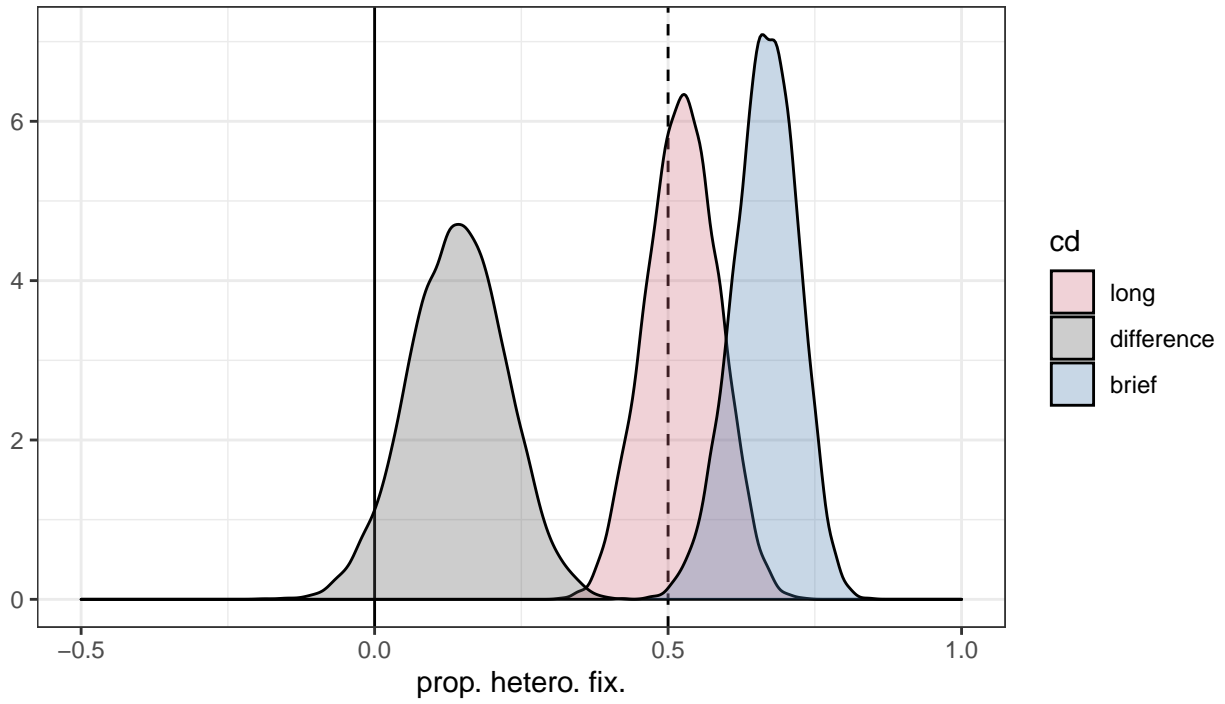
```
power_prior <- c(
  prior(normal(0.1, 0.25), class = "b", coef = "cdlong"),
  prior(normal(0.7, 0.25), class = "b", coef = "cdbrief"),
  prior(student_t(3, 0, 2), class = "sd"),
  prior(gamma(1, 10), class = "phi")
)
```

## Compiling the C++ model

## Start sampling

We can now plot these distributions to check that they seem reasonable.

## Power Predictions

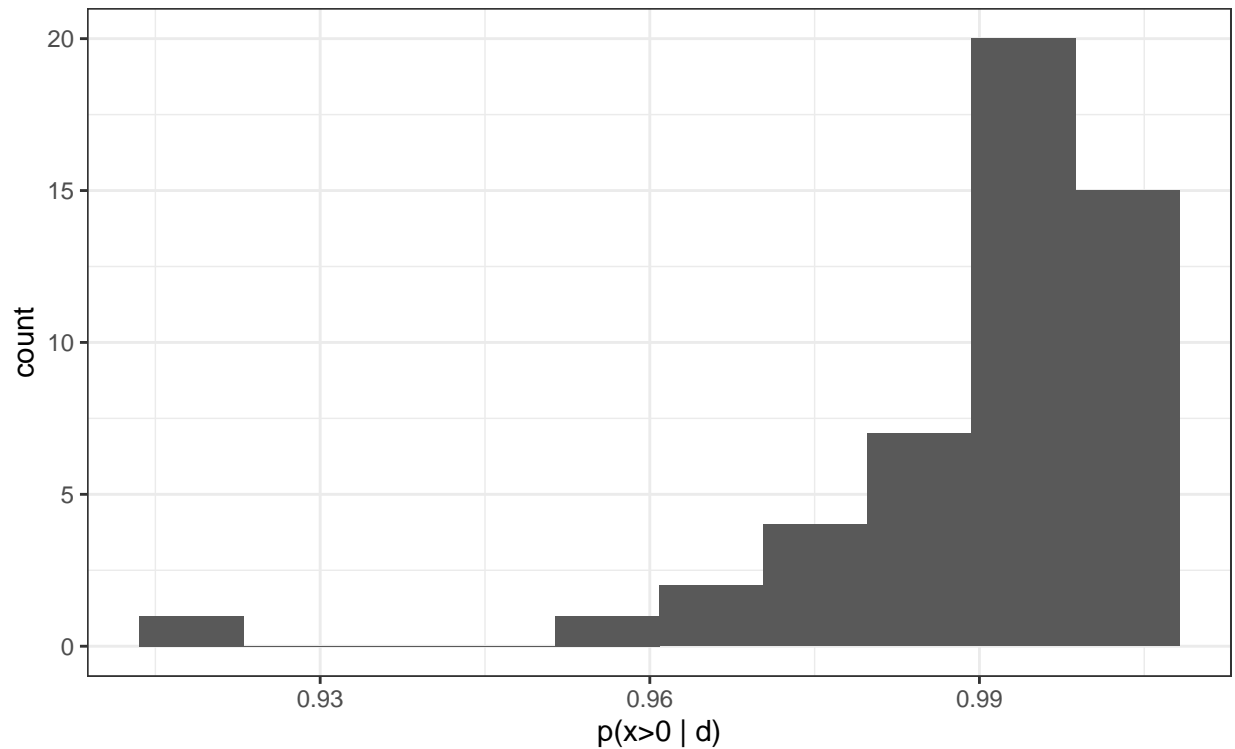


These corresponds to assuming distributions with the means presented below:

cd	mean prop. fix hetero.
brief	0.6096211
long	0.4915794

We now generate multiple (=50) simulated datasets with 15 observers and 32 correct target absent trials. We then compute  $p(\delta > 0|d)$ , (the probability, given the data, of seeing postive difference between the brief and long conditions) for each. The expected distribution of this statistic is shown below. We can see that in (almost?) every iteration, we get a value about 0.95.

And plot!



### 1.3 Compute and Plot Posterior

Now that we are confident that we have a sensible prior, and have carried out a power analysis, it is time to fit the model to the data.

```
my_model <- brm(
  data = d_strat,
  prop_hetero ~ 0 + cd + (cd | observer),
  family = "beta",
  prior = model_priors,
  iter = 10000,
  control = list(adapt_delta = 0.95))
```

```
## Compiling the C++ model
```

```
## recompiling to avoid crashing R session
```

```
## Start sampling
```

```
## Family: beta
```

```
## Links: mu = logit; phi = identity
```

```
## Formula: prop_hetero ~ 0 + cd + (cd | observer)
```

```
## Data: d_strat (Number of observations: 1520)
```

```
## Samples: 4 chains, each with iter = 10000; warmup = 5000; thin = 1;
```

```
## total post-warmup samples = 20000
```

```
##
```

```
## Group-Level Effects:
```

```
## ~observer (Number of levels: 18)
```

```
##
```

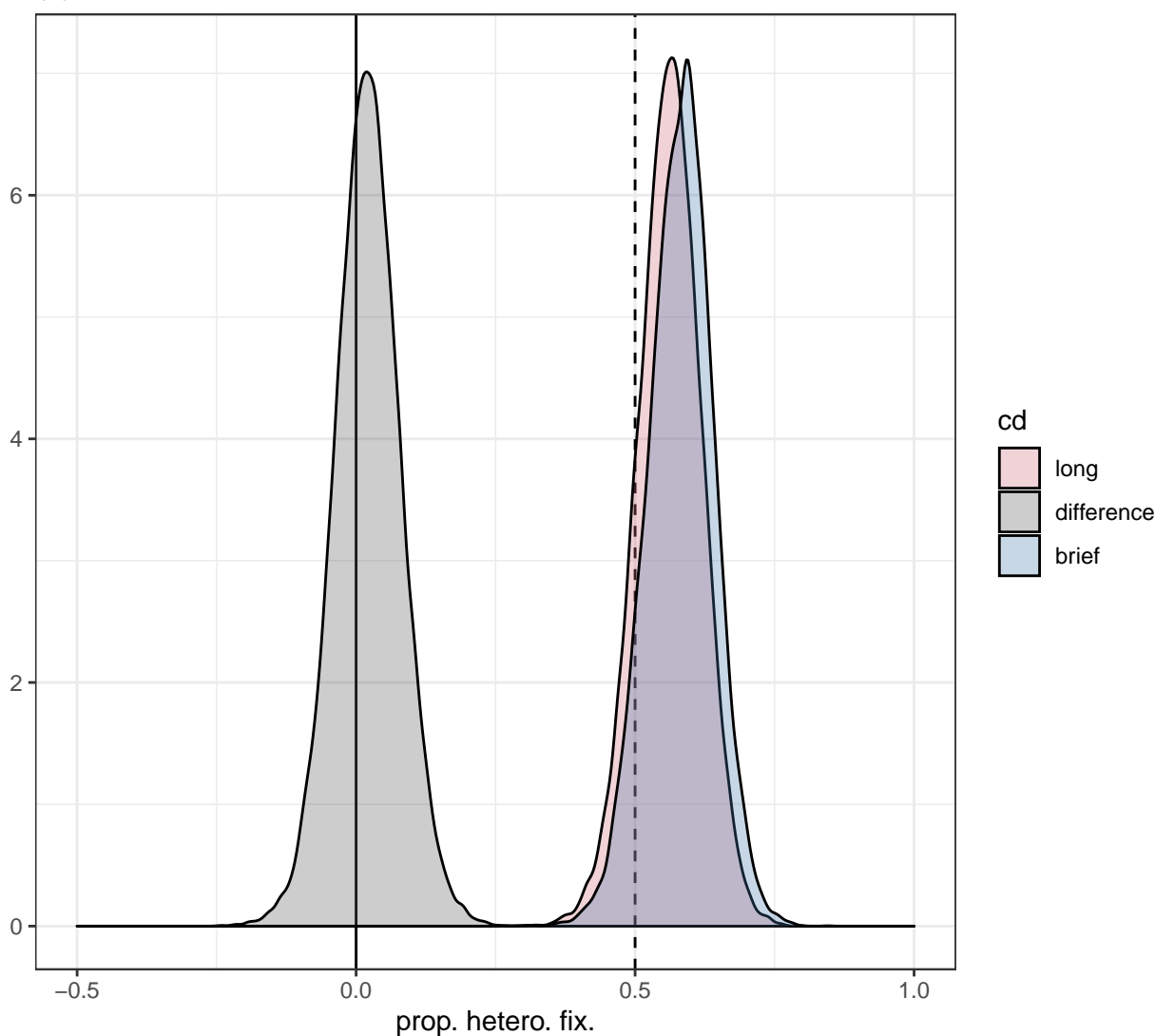
	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(Intercept)	1.06	0.20	0.74	1.53	1.00	4643	7710
sd(cdlong)	1.00	0.20	0.68	1.47	1.00	4901	8020

```
##
```

```
##
```

```
## cor(Intercept,cdlong)    -0.49      0.19    -0.79    -0.06 1.00      6121      8289
##
## Population-Level Effects:
##      Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## cdbrief      0.33     0.24   -0.15    0.82 1.00      3729      5880
## cdlong       0.25     0.24   -0.23    0.71 1.00      4868      7706
##
## Family Specific Parameters:
##      Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## phi        1.71     0.06    1.60    1.83 1.00     17215     12716
##
## Samples were drawn using sampling(NUTS). 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).
```

(c) Posterior



```
## Warning: Removed 460 rows containing non-finite values (stat_density).
```

long	long.lower	long.upper	brief	brief.lower	brief.upper	difference	difference.lower	difference.upper
0.5618581	0.4495512	0.675786	0.5835599	0.4618632	0.6914196	0.0202839	-0.0980948	0.135078

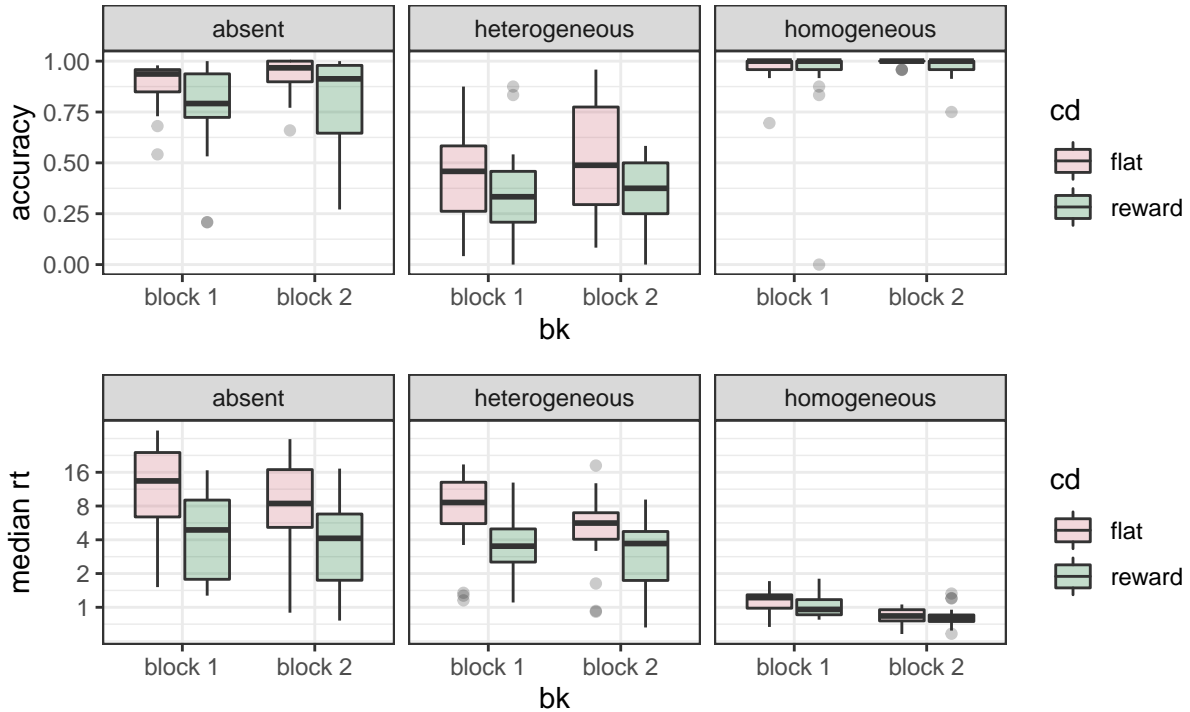
We can conclude that  $p(x > 0 \mid d) = 0.64055$ .

## 2 Experiment 2: Reward

### 2.1 Descriptive Statistics

#### 2.1.1 Accuracy and Reaction Time

After plotting the accuracy data, incorrect trials are removed from all further analysis.



### 2.2 Saccadic Strategy

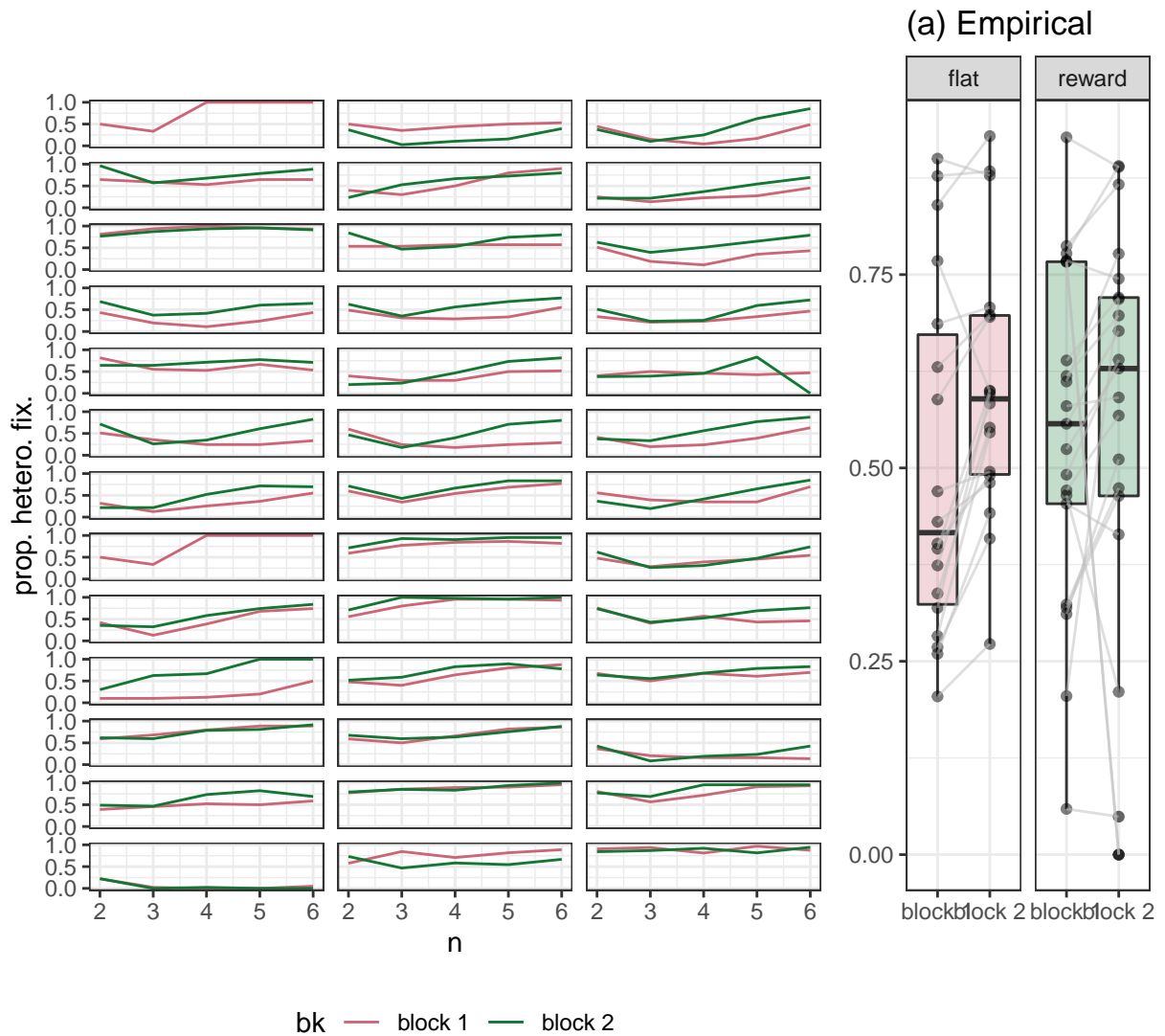
First, we need to merge (join) the fixation and accuracy data, so that we can take only correct target absent trials. We will compute the proportion of fixations to the heterogeneous side of the display for each fixation number, over all trials made by a participant.

Create a facet plot of each individual's strategy.

We can further summarise the data by creating a strategy measure, which is the proportion of all (2 - 6) fixations made by an observer over all trials.

```
## `summarise()` regrouping output by 'observer', 'bk' (override with `.groups` argument)
```





## 2.3 Bayesian Model of Saccadic Strategy

Summarise data so that we have one strategy score per trial per observer.

Note, as beta distributions are only defined over  $(0, 1)$ , values of 0 and 1 are impossible. To get around this, we will set any such values to 0.001 and 0.999 respectively.

### 2.3.1 Define Priors

We will use the same priors, and model structure, as above.

```
model_priors <- c(
  prior(normal(0, 1), class = "b"))

prior_model <- brm(
  data = d_strat,
  prop_hetero ~ 0 + cd + (cd | observer),
  sample_prior = "only",
  family = "beta",
```

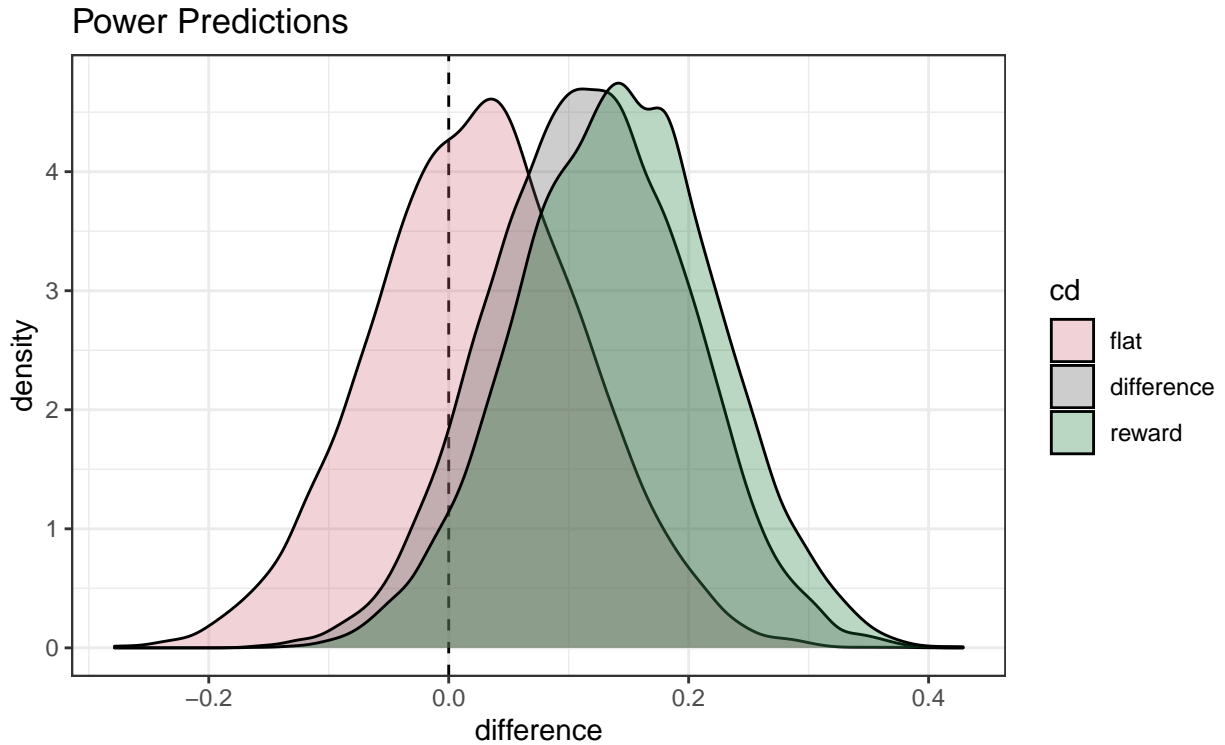
```
prior = model_priors,
iter = 10000,
control = list(adapt_delta = 0.95))
```

And plot, to see if it looks reasonable.

### 2.3.2 Power Analysis

We will carry out our power analysis by simulating our experiment assuming the distributions below.

We can now plot these distributions to check that they seem reasonable.

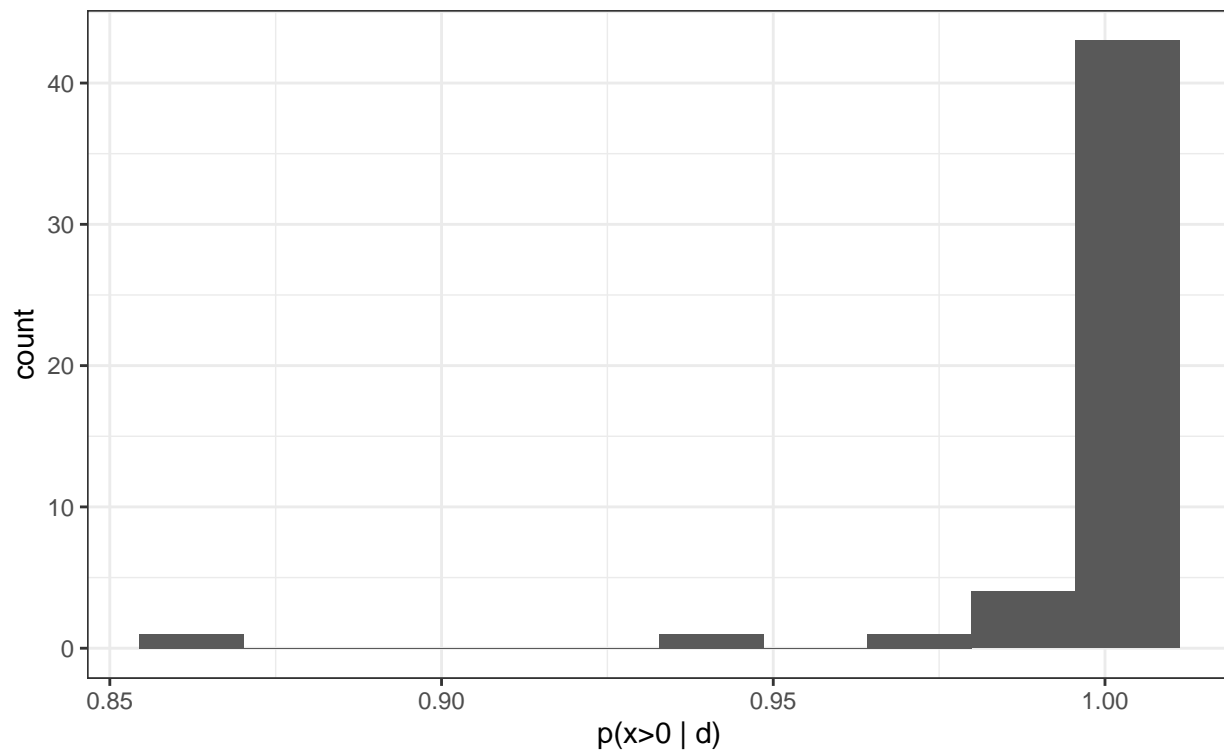


Next, we write a function to generate a simulated dataset.

Now we also need a function that will the key statistic that we are interested in: the probability, given the data, that observers were more strategic in the brief condition than the long.

Finally, we run this a number of times (50) to see the distribution of  $p(\delta > 0|d)$  assuming 15 observers and 32 correct target absent trials.

And plot!



```
## # A tibble: 1 x 1
##   over_90
##   <int>
## 1      49

## # A tibble: 3 x 2
##   cd      mean_ph
##   <chr>    <dbl>
## 1 flat    0.524
## 2 initial 0.523
## 3 reward  0.595
```

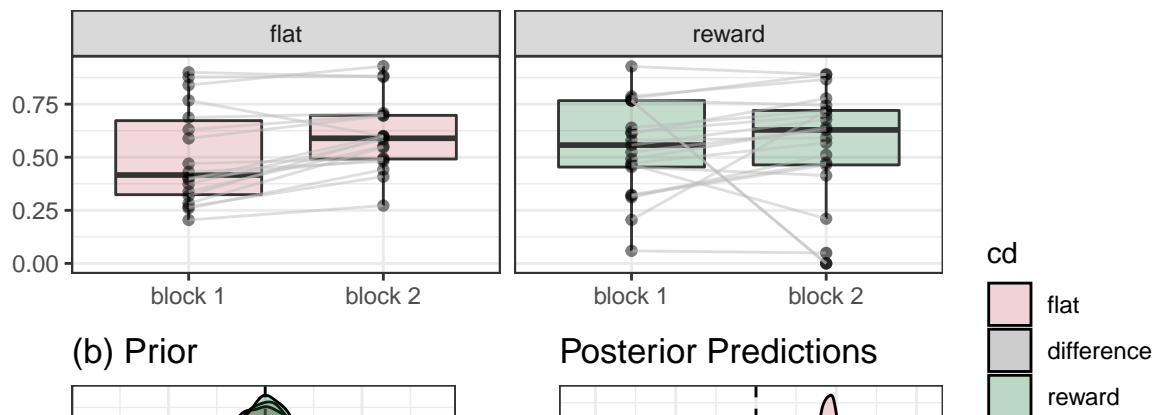
## 2.4 Now refit model using data

```
## Family: beta
## Links: mu = logit; phi = identity
## Formula: prop_hetero ~ 0 + cd + (cd | observer)
## Data: d_strat (Number of observations: 3025)
## Samples: 4 chains, each with iter = 10000; warmup = 5000; thin = 1;
##           total post-warmup samples = 20000
##
## Group-Level Effects:
## ~observer (Number of levels: 39)
##
```

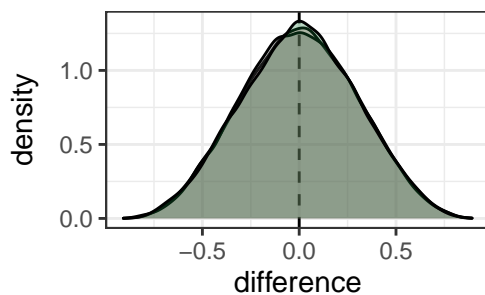
	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS
sd(Intercept)	0.87	0.11	0.69	1.11	1.00	5481
sd(cdreward)	0.48	0.14	0.26	0.80	1.00	8168
sd(cdflat)	0.35	0.10	0.18	0.56	1.00	10237
cor(Intercept,cdreward)	0.01	0.25	-0.46	0.48	1.00	11297
cor(Intercept,cdflat)	-0.57	0.20	-0.87	-0.11	1.00	15536
cor(cdreward,cdflat)	0.01	0.47	-0.84	0.84	1.00	2977

```
##                               Tail_ESS
## sd(Intercept)                 8814
## sd(cdreward)                  12277
## sd(cdflat)                    12701
## cor(Intercept,cdreward)       12046
## cor(Intercept,cdflat)         14843
## cor(cdreward,cdflat)          8162
##
## Population-Level Effects:
##      Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## cdinitial    0.01     0.14  -0.26   0.29 1.00    3024    5423
## cdreward     0.19     0.18  -0.17   0.55 1.00    4376    8079
## cdflat       0.38     0.13   0.12   0.65 1.00    4315    7665
##
## Family Specific Parameters:
##      Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## phi      1.86     0.04   1.78   1.95 1.00   27513    14492
##
## Samples were drawn using sampling(NUTS). 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).
```

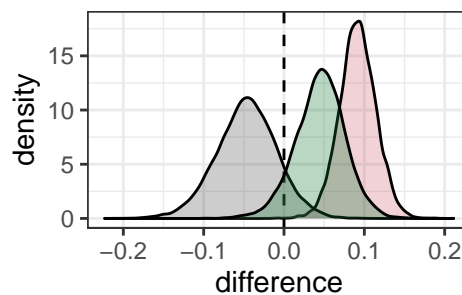
(a) Empirical



(b) Prior



Posterior Predictions



What is the the probability of a difference > 0, given the data?

```
## # A tibble: 1 x 1
##   prob_diff_greater_zero
##   <dbl>
## 1      0.102
##
## # A tibble: 1 x 12
##   flat flat.lower flat.upper reward reward.lower reward.upper difference
##   <dbl>   <dbl>     <dbl> <dbl>   <dbl>     <dbl>     <dbl>
## 1 0.102 0.000 0.200 0.102 0.000 0.200 0.102
```

```
## 1 0.0917      0.0474      0.137 0.0462      -0.0179      0.106      -0.0460
## # ... with 5 more variables: difference.lower <dbl>,
## #   difference.upper <dbl>, .width <dbl>, .point <chr>, .interval <chr>
```

## 2.5 Original Pre-Registered Analysis

We original pre-registered an analysis plan for this experiment using frequentist statistics. The results of this planned analysis are presented here.

### 2.5.1 Accuracy

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: accuracy ~ bk * cd + (1 | observer)
## Data: d_lmer_acc
##
## REML criterion at convergence: -137.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.7596 -0.3331  0.0032  0.4835  2.3775
##
## Random effects:
## Groups Name Variance Std.Dev.
## observer (Intercept) 0.006457 0.08036
## Residual 0.003678 0.06065
## Number of obs: 78, groups: observer, 39
##
## Fixed effects:
##              Estimate Std. Error    df t value Pr(>|t|)
## (Intercept)    0.796026   0.023729 52.634479  33.547 < 2e-16 ***
## bkbblock 2      0.043949   0.020215 37.000000   2.174  0.03617 *
## cdreward      -0.091066   0.032337 52.634479  -2.816  0.00683 **
## bkbblock 2:cdreward -0.009082   0.027549 37.000000  -0.330  0.74350
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) bkbblc2 cdrwr
## bkbblock 2    -0.426
## cdreward      -0.734  0.313
## bkbblck2:cd   0.313 -0.734 -0.426
##
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## bk      0.030104 0.030104     1    37  8.1851 0.006907 **
## cd      0.039275 0.039275     1    37 10.6788 0.002344 **
## bk:cd 0.000400 0.000400     1    37  0.1087 0.743499
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 2.5.2 Median Reaction Time

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: median_rt ~ bk * cd + (1 | observer)
## Data: d_lmer_rt
##
## REML criterion at convergence: 434.4
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.2991 -0.3078 -0.0809  0.3153  3.2528
##
## Random effects:
## Groups Name Variance Std.Dev.
## observer (Intercept) 26.257  5.124
## Residual 5.393  2.322
## Number of obs: 78, groups: observer, 39
##
## Fixed effects:
##              Estimate Std. Error    df t value Pr(>|t|)
## (Intercept)    11.4244    1.3260 43.8324   8.616 5.54e-11 ***
## bkbblock 2     -3.4926    0.7741 37.0000  -4.512 6.30e-05 ***
## cdreward       -7.1036    1.8071 43.8324  -3.931 0.000297 ***
## bkbblock 2:cdreward  2.9688    1.0549 37.0000   2.814 0.007786 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) bkbblc2 cdrwr
## bkbblock 2   -0.292
## cdreward     -0.734  0.214
## bkbblck2:cd  0.214 -0.734 -0.292
##
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## bk          78.174  78.174     1     37 14.4957 0.0005119 ***
## cd          57.004  57.004     1     37 10.5701 0.0024528 **
## bk:cd       42.713  42.713     1     37  7.9202 0.0077858 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: median_rt ~ bk * cd + (1 | observer)
## Data: d_lmer_rt
##
## REML criterion at convergence: 434.4
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.2991 -0.3078 -0.0809  0.3153  3.2528
##
## Random effects:
## Groups Name Variance Std.Dev.
```

```

## observer (Intercept) 26.257 5.124
## Residual 5.393 2.322
## Number of obs: 78, groups: observer, 39
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 11.4244 1.3260 43.8324 8.616 5.54e-11 ***
## bkbblock 2 -3.4926 0.7741 37.0000 -4.512 6.30e-05 ***
## cdreward -7.1036 1.8071 43.8324 -3.931 0.000297 ***
## bkbblock 2:cdreward 2.9688 1.0549 37.0000 2.814 0.007786 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) bkbblc2 cdrwr
## bkbblock 2 -0.292
## cdreward -0.734 0.214
## bkbblc2:cd 0.214 -0.734 -0.292
##
## Type III Analysis of Variance Table with Satterthwaite's method
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## bk 78.174 78.174 1 37 14.4957 0.0005119 ***
## cd 57.004 57.004 1 37 10.5701 0.0024528 **
## bk:cd 42.713 42.713 1 37 7.9202 0.0077858 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 2.5.3 Search Efficiency

```

## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: median_search_ef ~ bk * cd + (1 | observer)
## Data: d_lmer_se
##
## REML criterion at convergence: 2
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -2.0444 -0.4745 0.0963 0.4609 1.4285
##
## Random effects:
## Groups Name Variance Std.Dev.
## observer (Intercept) 0.05182 0.2276
## Residual 0.02207 0.1486
## Number of obs: 78, groups: observer, 39
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) 0.50256 0.04353 50.82578 11.546 8.07e-16 ***
## bkbblock 2 0.13314 0.04749 43.21037 2.804 0.00754 **
## cdreward -0.10718 0.06224 49.94386 -1.722 0.09125 .
## ---

```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr) bkblc2
## bkbblock 2 -0.274
## cdreward   0.000 -0.706
## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
## Missing cells for: bkbblock 2:cdinitial, bkbblock 1:cdreward, bkbblock 1:cdflat.
## Interpret type III hypotheses with care.
## Type III Analysis of Variance Table with Satterthwaite's method
##      Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## bk      0.173494 0.173494      1 43.210  7.8604 0.007539 **
## cd      0.065451 0.065451      1 49.944  2.9654 0.091255 .
## bk:cd
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#### 2.5.4 Discussion

The results are consistent with the analysis presented in the paper

### 3 Time-course Analysis

I will now look to see what happens to search strategy over time: both on the scale of an individual trial, within and across blocks, and between experimental condition! First, I will fit one model to the data from both experiments.

#### 3.1 Prior Predictions

```
model_priors <- c(
  prior(normal(0, 1.0), class = "b"))

m_prior <- brm(
  data = d_strat,
  hetero_fix ~ (0 + cd) * (0 + n) * bk * ts +
    (ts + n | observer) ,
  family = "bernoulli",
  sample_prior = "only",
  prior = model_priors,
  chains = 1)

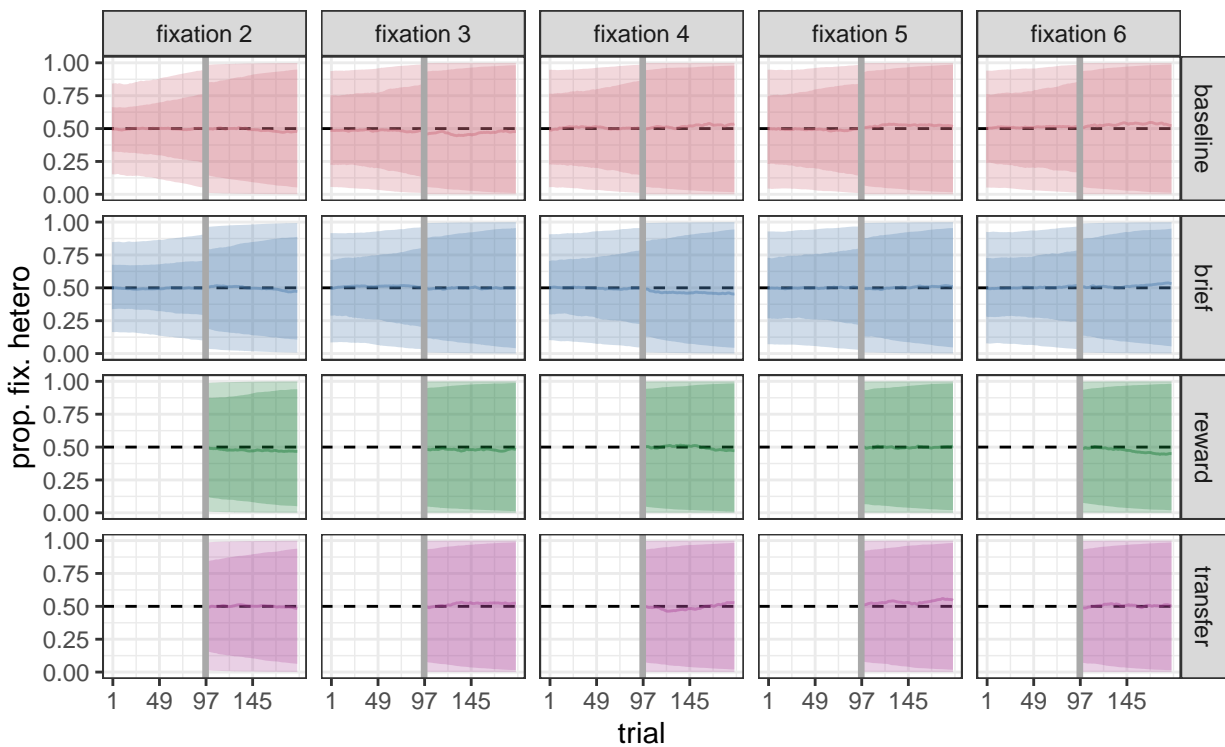
##
## SAMPLING FOR MODEL '3df5a26144c14b1cfd8e30285a5d9b38' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.015828 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 158.28 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
```



```
## Chain 1: Iteration: 1 / 2000 [ 0%] (Warmup)
## Chain 1: Iteration: 200 / 2000 [ 10%] (Warmup)
## Chain 1: Iteration: 400 / 2000 [ 20%] (Warmup)
## Chain 1: Iteration: 600 / 2000 [ 30%] (Warmup)
## Chain 1: Iteration: 800 / 2000 [ 40%] (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%] (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%] (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%] (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%] (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%] (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%] (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 184.764 seconds (Warm-up)
## Chain 1: 169.48 seconds (Sampling)
## Chain 1: 354.244 seconds (Total)
## Chain 1:
```

```
saveRDS(m_prior, "models/my_prior.model")
m_prior <- readRDS("models/my_prior.model")
```

```
## Warning: Removed 10220 row(s) containing missing values (geom_path).
```



## 3.2 Posterior Predictions

```
m_posterior <- brm(
  data = d_strat,
  hetero_fix ~ (0 + cd) * (0 + n) * bk * ts +
  (ts + n | observer) ,
```

```

family = "bernoulli",
prior = model_priors,
chains = 4)

m_posterior <- add_criterion(m_posterior, c("loo", "waic"))

saveRDS(m_posterior, "models/my_posterior.model")
m_posterior <- readRDS("models/my_posterior.model")

## Family: bernoulli
## Links: mu = logit
## Formula: hetero_fix ~ (0 + cd) * (0 + n) * bk * ts + (ts + n | observer)
## Data: d_strat (Number of observations: 21830)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##           total post-warmup samples = 4000
##
## Group-Level Effects:
## ~observer (Number of levels: 57)
##
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## sd(Intercept)      0.93      0.11    0.75    1.16 1.00    1685
## sd(ts)              0.57      0.07    0.45    0.71 1.00    1018
## sd(n3)              0.69      0.09    0.53    0.87 1.00    2126
## sd(n4)              0.91      0.10    0.73    1.13 1.00    1796
## sd(n5)              0.96      0.11    0.78    1.18 1.00    1776
## sd(n6)              0.95      0.11    0.76    1.18 1.00    2032
## cor(Intercept,ts)  -0.57      0.11   -0.75   -0.33 1.00    1287
## cor(Intercept,n3)  0.13      0.15   -0.16    0.42 1.00    1767
## cor(ts,n3)         0.20      0.15   -0.10    0.48 1.00    1429
## cor(Intercept,n4)  0.06      0.14   -0.22    0.33 1.00    1665
## cor(ts,n4)         0.20      0.13   -0.08    0.45 1.00    1374
## cor(n3,n4)         0.91      0.04    0.81    0.97 1.00    1914
## cor(Intercept,n5) -0.10      0.14   -0.36    0.17 1.00    1748
## cor(ts,n5)         0.26      0.13   -0.01    0.51 1.00    1402
## cor(n3,n5)         0.79      0.07    0.62    0.90 1.00    1631
## cor(n4,n5)         0.94      0.03    0.87    0.98 1.00    2773
## cor(Intercept,n6) -0.18      0.14   -0.45    0.09 1.00    2004
## cor(ts,n6)         0.25      0.14   -0.03    0.51 1.00    1567
## cor(n3,n6)         0.64      0.10    0.40    0.81 1.00    1572
## cor(n4,n6)         0.84      0.06    0.71    0.93 1.00    2321
## cor(n5,n6)         0.95      0.03    0.88    0.99 1.00    3058
##
##           Tail_ESS
## sd(Intercept)    2433
## sd(ts)           2030
## sd(n3)           2779
## sd(n4)           2620
## sd(n5)           2664
## sd(n6)           2452
## cor(Intercept,ts) 2168
## cor(Intercept,n3) 2517
## cor(ts,n3)        2550
## cor(Intercept,n4) 2428
## cor(ts,n4)        2485
## cor(n3,n4)        2658
## cor(Intercept,n5) 2569

```

```
## cor(ts,n5)          1936
## cor(n3,n5)          2551
## cor(n4,n5)          3480
## cor(Intercept,n6)   2527
## cor(ts,n6)          2073
## cor(n3,n6)          2083
## cor(n4,n6)          3036
## cor(n5,n6)          3293
```

```
##
```

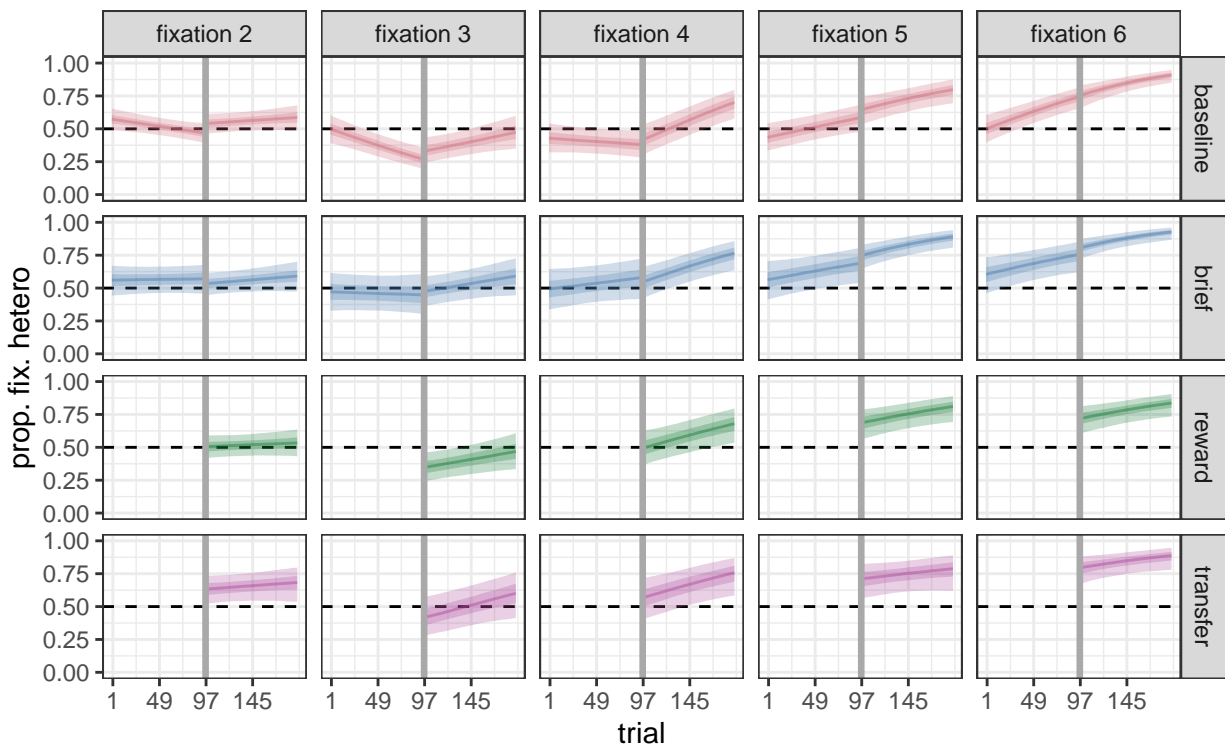
```
## Population-Level Effects:
```

##	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat
## cdbrief	0.24	0.28	-0.33	0.79	1.00
## cdbaseline	0.29	0.20	-0.10	0.69	1.00
## cdtransfer	0.34	0.77	-1.17	1.83	1.00
## cdreward	0.30	0.24	-0.17	0.78	1.00
## n3	-0.36	0.26	-0.85	0.15	1.00
## n4	-0.28	0.27	-0.80	0.26	1.00
## n5	0.01	0.29	-0.55	0.56	1.00
## n6	0.18	0.29	-0.38	0.76	1.00
## bkbblock2	-0.35	0.37	-1.09	0.36	1.00
## ts	0.05	0.26	-0.47	0.54	1.00
## cdbaseline:n3	0.06	0.30	-0.53	0.63	1.00
## cdtransfer:n3	-0.47	0.80	-2.01	1.07	1.00
## cdreward:n3	0.09	0.32	-0.54	0.73	1.00
## cdbaseline:n4	-0.30	0.32	-0.93	0.34	1.00
## cdtransfer:n4	-0.10	0.81	-1.66	1.50	1.00
## cdreward:n4	0.44	0.34	-0.25	1.09	1.00
## cdbaseline:n5	-0.56	0.33	-1.20	0.09	1.00
## cdtransfer:n5	-0.02	0.81	-1.62	1.58	1.00
## cdreward:n5	0.05	0.36	-0.63	0.74	1.00
## cdbaseline:n6	-0.47	0.34	-1.15	0.20	1.00
## cdtransfer:n6	-0.04	0.81	-1.62	1.57	1.00
## cdreward:n6	-0.09	0.36	-0.77	0.64	1.00
## cdbaseline:bkbblock2	0.02	0.42	-0.80	0.85	1.00
## cdtransfer:bkbblock2	0.34	0.77	-1.16	1.84	1.00
## cdreward:bkbblock2	-0.05	0.44	-0.89	0.81	1.00
## n3:bkbblock2	-0.12	0.46	-1.03	0.75	1.00
## n4:bkbblock2	-0.46	0.46	-1.37	0.44	1.00
## n5:bkbblock2	0.16	0.48	-0.78	1.10	1.00
## n6:bkbblock2	0.23	0.48	-0.68	1.16	1.00
## cdbaseline:ts	-0.47	0.30	-1.07	0.13	1.00
## cdtransfer:ts	-0.01	0.74	-1.49	1.42	1.00
## cdreward:ts	-0.54	0.33	-1.17	0.11	1.00
## n3:ts	-0.14	0.33	-0.79	0.50	1.00
## n4:ts	0.31	0.32	-0.32	0.94	1.00
## n5:ts	0.50	0.34	-0.16	1.18	1.00
## n6:ts	0.66	0.33	0.02	1.31	1.00
## bkbblock2:ts	0.20	0.30	-0.39	0.78	1.00
## cdbaseline:n3:bkbblock2	-0.85	0.57	-1.95	0.24	1.00
## cdtransfer:n3:bkbblock2	-0.48	0.80	-2.04	1.09	1.00
## cdreward:n3:bkbblock2	-0.67	0.57	-1.77	0.42	1.00
## cdbaseline:n4:bkbblock2	-0.47	0.56	-1.56	0.62	1.00
## cdtransfer:n4:bkbblock2	-0.10	0.79	-1.60	1.46	1.00
## cdreward:n4:bkbblock2	-0.41	0.58	-1.54	0.72	1.00

## cdbaseline:n5:bkbblock2	0.23	0.57	-0.87	1.34	1.00
## cdtransfer:n5:bkbblock2	0.00	0.81	-1.58	1.54	1.00
## cdreward:n5:bkbblock2	-0.02	0.60	-1.21	1.15	1.00
## cdbaseline:n6:bkbblock2	0.01	0.60	-1.18	1.18	1.00
## cdtransfer:n6:bkbblock2	-0.06	0.82	-1.62	1.57	1.00
## cdreward:n6:bkbblock2	0.02	0.62	-1.22	1.21	1.00
## cdbaseline:n3:ts	-0.43	0.40	-1.19	0.34	1.00
## cdtransfer:n3:ts	0.14	0.75	-1.35	1.62	1.00
## cdreward:n3:ts	-0.36	0.42	-1.18	0.48	1.00
## cdbaseline:n4:ts	-0.09	0.38	-0.84	0.65	1.00
## cdtransfer:n4:ts	-0.06	0.72	-1.47	1.35	1.00
## cdreward:n4:ts	-0.87	0.42	-1.69	-0.04	1.00
## cdbaseline:n5:ts	0.53	0.40	-0.25	1.30	1.00
## cdtransfer:n5:ts	-0.30	0.75	-1.72	1.16	1.00
## cdreward:n5:ts	-0.11	0.43	-0.98	0.74	1.00
## cdbaseline:n6:ts	0.82	0.39	0.05	1.61	1.00
## cdtransfer:n6:ts	-0.20	0.73	-1.66	1.24	1.00
## cdreward:n6:ts	0.06	0.44	-0.77	0.95	1.00
## cdbaseline:bkbblock2:ts	0.43	0.35	-0.24	1.12	1.00
## cdtransfer:bkbblock2:ts	-0.01	0.73	-1.44	1.45	1.00
## cdreward:bkbblock2:ts	0.42	0.36	-0.28	1.10	1.00
## n3:bkbblock2:ts	0.37	0.38	-0.38	1.11	1.00
## n4:bkbblock2:ts	0.47	0.37	-0.29	1.21	1.00
## n5:bkbblock2:ts	0.28	0.40	-0.52	1.08	1.00
## n6:bkbblock2:ts	0.22	0.40	-0.57	0.99	1.00
## cdbaseline:n3:bkbblock2:ts	0.61	0.46	-0.30	1.52	1.00
## cdtransfer:n3:bkbblock2:ts	0.16	0.74	-1.27	1.63	1.00
## cdreward:n3:bkbblock2:ts	0.52	0.47	-0.39	1.45	1.00
## cdbaseline:n4:bkbblock2:ts	0.33	0.45	-0.56	1.19	1.00
## cdtransfer:n4:bkbblock2:ts	-0.06	0.73	-1.47	1.33	1.00
## cdreward:n4:bkbblock2:ts	0.76	0.48	-0.18	1.69	1.00
## cdbaseline:n5:bkbblock2:ts	-0.71	0.47	-1.63	0.20	1.00
## cdtransfer:n5:bkbblock2:ts	-0.28	0.74	-1.74	1.20	1.00
## cdreward:n5:bkbblock2:ts	-0.10	0.50	-1.10	0.85	1.00
## cdbaseline:n6:bkbblock2:ts	-0.69	0.47	-1.61	0.22	1.00
## cdtransfer:n6:bkbblock2:ts	-0.18	0.73	-1.65	1.26	1.00
## cdreward:n6:bkbblock2:ts	-0.36	0.51	-1.36	0.65	1.00
##	Bulk_ESS	Tail_ESS			
## cdbrief	1529	2235			
## cdbaseline	1136	1685			
## cdtransfer	5938	3218			
## cdreward	1690	2254			
## n3	1985	2881			
## n4	1632	2413			
## n5	1648	2685			
## n6	1858	2658			
## bkbblock2	1859	2831			
## ts	1755	2408			
## cdbaseline:n3	1983	2627			
## cdtransfer:n3	5930	2581			
## cdreward:n3	2068	2697			
## cdbaseline:n4	1781	2431			
## cdtransfer:n4	6809	2998			
## cdreward:n4	1979	2744			

## cdbaseline:n5	1773	2889
## cdtransfer:n5	7153	2801
## cdreward:n5	1847	2302
## cdbaseline:n6	2150	3029
## cdtransfer:n6	6832	3005
## cdreward:n6	2295	2693
## cdbaseline:bkbblock2	2073	2632
## cdtransfer:bkbblock2	5472	3046
## cdreward:bkbblock2	2128	2988
## n3:bkbblock2	3382	3253
## n4:bkbblock2	3591	3195
## n5:bkbblock2	3561	3019
## n6:bkbblock2	3860	3265
## cdbaseline:ts	1819	2700
## cdtransfer:ts	5504	3063
## cdreward:ts	1791	2375
## n3:ts	2586	2962
## n4:ts	2602	3071
## n5:ts	2301	2919
## n6:ts	2856	3117
## bkbblock2:ts	1932	2807
## cdbaseline:n3:bkbblock2	4244	3432
## cdtransfer:n3:bkbblock2	6971	3221
## cdreward:n3:bkbblock2	4304	3144
## cdbaseline:n4:bkbblock2	3607	3081
## cdtransfer:n4:bkbblock2	6785	3169
## cdreward:n4:bkbblock2	3995	3161
## cdbaseline:n5:bkbblock2	4121	3413
## cdtransfer:n5:bkbblock2	5866	2765
## cdreward:n5:bkbblock2	4065	3410
## cdbaseline:n6:bkbblock2	4143	3064
## cdtransfer:n6:bkbblock2	6683	2859
## cdreward:n6:bkbblock2	4566	2972
## cdbaseline:n3:ts	2818	2989
## cdtransfer:n3:ts	6242	2965
## cdreward:n3:ts	2808	3118
## cdbaseline:n4:ts	2790	2725
## cdtransfer:n4:ts	6367	3228
## cdreward:n4:ts	3074	3507
## cdbaseline:n5:ts	2639	2857
## cdtransfer:n5:ts	5117	2845
## cdreward:n5:ts	2652	2461
## cdbaseline:n6:ts	3262	3168
## cdtransfer:n6:ts	6407	3217
## cdreward:n6:ts	3367	3298
## cdbaseline:bkbblock2:ts	2264	2788
## cdtransfer:bkbblock2:ts	6190	2884
## cdreward:bkbblock2:ts	2189	3141
## n3:bkbblock2:ts	2630	3021
## n4:bkbblock2:ts	2962	2823
## n5:bkbblock2:ts	2591	2886
## n6:bkbblock2:ts	3243	3463
## cdbaseline:n3:bkbblock2:ts	3242	3190
## cdtransfer:n3:bkbblock2:ts	6197	3244

```
## cdreward:n3:bkbblock2:ts      3214      3329
## cdbaseline:n4:bkbblock2:ts    3428      2979
## cdtransfer:n4:bkbblock2:ts    6603      3368
## cdreward:n4:bkbblock2:ts      2864      2779
## cdbaseline:n5:bkbblock2:ts    3226      3061
## cdtransfer:n5:bkbblock2:ts    5368      2545
## cdreward:n5:bkbblock2:ts      3028      2713
## cdbaseline:n6:bkbblock2:ts    3852      3383
## cdtransfer:n6:bkbblock2:ts    6255      2963
## cdreward:n6:bkbblock2:ts      3494      3051
##
## Samples were drawn using sampling(NUTS). 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).
## Warning: Removed 10220 row(s) containing missing values (geom_path).
```



```
## Warning: Removed 10220 row(s) containing missing values (geom_path).
##      observer      cd      bk      t
## Length:21830      brief :3509 Length:21830      Min.   : 1.00
## Class :character      baseline:9378 Class :character      1st Qu.: 49.00
## Mode  :character      transfer:2026 Mode  :character      Median : 97.00
##                               reward :6917                               Mean  : 97.23
##                                                             3rd Qu.:145.00
##                                                             Max.  :192.00
##
##      n      hetero_fix      ts      targ_side
## 2:4545      Min.   :0.0000      Min.   :0.000      Length:21830
## 3:4486      1st Qu.:0.0000      1st Qu.:0.500      Class :character
## 4:4387      Median :1.0000      Median :1.000      Mode  :character
## 5:4258      Mean   :0.5592      Mean   :1.002
## 6:4154      3rd Qu.:1.0000      3rd Qu.:1.500
```

x	x	x	x	x	x
0.3917148	0.0593147	7.16e-05	0.4776962	0.0712027	80
					40
					40
					20
					16

```
##           Max.    :1.0000    Max.    :1.990
##           rt           acc
##  Min.    : 0.271    Min.    :1
## 1st Qu.: 2.841    1st Qu.:1
## Median : 6.401    Median :1
## Mean   : 9.645    Mean    :1
## 3rd Qu.:13.027    3rd Qu.:1
## Max.   :53.535    Max.    :1
```

### 3.3 Can we easily simplify the model?

I now fit simpler models, removing either one of the four variables, or the four-way interaction.

```
## Compiling the C++ model
## Start sampling
## Compiling the C++ model
## recompiling to avoid crashing R session
## Start sampling
## Compiling the C++ model
## recompiling to avoid crashing R session
## Start sampling

## Warning in mw$n = c(sum(str_count(get_variables(m_posterior), "b_")),
## sum(str_count(get_variables(m_posterior_drop_bk), : Coercing LHS to a list
```

## 4 Session Info

```
## R version 3.6.1 (2019-07-05)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS Mojave 10.14.6
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_GB.UTF-8/en_GB.UTF-8/en_GB.UTF-8/C/en_GB.UTF-8/en_GB.UTF-8
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
```

```

## other attached packages:
## [1] RcppRoll_0.3.0 lmerTest_3.1-2 lme4_1.1-23 Matrix_1.2-17
## [5] patchwork_1.0.0 tidybayes_2.0.2 forcats_0.4.0 stringr_1.4.0
## [9] dplyr_1.0.0 purrr_0.3.4 readr_1.3.1 tidyr_1.1.0
## [13] tibble_3.0.1 ggplot2_3.3.2 tidyverse_1.2.1 brms_2.12.0
## [17] Rcpp_1.0.5
##
## loaded via a namespace (and not attached):
## [1] minqa_1.2.4 colorspace_1.4-1
## [3] ellipsis_0.3.1 ggribes_0.5.1
## [5] rsconnect_0.8.15 markdown_1.1
## [7] base64enc_0.1-3 rstudioapi_0.11
## [9] farver_2.0.3 rstan_2.19.3
## [11] svUnit_0.7-12 DT_0.14
## [13] fansi_0.4.1 lubridate_1.7.4
## [15] xml2_1.2.2 codetools_0.2-16
## [17] bridgesampling_0.7-2 splines_3.6.1
## [19] knitr_1.25 shinythemes_1.1.2
## [21] bayesplot_1.7.0 jsonlite_1.7.0
## [23] nloptr_1.2.2.1 broom_0.5.2
## [25] shiny_1.3.2 compiler_3.6.1
## [27] httr_1.4.1 backports_1.1.8
## [29] assertthat_0.2.1 cli_2.0.2
## [31] later_0.8.0 htmltools_0.3.6
## [33] prettyunits_1.1.1 tools_3.6.1
## [35] igraph_1.2.4.1 coda_0.19-3
## [37] gtable_0.3.0 glue_1.4.1
## [39] reshape2_1.4.3 ggthemes_4.2.0
## [41] cellranger_1.1.0 vctrs_0.3.1
## [43] nlme_3.1-140 crosstalk_1.0.0
## [45] xfun_0.8 ps_1.3.3
## [47] rvest_0.3.4 mime_0.7
## [49] miniUI_0.1.1.1 lifecycle_0.2.0
## [51] gtools_3.8.1 statmod_1.4.34
## [53] MASS_7.3-51.4 zoo_1.8-6
## [55] scales_1.1.1 colourpicker_1.0
## [57] hms_0.5.0 promises_1.0.1
## [59] Brodningnag_1.2-6 parallel_3.6.1
## [61] inline_0.3.15 shinystan_2.5.0
## [63] yaml_2.2.0 gridExtra_2.3
## [65] loo_2.3.0 StanHeaders_2.21.0-5
## [67] stringi_1.4.6 dygraphs_1.1.1.6
## [69] checkmate_2.0.0 boot_1.3-22
## [71] pkgbuild_1.0.8 rlang_0.4.6
## [73] pkgconfig_2.0.3 matrixStats_0.56.0
## [75] HDInterval_0.2.0 evaluate_0.14
## [77] lattice_0.20-38 labeling_0.3
## [79] rstantools_2.0.0 htmlwidgets_1.3
## [81] processx_3.4.3 tidyselect_1.1.0
## [83] plyr_1.8.5 magrittr_1.5
## [85] bookdown_0.18 R6_2.4.1
## [87] generics_0.0.2 pillar_1.4.4
## [89] haven_2.1.1 withr_2.2.0
## [91] xts_0.11-2 abind_1.4-5

```



```
## [93] modelr_0.1.5          crayon_1.3.4
## [95] arrayhelpers_1.0-20160527 utf8_1.1.4
## [97] rmarkdown_2.1          grid_3.6.1
## [99] readxl_1.3.1           callr_3.4.3
## [101] threejs_0.3.1          digest_0.6.25
## [103] xtable_1.8-4           numDeriv_2016.8-1.1
## [105] httpuv_1.5.1           RcppParallel_5.0.2
## [107] stats4_3.6.1           munsell_0.5.0
## [109] shinyjs_1.0
```